Retail Investors' Attention and Insider Trading♣

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Abstract

We document a significant increase in opportunistic insider trades when retail investors are paying greater attention to the stock. Using Google SVI to proxy for their level of attention, we find that a higher (lower) SVI on a stock is associated with more insider sales (purchases) of the stock and greater abnormal returns on the sales (purchases). A value-weighted long-short portfolio mimicking insider trades would earn an abnormal return of 1.19% per month (14.28% per year), excluding transaction costs. We also find that the SVI-related insider traders tend to be non-independent directors who have long tenures but no senior executive positions in their firm and the firm tends to exhibit weaker governance, lower reputation, and poorer social responsibility. Our results are stronger for lottery-type stocks but are weaker for stocks with large attention of local investors. Interestingly, the risk of SEC investigation and litigation is lower on SVI-related insider sales and this type of sales actually rises following an increase in news releases of SEC enforcement action. Our results are robust to various identification tests. Overall, certain insiders appear to engage in trades to take advantage of variations of retail investors' attention to their stock.

Keywords: Investor Attention; Google SVI; Insider Trading

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1. Introduction

Insider trades have long been documented to earn significant abnormal returns (e.g., Seyhun, 1986). In most of the exisitng papers in the literature, insiders possess superior fundamental information about their own firm and therefore are able to exploit their informational advantage for informed trades. For example, insider purchases have been documented to display significant information contents than insider sales[1]. This is particularly evident when those trades are non-routine (Cohen, Malloy, and Pomorski, 2012) and when the firms release the bad news (Bonaime & Ryngaert, 2013). More recently, Alldredge and Cicero (2015) show that insiders may be able to profitably trade on publically available fundamental information about their customers due to their quicker and better appreciation of the dynamics of supplier- and customer-firm relationship. While these studies have mostly focused on fundamental information as the source of insiders' information advantage, we investigate the possilibity that insiders can exploit pricing errors, especially those driven by retail investor attention.

Research has found that investor attention affects stock price. Barber and Odean's (2008) show that retail investors, with limited attention, are more likely to net buyers of stocks on high attention days[2]. By extending their findings, Keloharju, Knupfer, and Linnainmaa (2012) show that investors's familarity and hence their attentiveness to a product can spill-over to their financial decisions. Using Google's Search Volume Index (SVI) on a stock to proxy for retail investors' attention, Da, Engelberg, and Gao (2011) find that a higher SVI is associated with a transient rise in the stock price. We further hypothesize that, if this buying pressure during high attention periods causes the stock price to deviate from its fundamental value, the firm's insiders would be in a unique position to engage in trades that take advantage of such mispricing. For example, a spike in stock price that is unsupported by the firm's fundamentals could provide insiders with a good opportunity to unload their shares at an attractive price.

[1] Lakonishok and Lee (2001) and Jeng, Metrick, and Zeckhauser (2003) argue that this is because that insiders may have other reasons to sell their shares such as reducing their portfolio concentration.

[2] Similarly, investors tend to make their financial decisions when attracted by new or media coverage (Fang and Peress, 2009)), local press coverage (Engelberg and Parsons, 2011), local media slant (Gurun and Butler, 2012), important corporate events such as mergers and acquisitions (Ahern and Sosyura ,2014).

We study the link between retail investors' attention and insider trading by investigating whether a change of Google SVI on a stock affects the direction (buy or sell), volume, and profitability of insiders' trades on the stock. As Da, Engelberg, and Gao (2011), we use Google SVI to capture retail investors' attention to stock and construct the stock's monthly abnormal SVI (ABSVI). Following Cohen, Malloy, and Pomorski (2012), we focus on non-routine – opportunistic – insider trades.

Our results support a strong link between the ABSVI and insider trading activities. We find that a 1% increase SVI in a month predicts a 0.21% decrease of abnormal return on the stock in the subsequent month, suggesting that insiders would benefit by selling (or refraining from buying) shares when the volume of Google search is high on the stock. Indeed, a higher (lower) ABSVI- Log (ABSVI) Positive (Negative) is associated with 18,619 more insider sales (4,164 more insider purchases); that is, the pattern of insider trading is contrarian to retail investors' attention level and the contrarian trades generate significant abnormal returns. The observation that insider trades tend to be contrarian is broadly in line with the findings in other studies (e.g., Lakonishok and Lee, 2001; Jeng, Metrick, and Zeckhauser, 2003; Cohen, Malloy, and Pomorski, 2012). However, our focus on how retail investors' attention affects insider trading is new and interesting. Furthermore, potential profits of such insider trades are substantial. We show that a long-short portfolio mimicking attention-based insider trading would generate an abnormal return of about 119 basis points per month (14.28 % per year), excluding transaction costs.

An interesting question concerns which insiders are more likely to engage in SVI-related trades. We find that the insider traders tend to be non-independent directors who have long tenures but have no senior positions (CEO, CFO, COO, and Chair of the board) in their firms. The firms exhibit weaker governance, lower reputation, and poorer social responsibility. They also operate in more states, have more concentrated product sales, and are financially healthier. All these are largely consistent with the characteristics of opportunistic insider traders and their firms documented in Cohen, Malloy, and Pomorski (2012).

Research has found that lottery-type stocks, ones that have a low price, high idiosyncratic volatility and skewness, attract less sophisticated retail investors (Kumar, 2009). If the SVI on a lottery-type stock reflects the level of interest of less sophisticated investors in the stock, the firm's insiders would benefit more from SVI-related trades. Consistent with this prediction, we find that our basic results are more pronounced for lottery-type stocks. In particular, this type of stock is more likely to be sold (bought) by insiders when the stock's SVI – a proxy of retail investors' attention to the stock – is higher (lower).

Other measures have been used to proxy for investor attention, including news and media headlines or reports (Barber and Odean, 2008; Yuan, 2008; Fang and Peress, 2009), extreme returns or trading volumes (Gervais, Kaniel, and Mingelgrin, 2001; Barber and Odean, 2008; Hou, Xiong, and Peng, 2009), and advertising expenditure (Grullon, Kanatas, and Weston, 2004; Chemmanur and Yan, 2009; Lou, 2014). Da, Engelberg, and Gao (2011) note that Google's SVI is a better measure of investor attention because it is a direct, reliable, and timely reflection of investor interest in the stock. Clearly, individuals who take time and effort to Google-search a stock are self-revealing of their genuine interest in the stock (Ding and Hou, 2015). The other measures do not capture this interest in a timely manner or fail to explain a large variation of SVI. For example, news coverage, a popular proxy for investor attention, fails to explain a large volume of Google searches. The SVI measure possesses two additional advantages: it is a continuous measure and it does not assume that investors are actually aware of the news.

One concern is that a stock's abnormal SVI (ABSVI) is endogenous and may simply reflect retail investors' reactions to information flows such as news, reports or other items that affect the stock. An implication is that if the effect of the information flow is accounted for, the ABSVI would have little relevance to insider trading. We address this concern with several additional analyses. First, if information flow is driving our results, we would expect that the flow would affect institutional investors' search activities. We control for abnormal institutional search activities and find our results to be robust. Second, we control for factors that are known to affect investor attention, such as earnings surprise, advertising expenditure to sales, macro variables on GDP data and FOMC interest rate decisions, earning announcement dummy, previous return and trading volume, as well as the lottery features. After controlling for these factors, the unexplained component of ABSVI remains a significant factor to opportunistic insider trades.

Third, we take advantage of exogenous variations in investor attention by performing subsample analyses on holiday versus non-holiday months. Liu, Peng and Tang (2016) find that abnormal attention is low for summer and December months. We find that insiders indeed tend to sell less on the holiday months than on non-holiday months. We also carry out an IV-test using holiday months and macro variables as instruments and our test results support the results. Further tests support the validity of our instruments.

Fourth, we perform another subsample analysis by classifying a firm-month as either an earnings news month if the firm releases its earnings in the month, or a non-earnings news month if it does not. While our results are more pronounced for the subsample of earnings news month – indicating the importance of the news – they remain significant with the same signs for the subsample of non-earnings news month. To the extent that the unexplained part of ABSVI reflects changes in retail investors' sentiment towards the stock, our results suggest that opportunistic insider trading may be taking advantage of retail sentiment that is unrelated to the stock's fundamentals.

Another concern is that the SVI may be influenced by insider trading activities. For example, increased insider trading activities may cause investors to pay more attention to the stock by carrying out more Google searches. To address this issue, We perform two checks, using regulatory changes as exogeneous shocks. The first check utilizes a political regime change. We decompose our sample period of 2004-2014 into two subsample periods of 2004-2008 and 2009-2014, with the former being the years of the more laissez faire Republican Bush Administration and the later being those of the more activist Democratic Obama Administraion. The presumption is that the Obama Administration would be more active in taking enforcement actions against questionable insider trades and thus would have a stronger deterrence on opportunistic insider sales. However, our results remain unchanged during the two subsample periods.

In the second check, we use as exogneous shocks the number of news releases of SEC investigation and litigation against illegal insider trading. More SEC activities would presumably have a greater deterence effect on insider sales in the subsequent month. Cohen, Malloy, and Pomorski (2012) document an overall reduction in opportunistic insider sales, following an increase in SEC investigation and litigation.[3] Now, if insider sales were to affect the SVI, we

[3] The SEC defines illegal insider trading as insiders buy or sell a security, in breach a fiduciary duity or other relationship of trust and confidence, while in possession of material, nonpublic information about the security. For

would expect a lower SVI, following the month of more active SEC. This is not the case; there are no discernible changes in the SVI surrounding SEC actions.

Interestingly, when we classify opportunistic insider sales as being either SVI-related or non-SVI-related. We find that following the month of increased SEC enforcement activities, insiders' non-SVI-related sales decline but their SVI-related sales actually increase. The latter is in contrast to Cohen, Malloy, and Pomorski's (2012) finding of an overall decline in opportunitistic insider sales. It is possible that insiders view the SVI-related sales as relying more on publicly available information and therefore being less likely to be subject to regulatory sanctions. Consistent with this point of view, we find that SVI-related insider sales have a lower risk of being investigated and litigated by the SEC.

The rest of the paper is organized as follows. Section 2 reviews the literature on investor attention and on insider trading and develops testable hypotheses. Section 3 describes the sample selection procedures and methodology and provides summary statistics. Section 4 presents the empirical findings. Section 5 concludes.

examples, on September 14, 2014, the SEC charged two former Wells Fargo employees for trading on an analyst rating change on their firm stock before the report was publicly available, and on November 21, 2014, the SEC charged a former CEO of GenTek, who had tipped a close friend of non-public information concerning his firm's forthcoming merger.

2. Literature Review and Hypothesis Development

2.1 Investor Attention

Merton (1987) introduces the concept of investors' attention to the field of finance, arguing that their attention is relevent to stock market activities because stock price is affected by the firm's general visibiliy such as publicity, popularity, and social image in the marketplace.[4] Hirshleifer (2001) suggests that with limited attention, investors focus only on a subset of available information, leading to the potential misvaluation of assets. Limited attention or increased market-wide uncertainty can also cause investors to pay more attention to the information that has broader sector or market implications and less on that of firm-specific nature (Peng and Xiong, 2006; Peng, Xiong, and Bollerslev, 2007). Barber and Odean (2008) find that individual investors increase their informational searches on a stock that catches their attention and are predisposed to buy the stock, exerting an upward pressure on its price.

What attracts individual investors' attention to a particular stock? Keloharju, Knupfer, and Linnainmaa (2012) suggest that individuals' familarity with a firm's products may spill over to an interest in the stock. Fang and Peress (2009) argue that news or media coverage is another channel that attracts individuals to a stock, and this channel is especially important for stocks of small firms or with large individual ownerships, low analyst coverage, and high idiosyncratic risk. Indeed, Engelberg and Parsons (2011) show that local press coverage has a strong influence on local investors' trading interests in the stock. Further, feedback loops may develop among media coverage, investor sentiment, and stock price. For example, pessimism of the media may exert downward pressure on the price of stock, resulting in poor stock returns; the poor returns in turn reforce and can give rise to additional media pessimism. With this in mind, firms may choose to manage messages or inflence media coverage. Ahern and Sosyura (2014) report that during important corporate events such as mergers and acquisitions, managers actively influence

[4] Merton's argument builds on a large body of psychological research suggesting that human attention is a scarce resource. The scarcity of attention refers to both selection and intensity since one always has alternatives to engage in (Kahneman,1973). Pashler & Johnston (1998) argue that human beings are constrained by their cognitive limits, so that mutiple tasking often does not work out successfully. Fischhoff, Slovic, and Lichtenstein (1977) argue that people often fail to filter in relevent information when they allocate their attention and hence underweigh the probablities of contingencies that are not explicitly available at the time of decision making.

media coverage to affect their stock prices. Gurun and Butler (2012) find that advertising spending steers local media to put more "postive slant" in its reporting of local firms.

Although media coverage has been used to proxy for investor attention, the availability of Google's Search Volume Index (SVI) on individual stocks offers a direct measure of retail investors' interest in particular stocks (Da, Engelberg, and Gao, 2011; Ben-Rephael, Da, and Israelsen, 2017). Da, Engelberg, and Gao (2011) find that a higher SVI on a stock is associated with more contemporary retail purchases of the stock, resulting in a temporary spike in the stock price. Relatedly, Joseph and Zhang (2011) find that the SVI predicts stock returns and trading volume, especially for more volatile or difficult-to-arbitrage stocks. In Vozlyublennaia (2014), the SVI is seen to reflect investors' demand for information.

Since retail investors do not usually possess superior information when they trade, more trades by these investors arising, for example, from their increased attention to a stock implies an increase in "noise trading" and hence liquidity on the stock. Consistent with the view that a larger volunme of Google searches on a stock improves its liquidity, Ding and Hou (2015) document a negative relationship between a stock's SVI and its bid-ask spreads. Now, it is well known that noise trading provides camouflage for informed trades, enabling informed traders (e.g., insiders) to profit from trading on their private information (e.g., Kyle, 1985; Kyle and Wang, 1997).[5] Moreover, noise trading arising from retail investors' changes of sentiment can affect stock price by making rational arbitrage riskier (Shleifer and Summers, 1990), and noise trading in general can have a greater impact on stock price than implied by its size because uninformed but rational investors may take noise as containing real information (Mendel and Shleifer, 2012).[6]

[5] In an equilibrium model, Kyle (1985) shows that insider trading is profitable only at the expenses of noise traders, and the higher the level of noise trading, the greater are the insider profits. To the extent that a rise (fall) in the Google SVI predicts an increased (a decreased) level of noise trading, our empirical findings are consistent with the implication of the Kyle model. Informed traders who profit from noise traders are sometimes referred to as "smart money." For example, Individual Investor (in its February 1998 issue, pp. 54) summarizes the smart money as "company executives and directors" who "know their business more intimately than any Wall Street analyst even would" and "know when a new product is flying out the door, when inventories are pilling up, whether profit magins are expanding or wheter production costs are raising."

[6] In this model, unlike insiders who possess valuable information or noise traders who are vulnerable to sentiment shocks, rational outsiders are only able to learn information from the stock price they observe.

2.2 Insider Trading

Empirical studies on insider trading in the U.S. has long established that corporate insiders have better information about their firm and earn significant abnormal returns on their trades of own firm stock (e.g., Seyhun, 1986). The existing literatures describe that insider trades indeed predict future abnormal returns. For example, insiders tend to sell more before they their accounting misstatement is revealed (Agrawal & Cooper, 2015), generate substantial returns using their social networks (Ahern, 2017)[7], are mostly opportunistic in nature prior to the quarterly eanings announcements (Ali & Hirshleifer, 2017).[8] Hence, if the market is semi-stronge efficient, this return prediction should be an outcome of insiders extensively using inside information.

Further research documents asymmetric profits and information content between insider purchases and sales of shares. Lakonishok and Lee (2001) find that insider buying is more informative than selling, and Jeng, Metrick, and Zeckhauser (2003) document significant abnormal returns only on insider purchases of shares. An explanation for the apparent lack of information content on insider sales is that insiders may have other important reasons to sell shares – for example, to reduce the portfolio concentration. More recently, Cohen, Malloy, and Pomorski (2012) classify insider trades into "routine" and "non-routine" types and show that only non-routine (or opportunistic) trades are informative and generate abnormal returns. Additionally, they find that opportunistic traders tend to be non-independent directors who have long tenures but no senior executive responsibilities in their firms, and the firms also tend to have weaker governance and external monitoring. Hillier, Korczak, and Korczak (2015) examine how insiders' attributes affect the performance of their trades and find that such personal traits as age, gender, and education are important to the performance.

Our paper builds on the recent research on insider trading. Following Cohen, Malloy, and Pomorski (2012), we also classify insider trades as being either routine or opportunistic (non-routine). Insider trades that are based on Google's SVI are clearly opportunistic. In Alldredge and Cicero (2015), supply-firm insiders profit by selling their own firm's shares when newly

[7] Ahern (2017) defines social networks based on family, friends, and geographic proximity.
[8] Example of other works include Agrawal and Nasser (2012), Agrawal and Cooper (2014), Cicero and Wintoki (2014).

public information sheds negative light on the firm's major customers. While in Alldredge and Cicero (2015), insiders' information advantage is due to fundamental information, we focus on a setting where insiders information advantage resides in pricing errors generated by retail attention. In this regard, our paper contributes to the insider trading literature by providing a new channel that emphasizes the role of liquidity or noise traders in providing the basis for insiders' trading profits.

Other research suggests that insiders time their trades to certain corporate activities. Lo and Cheng (2006) find that managerial insiders time the release of their firm's bad news before purchases of shares. Bonaime & Ryngaert (2013) document more frequent insider trades in quarters when their firm is buying back shares. Furthermore, when their firm is repurchasing shares, insiders who also buy earn higher abnormal returns on the purchases, and insiders who sell tend to be from a firm that offers a large quantity of executive stock options or that has low stock liquidity and a low equity book-to-market ratio. Evidence also suggests that managerial insiders take strategic actions to generate profitable trading opportunities. Lou (2014) finds that managers increase their firm's advertising expenditure before the firm's equity issues and before their sales of shares. Ahern and Sosyura (2014) suggest that managers manipulate media coverage to influence stock price during important corporate events such as mergers and acquisitions. We too examine how insiders may time their trades to increase trading profits. However, we differ in that insiders are shown to trade on the basis of shifting retail investors' attenton to their firm stock, as proxied by the stock's SVI. Such trades may be less likely subject to regulatory enforcement actions against illegal insider trading**.**

2.3 Hypothesis Development

Researchers have identified a number of pitfalls of retail investors that may be exploited by sophisticated investors. For example, retail investors are informationally disadvantaged (Kyle, 1985), and they may be less than fully rational in investment decisions. More specifically, retail investors tend to exhibit overconfidence (Fischhoff, Slovic, and Lichtenstein, 1977), trade aggressively and take excessive risks (Hirshleifer and Teoh, 2003). Their trades are significantly influenced by sentiments (Shleifer and Summers, 1990) and earn negative alphas (Han and Kumar, 2013). Moreover, trading behaviors of retail investors may result in misleading signals to rational but insufficiently informed investors, affecting the latter's ability to arbitrage (Mendel and Shleifer, 2011). All these suggest that corporate insiders, with their informational advantage, may be in a unique position to exploit the pitfalls of retail investors. Insiders may prefer the type of trades that profit from the behavior biases of retail investors because such trades that rely largely on publicly available information would be less likely to face investor lawsuit and regulatory enforcement. In particular, an increase in the buying or selling interest of retail investors, driven by their changing sentiments or perceptions but unsupported by the fundamental value of the stock, may present insiders with good opportunities for contrarian trades.

As in Da, Engelberg, and Gao (2011), Google's SVI captures retail investors' level of attention to, or interest in, a particular stock. Since retail investors are net buyers of stock that catches their attention (Barber and Odean, 2008; Joseph, Wintoki, and Zhang, 2011), their aggregate buying could exert pressure on the stock price, causing it to deviate from the intrisic value. In particular, if an increase in a stock's SVI indicates a rising interest of retail investors in the stock, it would result in a (temporary) rise in the stock price, thereby providing an opportunity for the firm's insiders to trade on this mispricing. Thus, our main hypothesis contends that an increase in the level of retail investors' attention to a stock – a higher ABSVI – is associated with more active and profitable insider trades.

Hypothesis 1 (H1): A higher level of retail investors' attention (a higher Abnormal Google SVI, ABSVI) leads to a larger volume and greater profit of insider trading.

It is possible that the greater attention of retial investors might stimulate the flow and dissemination of firm-specific information, making stock price more informative and reducing opportunities for profitable insider trading. If this is the case, a higher ABSVI – an increase in investor attention – would be associated with fewer and less profitable insider trades. Related to this alternative point of view, sone studies suggest that insufficient attention of investors can be detrimental to their welfare. For example, Daniel and Hirshleifer (2002) argue that inattentive investors provide opportunities for the firm to exploit them by issuing overvalued equity shares, by managing earnings upward or guiding analyst forecasts, or by lobbying to alter accounting regulations. Hirshleifer and Teoh (2003) suggest that investors' limited attention could be a source of mispricing by causing them to allocate insufficient time and effort to understand the salient content of firm disclosures. In contrast, Vozlyublennaia (2014) finds that a higher level of investor attention is associated with a lower predictability of stock returns. Based on these arguments, a competing hypothesis is that an increase in retail investors' attention to a stock – a higher ABSVI – could diminish opportunities for profitable insider trading.

Hypothesis 2 (H2): A higher level of retail investors' attention (a higher Abnormal Google SVI, ABSVI) leads to a smaller volume and lower profit of insider trading.

3. Data and Methodology

3.1 Data

We obtain data for our analysis from several sources. Insider trading data is from Table 1 of the Thomson Reuters Insider Database, which includes all equity-related transactions filed by insiders to the SEC via Forms 3, 4, and 5.[9] To ensure accuracy of insider trading data, we retain only transactions that are verified by Thomson Reuters based on a cleanse code of R, H, L, C, or Y. We exclude observations with transaction prices that are either more than three times or less than one third of the closing price on the transaction day since they are very likely to have resulted from data errors.

We focus on opportunistic (non-routine) insider trades by excluding trades that are deemed routine. As in Cohen, Malloy, and Pomorski (2012), a routine trade is one executed by an insider who made a similar trade in the same month of the year for the last three years. We drop trades that are linked to insiders' stock options transactions. With these exclusions, our sample consists of only opportunistic open-market buying or selling by insiders. We aggregate insider trading data at a monthly firm level. Seyhun (1998) argues that aggregate insider trading predicts stock movement and may be used to time the market**.** We define a sale (purchase) month as a calendar month in which at least one insider trades his/her firm's shares, resulting in a net decrease (increase) in his/her equity stake. If we observe a net sale by one insider and a net purchase by another at the same firm-month, this observation is excluded because of ambiguity concerning the direction of insider trades.

[9] Form 3 includes all insiders who register equity securities for the first time with the SEC. Form 4 documents any changes of ownership upon a transaction that must be reported within two business days. Form 5 reports any missing transactions on Form 4 from those insiders who are eligible for deferred reporting.

As Da, Engelberg, and Gao (2011), we use Google's Search Volume Index (SVI) to proxy for retail investors' attention to a particular stock since most Google searches on a stock are carried out by individual investors having some interest in the stock.[10] The SVI also captures investors' attention to the stock in a more direct and timely fashion than do measures such as extreme returns or news items.[11] We collect SVI information between years 2004 and 2014 by manually inputting a stock's ticker symbol into the Google Trend and downloading its SVI data into a CSV file. After compiling the data for all tickers, we divide them into two groups based on the frequency of availability of SVI data. An "attention" group consists of all stocks whose ticker symbols have weekly SVI information, indicating frequent searches on the tickers. A "non-attention" group, on the other hand, contains stocks whose ticker symbols do not have weekly SVI information; that is, these tickers are searched so infrequently that they either have no SVI or only monthly SVI information.[12] As Da, Engelberg, and Gao (2011), we exclude ambigious ticker symbols, for examples A, AUTO, ALL, B, BABY, BED, DNA, GPS, GAS, and GOLF, since they could be associated with things unrelated to stock.[13] We collect a stock's SVI at two different points in time to ensure that our sample is consistent over time.

Other data sources include stock market return data and delisting information from the Center for Research in Security Prices (CRSP) and firm characteristic data (balance sheet and income statement items) from the Compustat North America. Our sample contains only common stocks (CRSP share codes 10 and 11) and excludes illiquid stocks (those with a price of less than $5 or a market capitalization of less than $100 million). All variables are winsorized at 1% and 99% to minimize outlier effects. Combining the SVI and insider trading data with the information on stock returns and firm characteristics results in a total of 92,834 firm-month observations from January 2004 through November 2014.[14] The attention sample has 52,477 net sale months (3,096 unique firms) and 16,997 net purchase months (2,667 unique firms) while the

[10] The SVI is a relative measure that is constructed by Google Trends as the search interest relative to the highest point on the chart.
[11] Da, Engelberg, and Gao (2011) show a postive but weak correlation between Google SVI and other attention measures such as news coverage. They argue that this is because Google SVI is a continuous measure and news coverage does not guarantee investors' attention unless they are actually aware of the news.
[12] For Robustness checks, our inferences do not vary if monthly SVI firms are excluded from the non-attention sample and included in attention sample although significance levels become weaker because we include low attention firms.
[13] We also run the same regressions without excluding those ambiguous tickers, our results remain unchanged.
[14] Our sample ends on November 2014 because monthly CRSP return data are available only till December 2014.

non-attention sample has 15,739 net sale months (1,224 unique firms) and 7,621 net purchase months (1,063 unqiue firms).

A stock's monthly SVI is the arithmatic mean of its weekly SVI in the month,[15] and the stock's abnormal monthly SVI (ABSVI) is its SVI in the month scaled by that in the previous month. As an example, Figure 1 illustrates Apple stock's SVI (ticker: AAPL) between January 2004 and December 2004, where Panel A displays its weekly SVI and Panel B shows its monthly SVI derived from the weekly SVI. Comparing Panels A and B shows that the monthly SVI preserves the shifts of investor attention, especially during the months of significant increase or decrease. Checking Apple insiders' trading patterns following each monthly SVI, and using a + (-) sign to denote a net sale (purchase) month, we see in Panel B that insiders appear to have timed their trades with peaks and troughes of monthly SVI – high and low levels of retail investors' attention. In particular, Apple insiders executed more sell (buy) orders during peak (trough) SVI months. The aggregate volume of sales on peak months were substantially higher than that on trough months, and the total volume of insider trading decreased dramatically after peak months. The insiders' trading patterns suggest a correlation between their trades and retail investors' attention (proxied by its ABSVI). Barber & Odean (2008) argue that retail investors are net buyers of attention-grabbing stocks and their concentrated purchases result in a (temporary) rise in the stock price.[16] Thus, Panel B provides suggestive evidence that insiders could benefit by selling shares during the period when share prices are overvalued due to retail attention.

[Insert Figure 1 Here]

3.2 Methodology

Our approach to empirically test whether abnormal returns of opportunistic insider trades are related to retail investors' attention is as follows. First, we investigate abnormal returns following trades by insiders of firms in our attention sample vis-à-vis those in our non-attention

[15] There are instances where weekly SVI data near the end of a calendar month encompass the beginning days of next month. In such instances, we use a simple proportion to the number of days in a month to achieve the closest approximation of investor attention in the month. For example, between September 28th and October 4th of 2008, Apple has a weekly SVI of 69, and the portion of SVI that is allocated to September is 30 (3/7 of 69) and to October 39 (4/7 of 69).

[16] They define an attention-grabbing stock as one having an extreme one-day return, experiencing an abnormal trading volume, or being in the news.

sample. Next, within the attention sample, we check abnormal returns of insider trades when there is an abnormal level of attention. We compute stock abnormal returns in two ways. In the first, we compute stock return in the calendar month subsequent to a trading month, adjusting for the return of a comparable size decile profolio based on NYSE breakpoints. This method controls for market-related risk factors that affect firms of similar size. In the second, we calculate excess stock return as the stock return minus the risk-free rate and use the excess return as dependent variable in our baseline regression.[17] To address the question of whether investor attention affects insider trading, we regress one-month excess returns following the trade month onto equal-weighted market returns (to control for market risk) as well as control variables that count for risk factors such as firms' market values, book-to-market ratios, and past stock returns. Similar regressions are employed in Cohen, Malloy, and Pomorski (2011) and Alldredge and Cicero (2015).

[Insert Table 1 Here]

Table 1 presents the summary statistics of our sample. Panel A of Table 1 shows that our sample contains no selection bias as its characteristics are generally similar to the insider trading universe. Panel B shows that firms in the attention sample are substantially larger than those in the non-attention sample. We include our main variable (abnormal good search-ABSVI) as well as variables of sample firms' characteristics. The average ABSVI is 1.01 for insider sales sample versus 0.98 for insider purchases sample. The sample mean difference of 0.03 is statistically significant (T-value=13.13) as well as economically significant (%increase of ABSVI=3.06%). This implies that a higher (lower) ABSVI is associated with more insider sales (purchases). The mean market capitalization is \$6.74 billion (\$5.48 billion) for attention sample firms with insider sales (purchases), and is \$1.07 billion (\$0.66 billion) for non-attention firms with insider sales (purchases). Bigger firms have a larger investor base, and therefore, are more likely to attract investors' attention with active Google searches. However, the book-to-market ratio is only marginally different between attention and non-attention sample firms. Interestingly, attention firms with insider sales have more non-routine *traders* but fewer non-routine *trades* per firm-month than do non-attention firms with insider sales. This difference suggests that although

[17] A stock's excess return is defined as its monthly return minus the one-month risk-free rate reported in Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.

attention firms have more opportunistic insider traders, the insiders engage in sales only when circumstances warrant the sales. In comparison, attention firms with insider purchases have fewer non-routine traders and fewer non-routine trades per firm-month than do non-attention firms with insider purchase. These observations suggest that high (low) retail attention results in an upward (downward) pressure on stock prices (consistent with Barber & Odean, 2008), and induce more insider sales (purchases).

Figure 2 illustrates the time-series patterns of insider trading for years 2004 through 2014. Attention sample firms have fewer trades per insider in sale months and in most purchase months than do non-attention firms. The number of insider trades is also smaller for attention firms. These patterns are consistent with our contention that attention firm insiders are more likely to engage in *opportunistic* trades, for example, when greater investor attention suffices tradable *opportunities*. Our prelimiary observations remain consistent throughout the sample period.

[Insert Figure 2 Here]

Table 2 reports the distribution and average monthly ABSVI of our sample firms across the Fama and French 17 industry classifications. Panel A shows that our attention sample includes more financial companies (16.40%) and machinery and business equipment firms (12.05%) than does our non-attention sample. In the attention sample, 74.5% of financial companies are commercial banks (e.g., Bank of America Corp.: BAC) while the rest are insurance and other financial companies; 20.2% of the machinery and business equipment firms are producers of eletronic components (e.g., Microchip Technology: MCHP). These two industries are also the largest segments in the non-attention sample (financial companies 27.51% and machinery and business equipment firms 10.90%). In the non-attention sample, 60.6% of the financial companies are commercial banks (e.g., First United bankcorp: FUBC); 29.1% of the machinery and business equipment firms are manufactuers of eletronic components (e.g., CHIPPAC, Inc.: CHPC). The retail stores industry constitutes only a relatively small percentage in both attention and non-attention samples.

[Insert Table 2 Here]

Panel B of Table 2 depicts the level of abnormal attention – the average monthly ABSVI – during insider purchase and sale months across the 17 industries. Sale months are more likely than purchase months to be associated with higher levels of abnormal investor attention. Indeed, 13 out of 17 industries have a statistically significant higher abnormal attention level in sale months than in purchase months. Firms that operate in relatively small industries of mining and minerals, steel, and transportation have highest levels of investor abnormal attention during insider sale then purchase months, suggesting that these industries' insiders trade more during the months of high investor abnormal attention.

4. Empirical Findings

4.1 Investor Attention and the Profitability of Insider Trading

We first examine whether insiders' trading profits are related to investor attention. Similar to the approach in Cohen, Malloy, and Pomorski (2011) and in Alldredge and Cicero (2015), we define a calendar month as an insider sale (purchase) month if there is at least one net insider seller (buyer) of shares but no net insider buyer (seller) in the same month. Table 3 reports one-month cumulative abnormal returns (CARs) following the insider trade month, adjusted by NYSE size decile portfolio returns, where Panel A (B) displays the results following the insider sale (purchase) month. As mentioned, NYSE size decile portfolios control for market factors that affect firms of similar size.

Panel A of Table 3 shows that insider sales earn higher abnormal returns when investor attention to the stock is greater – when ABSVI is present. In particular, following insiders' sale months, CARs on average are -0.688% per month for our attention firm sample and -0.495% for our non-attention firm sample. The difference of CAR of 0.193% per month is statistically significant (T-statistics = 3.78). CARs are also less negative (-0.541%) in months in which attention firms receive no attention, and the difference of 0.147% per month (between -0.541% and -0.688%) is also statistically significant (T-statistics = 2.56). Translating into annualized returns, insider sales during high attention months results in 8.26% abnormal returns, while the abnormal return is only 6.49% (5.94%) during months of low (no) investor attention. These results suggest that investor attention, measured by the SVI, is an important contributor to the profitability of insider sales.

[Insert Table 3 Here]

We further examine the profitability of insider selling by various insider types. The difference of CAR between our attention and non-attention samples stems mainly from sales by attention firms' non-executive directors (only directors) and other non-executive insiders (other insiders), whose sales earn 0.446% and 0.249% more, respectively, than those of the same types of insiders of non-attention firms. In comparison, sales by top executives of attention firms earn 0.215% more than those of their counterparts in non-attention firms. In both attention and non-attention samples, however, when top-level officers do sell shares, their sales generate greater CARs than those of other insiders. This comparison suggests that when top executives sell shares, they likely rely on their superior information about own firms, while other insiders appear to also utilize opportunistic sales to take advantage of retail investors' increased attention.

Panel B of Table 3 presents the results of parallel tests on insider purchases. Consistent with the findings in previous research, average CARs following insider purchases are greater than those following insider sales. Within purchase firms, CARs from our attention sample are smaller than those from our non-attention sample. Average size-adjusted CARs following the insider purchase month are 1.010% for attention firms and 1.215% for non-attention firms, and the difference of 0.205% is statistically significant (T-statistics = 3.12). Similar patterns are evident on different classifications of insiders. Thus, when investors are paying greater attention (when the SVI is higher), purchases by insiders of all types earn lower CARs. The result again supports the argument that greater investor attention puts an upward pressure on stock price, making insider purchases less (sales more) profitable.

To analyze the role of investor attention on returns following insider trading, we perform mutivariate regressions that control for other risk factors. We regress stock excess returns % onto various explanatory varables including size and book-to-market ratio. Table 4 presents the results of the return analysis, where Panel A (B) presents the percentage of abnormal returns following the insider sale (purchase) month. In all model specifications, we include the firm fixed effect to control for potentially unobservable insider trading patterns that could be persistent. Panel A (B) presents return regressions following the insider sale (puchase) months, where attention measures are included as a dummy variable in Column 2, and as a continuous variable in Columns 3 through 7.

Column 1 in Panel A (B) presents a strong evidence of abnormal returns following the insider sale (puchase) month, where the intercept is a statistically significant amount of 6.3011 (2.5791). This is consistent with Cohen, Malloy, & Pomorski's (2011) result that opportunistic insider sales lead to positive abnormal returns in the following month. An explanation for this finding is that insiders have other reasons to sell shares, for example, to diversify their porfolio holdings. Thus, sales by insiders while investor attention is high present them with opportunities to unload their shares at lower opportunity costs (less foregone returns). Insider trading is subject to significant regulatory and policy constrains. Many large corporations put in place strict compliance policy to deter questionable insider trading (Lakonisjok and Lee, 2001) and a big part of securities regulation is SEC enforcement against illegal insider trading. The SEC tends to scrutinize more on insider sales than purchases (Agrawal and Cooper, 2015). Thus, when insiders do sell shares, they would want to minimize potential problems with the SEC. In this regard, insider sales that arise from a greater level of investors' attention may pose a lower risk of violating insider trading regulation.[18] Our evidence is consistent with this view. In Panel A of Table 4, Column 2 shows the coefficient on the attention dummy, indicating greater investor attention, is -0.2547 (T-statistics = 2.06) on insider sales, and in Panel B, it is -0.3131 (T-statistics = 2.73) on insider purchases. The negative coefficients suggest that a higher level of investor attention increases potential profits of insider sales but reduces those of insider purchases. Interestingly, intercepts become insignificant, implying the attention measure indeed captures the magnitude of abnormal returns.

[Insert Table 4 Here]

Column 3 shows that the coefficient of Log(ABSVI) is highly significant and negative on both insider sales (-0.2123 in Panel A) and purchases (-0.4737 in Panel B). Column 4 includes additional explanatory variables, including SVI Duration – the number of months between a trade month and the first month when a valid SVI was available. This variable can have two opposite effects on insiders' trading profits. On one hand, the SVI duration reflects a lengthy or durable interest of investors in the stock, creating more opportunities for insider trades. On the other hand, a sustained interest of investors may enable them to learn from experience and

[18] There are a substantial number of insiders who sell (purchase) shares when investors' attention is low (high). In later tests, we classify them as non-SVI-related trades.

become more sophisticated investors, reducing insider trading opportunities. Our evidence supports the latter conjecture. The coefficent of Log(SVI Duration) is positive on sales (0.1131 in Panel A) but negative on purchases (-1.0741 in Panel B), both statistically significant. That is, insiders' abnormal returns diminish on both their sales and purchases as the length of investors' attention increases. We include in Column 4 the Log(Analysts) variable, capturing the number of analysts covering the stock, to control for publicly available information which may affect retail investors' attention. We expect insiders' abnormal profits to diminish when more analysts cover the stock since more analysts provide more information to the public, thereby reducing insiders' informational advantage and dimishing their opportunities for profitable trades. Consistent with this prediction, the coefficient on Log(Analysts) is significant and positive on insider sales (0.0621 in Panel A), although the coefficient is insignificant on insider purchases (in Panel B).

To disentangle the main results from the information hypothsis, we further include the abnormal institutional searches (ABISVI) obtained from the Bloomberg terminal. To ensure the consistency and comparability of search measures, we utilitize the same approach as indicated by Google SVI to construct ABISVI. First, we aggregate the insitutional searches into the weekly measure. Then, the institutional search volume index (ISVI) is constructed as the weekly ISVI scaled by the highest point. As our monthly retail SVI measure, we average the weekly ISVI into the monthly level. Finally, the ABISVI is constructed as the monthly ISVI scaled by its previous month. If our results are mainly driven by the retail ABSVI, we would expect to observe the coefficient of ABISVI to be positive or even significant to attenuate potential abnormal returns. Column 5 provides consistent evidence that the coefficients of Log(ABISVI) are both positive although it remains only significant for the insider purchase sample. To summarize, the high level of institutional presence tend to deter the insider trading and this is particularly true for insider purchases. While controlling for all relevent variables on column 5, we find that in the insider sales sample, a 1% increase of SVI leads to a 0.2143% decrease on abnormal returns.

We further split the sample into high and low attention groups to disentangle the impact of SVI-related verses non-SVI-related trading on next month's excess returns. The results are presented in Columns 6 and 7, for firm-month observations with abnormal SVI (ABSVI) greater than one and less than one, respectively. We find that our results are mainly driven by insider sales when the ABSVI is greater than one – when the month's SVI is greater than that of last month – and by insider purchases when the ABSVI is less than one. In Panel A's Column 4, the coefficient of Log(ABSVI) is negative (-0.2327) and statistically significant (T-value = 3.18). The statistically insignificent coefficient of log(ABSVI) in Column 7 of Panel A suggests that when the retail investors' attention is low, insider sales do not generate abnormal profits.

In Panel B's Columns 6 and 7, we see that insider purchases are generally more informative and generate abnormal returns following their trades. However, taking advantaging of lower investor attention (depressed stock price) would also yield higher abnormal returns. In other words, insider purchases yield abnormal profits only when retail investors' interest is relatively low. We also observe that comparing with insider sales, the coefficients of log(ABSVI) are higher on excess returns of insider purchases, implying a stronger return predictability. This might be due to the fact that insiders display more hetergenities in their sales than purchases. Overall, our results suggest that a higher (lower) Google SVI benefits insiders' sales (purchases). The results are consistent with the main hypothesis that insiders profit by engaging in opportunistic trades to take advantage of stock price variations arising from changing levels of investor attention.[19]

4.2 Insider Trading Patterns

We perform Probit and Tobit regressions to further explore how investors' attention levels affect the likelihood and amount of insiders' trades.[20] We measure trades by the volume of insider sales or purchases in a given month. We conjecture that insiders execute trades when retail interest exerts a price pressure on the stock. Table 5 presents the results of limited dependent variable regressions that predict contemporaneously insider trading patterns. The dependent variable in Probit regressions is a Sale (Purchase) dummy, which equals one if a firm-month is a net sale (purchase) month. The dependent variable in Tobit regressions is Shares Sold (Purchased), which equal the number of shares, in thousands, that insiders sell (buy) during a sale (purchase) month. In all regressions, independent variables include Log(Size), Log(BM), the

[19] We also carry out additional robustness check by lumping both insider sales and purchases into the baseline regression following Cohen, Malloy, & Pomorski (2011) and the pooled regression shows the consistent result.
[20] Greene (2002) argues that applying the fixed effects to non-linear models such as Probit and Tobit tends to produce inconsistent and downward biased standard errors, and tend to over-estimate the coefficients. Hence, we exclude the firm fixed effect from our non-linear models. Instead, those non-linear models are based on the two-way clustering (firms and transaction months).

contemporaneous equally weighted market return $Market_t$, Advertising/Sales ratio, Log(Price), and Log(Turnover).[21] The independent variable of particular interest is either Log(ABSVI) or a dummy variable indicating whether Log(ABSVI) is positive (predicting sales) or negative (predicting purchases). If the coefficients of these variables have correct signs and are statistically significant, the results would further support the argument that insiders trade when abnormal investor attention presents a profitable trading opportunity.

[Insert Table 5 Here]

Table 5 displays the results of Probit and Tobit regressions, where Columns 1 through 6 show predictions on insider sales, and Columns 7 through 12 on insider purchases. Overall, insiders trade more often and transact more shares when there is abnormal investor attention (when their trades would be more likely to be profitable). The marginal effect associated with the Log(ABSVI) Positive dummy in Column 2 shows that insiders are 12.5% more likely to sell shares when there is an increase in investor attention. Similarly, the same coefficient of Tobit regression in Column 5 shows that insiders sell 18,619 more shares when Log(ABSVI) is positive. On the purchase side, insiders buy more shares and more frequently when investors are less attentive. The marginal effect associated with the log(ABSVI) Negative dummy in Column 8 shows that insiders are 3.37% more likely to buy shares when there is a lack of investor attention, and the same coefficient of Tobit model in Column 11 indicates that insiders buy 4,164 more shares under the same circumstance. In Columns 3, 6, 9, and 12, we also include the abnormal institutional searches into the baseline regressions and negative (positive) coefficients of Log(ABISVI) on Columns 3 and 6 (Columns 9 and 12) indicate that institutional investors' searches indeed attenuate the insiders' tendencies on engaging trades based on the heightened retail investors' interests (ABSVI).

4.3 Which Insiders Take the Trading Opportunities?

Our preliminary results in Table 3 suggest that insiders who are more likely to benefit from attention-related insider trades tend to be non-executive, non-independent directors. We now formally investigate this possibility, using limited dependent variable regressions. We

[21] In Appendix: Variable Definitions and Sources of Main Variables, we provide detailed definitions of all these and other variables.

classify insiders as top-level officers, insider directors, independent directors, and others, based on the role classification codes defined in the insider filing database. Top-level officers are the firm's chief executive officer, chief financial officer, chief operating officer, and the chair of its board (role classification codes: CEO, CFO, CO, and CB). Insider directors are those having an employment contract with, or having a beneficial interest in, the firm, excluding the top-level officers (role classification codes: DO, H, and OD). All other directors are taken to be independent directors.

[Insert Table 6 Here]

To test the role played by insider type, we subgroup our insider sample based on three insider role classifications: top-level officers, independent directors, and other insiders. We aggregate each insider category at the firm-level. Table 6 presents the results of Logit regressions, where in Columns 1, 3, and 5, the dependent variable is the sale dummy, and in Columns 2, 4, and 6, it is the number of shares sold (in thousands). The coefficients of Log(ABSVI) are negative on Top-level Officers and on Independent Directors, but are positive on Insider Directors, confirming our earlier observation that non-senior-executive, inside directors are the insiders who are likely to trade on the basis of investors' attention. Top executives and independent directors are less likely to engage in such opportunistic trades possbily because of their greater concerns for reputation. The results of Tobit regressions in Columns 2, 4 and 6 support a simlar conclusion.

4.4. Characteristics of Opportunistic Traders and their Firms

Having identified that non-senior-executive, non-independent directors tend to engage in opportunistic trades related to abnormal retail investor attention (ABSVI), we now explore the characteristics of insider traders and their firms. We employ a logit model where the dependent variable is a dummy that equals one if an insider is a non-senior-executive, non-independent director. Independent variables in the regression include major categories of insider and firm level characteristics such as the insider's tenure in the firm as well as the firm's geographical dispersion, governance, financial constraints, product dispersion, social responsibility, reputation and fame. We measure insider tenure as the log of the number of years the insider is active in the firm. Geographical dispersion is measured as the log of the number of states in which the firm operates. Governance is based on the G-index from Gompers, Ishii, & Metrick (2003), with the poor governance dummy equal to one if the firm's G-index is 90 percentile or higher of the distribution (G-index >= 12 and a larger number indicating poorer governance). Financial constraint is based on the SA index introduced by Hadlock & Pierce (2010).[22] Corporate social responsibility is measured by the KLD index from the KLD Social Ratings database.[23] Product dispersion is the product-sales based Herfindahl-Hirschman index from Compustat Product database. For the reputation and fame variable, we manually collect the Fortune magazine ranked 100 best companies to work for between 2004 and 2014 and we create the Fortune100 dummy to proxy for good corporate reputation. Our particular interests rely on the interaction term between each independent variable and the high abnormal SVI dummy (HABSVIDUM). We define the HABSVIDUM as equals to one when at least 6 out of 12 calendar months result in ABSVI larger than one, and zero otherwise.

[Insert Table 7 Here]

Table 7 shows that when high abnormal retail attention is present, non-senior-executive, non-independent insider traders are more likely to have a longer tenure in their firms, and the firms tend to have poor governance, to be socially less responsible, and not to be in the list of Fortune 100 best companies. Moreover, the firms operate in more states, have more concentrated product-sales, and are financially less constrained. Specifically, the coefficient of interaction between Log(Number of Years Active) and HABSVIDUM in Column 1 is positive and significant, indicating that insiders having longer tenure in the firm tend to engage this type of trades. As Cohen, Malloy, & Pomorski (2011), we include the number of trades to isolate the effect of time in the firm, conditioned on the trading activity of individual insider. Here, the coefficient of Log(Number of Trades) is negative and significant, suggesting that while those type of insiders trades less in general, they actively trade when an attention-related opportunity presents itself. Thus, conditioned on the same amount of trades, an insider who has a longer tenure in a firm is more likely to trade opportunistically.

[22] The SA Index is computed as (-0.737*Size) + (0.043* Size^2)-(0.040* Age), where Size is the log of inflation-adjusted book asset, and Age is the number of years the firm is listed with a non-missing stock price on Compustat. The size is capped at the log of $4.5 billion, and age is winsorized at thirty-seven years.

[23] The KLD index is computed by considering seven dimensions: Corporate Governance, Human Rights, Community, Diversity, Employee Relations, Environment, and Product. The KLD is computed by subtracting total weaknesses from total strengths from the seven dimensions.

Column 2 of Table 7 examines the effect of firm geographical dispersion: the log of the number of states the firm operates. The coefficient of interaction to HABSVIDUM is positive and significant, suggesting that the number of states in which a firm operates positively predicts the likelihood that a non-senior-executive, non-independent insider of the firm will engage in opportunistic trades and this effect is stronger when abnormal investor attention is present. This finding differs somewhat from that in Cohen, Malloy, and Pomorski (2011) possibly because we focus only on certain opportunistic traders. In particular, firms that operate in more states are likely to attract a larger base of retail investors, creating more opportunities for profitable insider trades.

The effects of corporate governance, financial constraints, and product concentration with HABSVIDUM are shown in Columns 3 through 5 of Table 7. In Column 3, the coefficent of the poor governance dummy interacting HABSVIDUM is positive and significant, indicating that an opportunistic trader is more likely associated with a poorly govened firm. In Column 4, an opportunistic insider trader is more likely linked to a financially less constrained firm. This result is consistent with the argument that retail investors are more likely to be interested in firms that are doing well financially. In Column 5, we see a positive, although weakly significant, coefficient on product concentration. It is possible that when a firm's revenue source is concentrated on fewer products, less corporate diversification might motivate insiders to engage in more trades when the opportunities are present. Overall, our results support that opportunistic insider traders are more likely from firms that have poorer governance, that are financially less constrained, and that have more concentrated products.

Columns 6 through 8 turn to aspects of social responsibility and reputation of firms. The result in Column 6 is based on the KLD-corporate social responsibility of companies. The KLD measure is an index based on seven dimensions: corporate governance, human rights, community, diversity, employee relations, environment, and product. A higher KLD index means a higher level of social awareness and integrity. The negative coefficient of interaction between this measure and HABSVIDUM suggests that opportunistic insiders engaging in this type of trades are more likely from social less responsible firms. In Columns 7 and 8, we check whether a firm in our sample has been in the list of Fortune 100 best companies to work for. The best companies may attract more investors' attention, thereby creating more opportunities for insider trading. However, such firms may also bear greater reputation costs if opportunistic insider trades are exposed. The negative coefficients of the Fortune100 dummy and Log(Nomination Ranks) interacting with HABSVIDUM support the latter argument that reputable firms value more highly their public image and reputation, and therefore, their insiders of all types are less likely to engage in trades that take advantage of retail investors.

4.5. Do Lottery-type Stocks Have More SVI-related Insider Trading?

Kumar (2009) finds that individual investors who are young, urban, single, relatively poor and less educated tend to overweigh stocks with lottery features in their portfolios. Kumar labels a stock as lottery-type if it has a low per share price, high idiosyncratic volatility and skewness. The idea is that a lottery-type stock, like a lottery ticket, can provide the buyer with a huge reward but only with a very low probability. An implication of Kumar's study is that lottery stock buyers are generally less sophisticated investors who may have limited resources and abilities to process relevant information. If this implication is true, we expect that insiders of lottery-stock firms would have greater opportunities to engage in SVI-related trades that take advantage of varying attention of individual investors on the stocks.

We follow Kumar's (2009) approach to identify lottery-type stocks. We first compute idiosyncratic volatility and skewness for each stock at month t using the CRSP return data of previous six months (t-6 to t-1). As in Kumar (2009) and Ang, Xing, and Zhang (2006), idiosyncratic volatility is calculated as follows:

$$Idovol_{i,t} = \frac{\sum_{d \epsilon T_i(t)} \varepsilon_{i,d}^2}{D_i(t)}, \tag{1}$$

where stock price in month t is the closing price at the end of month t-1, $T_i(t)$ is the set of CRSP daily returns for firm i in month t, $D_i(t)$ is the number of trading days for firm i in month t, and $\varepsilon_{i,d}$ is the residual on trading day d for firm i from regressing firm i's daily return on the four factor model over the period $T_i(t)$. For idiosyncratic skewness, we follow Harvey and Siddique (2000) and Kumar (2009), and use the following equation:

$$Idovol_{i,t} = \frac{\sum_{d \epsilon T_i(t)} \varepsilon_{i,d}^3}{\sigma_{i,t}^3}, \tag{2}$$

where $T_i(t)$, $D_i(t)$, and $\varepsilon_{i,d}$ are the same as in Equation (1), and $\sigma_{i,t}$ is the squared root of $Idovol_{i,t}$ estimated from Equation (1). A stock in our sample is lottery-type if its price is in the bottom half of distribution while its idiosyncratic volatility and skewness are both in the top half. All other stocks in our sample are classified as non-lottery type stocks.[24]

[Insert Table 8 Here]

Table 8 presents the descriptive statistics of lottery-type stocks and the results of firm-level regressions. In Panel A, we compare lottery-type and non-lottery stocks based on the three characteristics of stock price, idiosyncratic volatility and skewness. Our sample has 1,093 lottery-type stocks and 4,029 non-lottery stocks. Lottery-type stocks have a much lower average price (6.40 vs. 23.68), much higher average idiosyncratic volatility (21.99 vs. 8.11) and skewness (2.10 vs. 0.29). In our firm-level regressions, we introduce a dummy variable, Lottery, which equals one if the stock is lottery-type at the end of month t-1.[25] Our main interests are the lottery dummy and its interaction term with abnormal retail attention measures such as Log(ABSVI), the Log(ABSVI) Positive or Log(ABSVI) Negative dummy. We also construct a jump (fall) dummy to capture an extreme increase (decrease) in the level of investor attention over that of the previous month. The Jump (Fall) dummy equals one when ABSVI is in the top (bottom) 10 percentile. Panel B (C) of Table 8 presents the results of our Logit and Tobit regressions on net sales (purchases). Specifically, taking Column 2 from both panels for an example, the coefficient of lottery is -0.282 with t value of -4.26 (0.271 with t value of 4.08) in Panel B (C). More interestingly, the coefficients of interaction between lottery with abnormal attention dummy, Log(ABSVI) Positive, are 0.041 with t value of 3.08 (-0.240 with t value of 2.55). Column 6 indicates similar findings using tobit regressions. The coefficient of lottery dummy -60.354 with t value of -2.92 (30.912 with t value of 3.59) in panel B (C). The coefficients of interaction term are positive (73.497 with t value of 2.34) and negative (-22.533 with t value of -1.84). The results are economically significant as well. Using the those from Columns 2 and 6 from both panels, we conclude that under the presence of abnormal retail

[24] Kumar (2009) defines non-lottery type stocks as those that belong to none of the three categories. In our paper, our main interest is to examine the impact of lottery-type stocks on SVI-related trades, and our grouping approach is not expected to result in biased results.

[25] We use the lottery dummy at the end of month t-1 to regress on the month t's insider trading activity in order to establish a causality relationship.

attention – when log(ABSVI) is positive – insiders are 10.02% more likey (4.45% less likely) to engage sales (purchases) on the lottery than non-lottery stocks, and when they do, they sell 13,143 (purchase) more shares (8,379 less shares) which are associated with the lottery features. Within all model specifications, abnormal retail attention measures remain statistically significant, providing further support to our conjecture. Indeed, a greater interest of retail investors in a lottery-type stock (a higher ABSVI on the stock) appears to create more profitable opportunities for insider trading.

4.6. SEC Enforcement Activities and Opportunistic Insider Sales

In this section, we examine whether insiders change their SVI-related trading behaviors upon news releases of SEC enforcement actions on illegal insider trading activities. We focus on the impact of SEC actions on opportunistic insider sales because such sales are most likely to trigger SEC investigations (Cohen, Malloy, and Pomorski, 2012). We classify opportunistic insider sales into two categories: SVI-related and non-SVI-related. An opportunistic sale is SVI-related if it takes place in a month when there is an increase in investors' searches on the stock – when ABSVI > 1. All other opportunistic sales are defined as non-SVI-related. It is possible that insiders may believe that the sales of shares when retail investors are paying more attention are less likely to be subject to SEC investigation. If this view is correct, we expect insiders to engage in *more* SVI-related sales following the releases of SEC actions on illegal insider trading. This prediction is in contrast to the finding in Cohen, Malloy, and Pomorski (2012) that following such releases, there is an overall reduction in opportunistic insider sales.

To test our conjecture, we regress the ratio of SVI-related sales to total opportunistic sales in month t onto the number of releases of SEC litigation on illegal insider trading in month t-1. The independent variable of interest is the natural log of one plus the number of releases of SEC cases against insider trading in month t-1. We include in the regression the fraction of positive Log(ABSVI) at month t and t-1, where the fraction of positive Log(ABSVI) is defined as the number of months that have positive Log(ABSVI) divided by the total number of months that ABSVIs are available. Control variables include an equally weighted market return in month t, the standard deviation of daily market returns in month t-1, and cumulative equally weighted market returns of past 3, 6, and 12 months.

[Insert Table 9 Here]

Table 9 reports the results of the test. Panel A shows that SVI-related sales increase significantly following the news releases of SEC actions. The evidence indicates that SEC cases result in *more* SVI-related insider sales even though they dampen overall opportunistic sales. In other words, when there are greater concerns about regulatory scrutiny of insider trading, insiders appear to prefer SVI-related sales to other opportunistic sales. The coefficient of the number of SEC releases (Num SEC Release_{t-1}) is 0.073 (t = 4.37).[26] The coefficient of the fraction of positve Log(ABSVI) at month t is positive and significant, suggesting that abnormal investors' attention attracts more SVI-related insider sales. Interestingly, the coefficient of the fraction of positve Log(ABSVI) at month t-1 is negative and significant, indicating that after taking advantage of heightened retail investors' attention, insiders reduce their sales, presumably to reduce the risk of SEC action since the other forms of sales would run a greater risk of SEC sacntion.

In Panel B of Table 9, we rerun firm-level Probit and Tobit regressions where the dependent variables are the sales dummy and the number of shares sold, respectively. The coefficients of Num SEC Release_{t-1} are negative and significant, consistent with a deterrence effect on overall opportunistic sales. However, the coefficients of interaction term between Log(ABSVI)_t and Num SEC Release_{t-1} are positive and significant, indicating that insiders change their trading behaviors by trading more on the basis of retail interest. These results imply the economic significance. Using Columns 3 and 6 as examples, the results indicate that when abnormal retail attention presents profitable trading opportunities, one additional litigation case above the mean level (5.6) initiated by the SEC in the previous month would increase by 2.14% the probability of insiders engaging in ABSVI-sales and the insiders would sell 2,625 more shares.

Panel C examines the probability of an insider trader being investigated by the SEC. The observations are at the insider level with insider characteristics constructed based on all trades

[26] Summary Statistics for our litigation data are as follows: the average number of insider trading-related cases the SEC makes in a given month is 5.6 (median 5.5), with a standard deviation of 2.61(max=12, 75th percentile=7, 25th percentile=4, min=0).

and sales of each insider.[27] Column 1 shows that an insider who engages in SVI-related trades has a lower likelihood of subsequently being investigated or sued by the SEC. In Column 2, we partition the number of insider trades on the basis of being SVI-related and non-SVI-related. The coefficient on the number of Non_SVI_Related Trades is positive and significant (t=2.56) while that on SVI_Related Trades remain insignificant. The result suggests that it is the *non-SVI-related trades* that trigger SEC actions. We also construct the percentage of SVI-related sales dummy (% SVI_Related) which equals one when the number of SVI-related sales (trades) is greater than that of non-SVI-related sales (trades). The coefficients of % SVI_Related sales and trades dummies are negative and marginally significant. Overall, our evidence supports the argument that SVI-related sales are less likely to face SEC actions, and therefore, such sale activities actually increase following the news of SEC actions.

4.7. Information- or Sentiment-driven Insider Trading?

One concern is that Google's SVI simply reflects investors' interest in real news or information relevant to the stock. In other words, the SVI represents the variation of publicly available firm-level information flow. We now check whether our results are driven mainly by the information flow on particular stocks or by changing sentiments of retail investors on the stocks. For this purpose, we regress Log(ABSVI) onto variables that are known to affect the SVI such as abnormal institutional searches (ABISVI), earning surprise, advertising to sales, major macro variables of GDP final and FOMC rate decisions, as well as year and industry dummies. We extract the information about firms' earning announcements from I/B/E/S and adjust the announcement days into the CRSP trading days. We construct the magnitude of earnings surprise using the following equation:

$$SUE_{i,q} = \frac{Actual\ EPS_{i,q} - Median\ Forecasted\ EPS_{i,q}}{P_{i,q}} \tag{2}$$

In the above, $Actual\ EPS_{i,q}$ is actual earnings per share (EPS) for firm i at quarter q, $Median\ Forecasted\ EPS_{i,q}$ is the median estimate of EPS among those posted 90 days prior to the earnings report day, and $P_{i,q}$ is the price per share for firm i at the end of quarter q from Compustat. We include two manually collected major macro news variables: GDP final and

[27] We define the number of trades here as the number of an insider executing each transaction and the number of sales as the total number of shares sold.

FOMC rate decisions, which Bloomberg considers to have most relevance to investors. We run the following regression to decompose Log(ABSVI):

$$
\begin{aligned}
Log(ABSVI)_{i,t} \\
&= \alpha_i * Log(ABISVI)_{i,t} + \beta_i * SUE_{i,Q(t)-1} + \gamma_i * \frac{Adv}{sale}_{i,Y(t)-1} + \delta_i * GDP_{Final_{t-1}} \\
&+ \theta_i * FOMC_{t-1} + \vartheta_i * Earndum_{i,t} + \rho_i * Ret_{i,t-1} + \sigma_i * Vol_{i,t-1} \\
&+ \tau_i * \log(Max\ price)_{i,t-1} + \varphi_i * Idiovol_{i,t-1} + Year + Industry + \varepsilon_{i,t} \qquad (3)
\end{aligned}
$$

In the above, $Log(ABISVI)_{i,t}$ is the nature logarithm of abnormal institutional search volume index on firm i at the month t; $SUE_{i,Q(t)-1}$ is firm i's earnings surprise at the quarter immediately before month t; $Adv/sale_{i,Y(t)-1}$ is the firm's advertising to sale ratio in the previous year; and GDP_Final_{t-1} and $FOMC_{t-1}$ are dummy variables that equal one if there is a release of the macro information in month t-1. We control for the contemporaneous variable and create $Earndum_{i,t}$, which is equal to one if a firm makes a earning announcement in month t and zero if otherwise. We include also the previous monthly return ($Ret_{i,t-1}$) and trading volume ($Vol_{i,t-1}$) as well as lottery features ($Max\ Price_{i,t-1} + Idiovol_{i,t-1}$).

We take the predicted value as the information component of Log(ABSVI) – denoted Log(ABSVI-Information) – and the residual value as its non-information or sentiment component – denoted Log(ABSVI-Sentiment). Table 11 presents the effects of the two components of ABSVI on opportunistic insider trading. As shown in the respective coefficients, the sentiment component delivers stronger and more consistent impacts on insider trading whereas the information component becomes insignificant in most instances. Thus, our results are more in line with retail investors' shifting sentiments creating opportunities for profitable insider trades.

[Insert Table 10 Here]

4.8. Exogenous Variations in Attention with IV Regressions

Liu, Peng, and Tang (2016) show that investors' abnormal attention is lower in summer months than in other months; the abnormal attention is also lower on Friday than on other weekdays. Based on these findings, we undertake two additional tests of robustness of our main results. First, we examine subsamples where attention is measured during summer months (July and August) and during non-summer months. The fluctuation in investor attention during calendar months is more likely the result of exogenous variations to investor sentiment than fundamental-driven. We run the t-test of our abnormal attention measures and insider trading volume. Second, we separate our sample based on daily insider-level trades on Friday and on non-Friday weekdays. Table 12 shows that abnormal attention is generally lower in the summer months than in non-summer months, so are insiders' opportunistic selling activities. These patterns are also evident in Figure 3 of insiders' monthly trading volume (in thousands), showing a significant decrease of insider sales and a significant increase of insider purchases during the summer months. Similarly, looking at daily insider sales, we see that insiders sell less (and buy more) on Friday than on other weekdays. Overall, the patterns reaffirm our earlier results that insiders trade strategically based on investors' shifting sentiment.

[Insert Table 11 Here]

To formally account for the potential endogeneity of our abnormal attention measure, we utilize the instrument variable approach by using the summer dummy, GDP final dummy, and FOMC dummy as our instruments. The summer dummy is based on the empirical findings in Table 11 and Figure 3 that a lower level of investor attention in the summer months leads to lower (higher) incidents of opportunistic insider selling (buying). Liu, Peng and Tang (2016) also show that investor attention to individual stocks can be distracted during periods of macro information shocks. Thus, we expect two macro variables, GDP final dummy and FOMC dummy, have an impact on retail investors' attention and should not be correlated with firm fundamentals.

[Insert Figure 3 Here]

Our first stage regression includes the summer dummy, GDP final dummy, and FOMC dummy, as well as control variables such as log(size), log(bm), contemporaneous earnings dummy, previous monthly return, absolute value of previous monthly return, previous monthly market return, earnings surprise, number of earnings announcements of previous month released within the same industry (defined using first two digit sic), year, and industry. Then, we include all control variables from the baseline regression and the first stage into the second stage IV tests. In terms of the validity of our instruments, they must satisfy two conditions. First, they need to be relevant. This means that they are directly correlated with the endogenous variable Log(ABSVI)/Log(ABSVI) Positive/ Log(ABSVI) Negative. Second, they need to be exogenous (exclusion restriction condition) to our dependent variables once they and other covariates have been controlled for. The F-statistic equals to 57.27, 39.10, and 41.86, respectively. They are much higher than 10, the "Rule of thumb" critical value proposed by (Staiger and Stock, 1997). Following Stock and Yogo (2005), the Cragg-Donald Walk F-Statistics for the three instruments are 71.01, 47.82, and 49.34, respectively, all are well above the Critical value (22.30).[28] This suggests that we can reject the weak instrument hypothesis. We also check whether our instruments satisfy the exclusion restriction condition. This requires that our choices of instruments are not correlated with the error term. As we use more than one instrument, we can check this using over-identification test. The Sargan Statistics equal to 2.610, 2.208, and 2.479, respectively, corresponding to p-values of 0.271, 0.332, and 0.290. Hence, there is no evidence that our instruments violate the exclusion restriction condition, suggesting that our instruments are exogenous to the structural equations.

[Insert Table 12 Here]

Panel A of Table 12 shows the second-stage regression results while the results in Panel B indicate that our instruments are valid. Consistent with our baseline regression results, all coefficients are significant with correct signs. They imply that when there is an increase (decrease) of retail investor search interests – a positive (negative) Log(ABSVI) – insiders are more likely to behave opportunistically to engage in sales (purchases) and do so in a larger quantity. For example, in Columns 2 and 4, the coefficients of Log(ABSVI) Positive dummy are 0.399 (t-value=1.98) and 24.625 (t-value=5.09), respectively, and in Columns 6 and 8, the coefficients of Log(ABSVI) Negative dummy are 0.467 (t-value=2.20) and 20.888 (t-value=2.95). Overall, the results reaffirm our prediction.

We address further the concerns of causality and endogeneity by performing two sub-sample analyses and present our results on appendix. First, we create one subsample for months of earnings annoucements and another for months of no earnings annoucements. Our results

[28] Stock and Yogo (2005) suggest that, for one endogenous regressor (n=1) and three instruments (K=3), the critical value for weak instrument based on the maximum size bias at the 5% significance level is 22.30. Refer to Table 5.2 in Stock and Yogo (2005) for more details.

remain significant in the months of no earnings annoucement, suggesting that the relation between investor attention and insider selling is unlikely to be driven by information related to earnings announcements.

Second, we address the reverse causality that abnormal attention can be triggered by insider trading activities. We utilize a political regime change that serves as an exogenous shock. We decompose our whole sample period of 2004-2014 into two subsample periods of 2004-2008 and 2009-2014 with the former being under the more laissez faire Republican Bush Administration and the later under the more activist Democratic Obama Administraion. Presumably, during the Obama Administration, the government would be more active at taking enforcement actions against legally questionable insider trading and thus any deterrence effect on opportunistic insider trades would be stronger during this period. However, our results remain essentially the same for the two subsample periods, suggesting that the SVI-related insider trading is unaffected by the enforcement environment. Overall, our IV and regime change tests confirm that the attention-driven oppotunisitic insider trading is not entirely driven by fundamental shocks, and that trading on such mispricing is not affected by regulation changes.

4.9. Portfolio Returns from SVI-Based Trading Strategy

We now examine the returns of portfolios formed according to our SVI-related trading classifications. The main question is whether insiders' SVI-related trading behaviors predict future returns. To address this question, we create quintiles using the monthly ABSVI and each firm's monthly net transaction volume (net sales or purchases). Specifically, we base the portfolios on our classifications of SVI-related trades at the firm level. We focus on firm-months that have either a positive or negative Log(ABSVI) by excluding those that have a zero Log(ABSVI). For each subsample, we classify a firm based on its net transaction volume (number of shares). For example, if a firm has more insider sales (purchases) than purchases (sales), we group the firm into a net sale (purchase) portfolio. In essence, we create two portfolios for net sale: one insider sale portfolio when Log(ABSVI) is positive (positive attention sale portfolio) and another insider sale portfolio when Log(ABSVI) is negative (negative attention sale portfolio). Likewise, we create two net purchase portfolios: one when Log(ABSVI) is positive (positive attention purchase portfolio)and another when it is negative (negative attention purchase portfolio). We hold these four portfolios during the month following insider trades, and then rebalance all portfolios at the end of month, using new information on each firm's Log(ABSVI) and net transaction volume for the month.

[Insert Table 14 Here]

Table 13presents raw portfolio returns and risk-adjusted alphas for the CAPM, Fama-French, Carhart four-factor, as well as five-factor model that includes the Pastor-Stambaugh liquidity factor. It also reports on both value-weighted and equal-weighted portfolios. The L/S buys (sells) portfolio is created by longing the negative attention purchase portfolio (positive attention sale portfolio) and shorting positive attention purchase portfolio (negative attention sale portfolio).Our results show that a portfolio strategy based on opportunistic insider trades when the ABSVI is low would earn significant abnormal returns. In comparison, a portfolio strategy based on opportunistic trades when the ABSVI is high would only earn insignificant and sometimes even negative risk-adjusted returns. Furthermore, an equally weighted long-short portfolio that is long on what insiders buy when Log(ABSVI) is negative and short on what insiders sell when Log(ABSVI) is positive would generate a five-factor alpha of 232 basis points (t = 7.08) or 27.84% per year before transaction costs. A one directional portfolio strategy, whether it is based on buy or sell, however, would generate a consistently negative alpha for all model specifications. In the lower half of Table 14, we present the return results of value-weighted portfolios; here, the five-factor alpha is 119 basis points (t = 3.08) or 14.28% per year before transaction costs. Taken together, our return analysis suggests that a trading strategy that follows insiders' SVI-related trades would earn economically and statistically significant abnormal returns.

5. Conclusion

This paper explores how insiders may engage in opportunistic trades to take advantage of varying attention of retail investors to their firm's stock. Our analysis rests on the premise that retail investors exhibit behavior biases which could result in mispricing and create opportunities for profitable insider trades. Our results indicate that insiders can indeed profit by timing their sales of shares when there is an increase in retail investors' attention (proxied by ABSVI). Exploring further this finding using the Limited Depedent Variable regression, we find that a higher level of abnormal investor attention increases the likelihood of insiders' selling and also the quantity of their sales while decreasing the likelihood of insiders' buying and the quantity of their purchases. In other words, we document a pattern of opportunistic insider trades that are contrarian to the level of retail interest in the stock.

While the level of investor attention is significantly and positively associated with insiders' abnormal returns on sales, we observe no significant relationship between the attention level and abnormal returns on insiders' purchases. This result is consistent with the contention that retail investors' attention affects mostly their buying rather than selling decisions, with a higher attention level predicts a short-term price rise. Exploring further this finding using multivariate regressions, we find that investors' abnormal attention has a significant negative effect on the following month's excess returns. This negative effect, however, appears to be attenuated by the longevity of attention, implying that as retail investors' active searches on the same firm persists, they may be learning from experience and becoming less sentimental and more rational in their trading decisions. Including institutional searches into our analysis do not affect our documented behaviors of opportunistic insider trading.

We find that insiders involved in the SVI-related opportunistic trades tend to be non-senior-executive, non-independent directors. These insiders may be less concerned about firm and individual repuation and may therefore value more the opportunistic trading profits. Exploring further, we find that the opportunistic traders are more likely to have a long tenure in their firm, and to be from a firm that has weak corporate governance, low awareness of corporate social responsibility, and low reputation costs in the eyes of the public. The firm also operates in more states, has a higher product sale concentration, and is less financially constrained.

We conduct subsample analyses to further explore variations in investor attention and insider trading. One is that retail investors may find lottery-type stocks more appealing and hence their optimistic sentiment on such stocks may create even greater opportunities for profitable insider trades. Our evidence supports this conjecture. We also explore SEC enforcement risk associated with SVI-related trades. Interestingly, we find evidence that insider trading associated with an abnormal SVI faces a lower risk of SEC enforcement action, and thus, the amount of SVI-related trades actually increases following the releases of SEC litigation cases.

It is possible that investors' level of attention may simply refect their demand for newly public information about the firm; that is, corporate news or events rather than investor sentiment may be driving the level of attention. To address this issue, we disentangle ABSVI into two components: the first is part of ABSVI that is explained by arrivals of firm or market information while the second is the part that is left unexplained – which we refer to as the sentiment component. We show that our results are driven more by the sentiment component. We carry out additional IV and subsample tests. The results of the tests indicate that the SVI is unlikely to be affected by insider trading.

The potential profits of the sort of insider trades we examine are statistically and economically significant. For example, a value-weighted (equal-weighted) mimicking portfolio that is long on what insiders buy when the ABSVI is negative and is short on what they sell when the ABSVI is positive would generate a significant five-factor alpha of about 119 (232) basis points per month, or 14.28 % (27.84%) per year, before transaction costs.

In sum, our evidence provides a new channel for insider trading: they strategically exploit mispricing of their firm's stock arising from retail investors' shifting sentiment. This channel maybe particularly attractive, if this type of trades is less likely to subject them to investor litigation and SEC enforcement actions.

Appendix: Variable Definitions and Sources of Main Variables

Variable	Definition	Source
Panel A: Investors' Attention Measure		
Monthly SVI	Arithmetic average of weekly SVI	Google Trends
Log(ABSVI)	Natural logarithm of monthly retail SVI scaled by previous month's retail SVI	Google Trends
Log(SVI Duration)	Natural logarithm of number of months that separate the trade month and first valid SVI month	Google Trends
Log(ABISVI)	Natural logarithm of monthly institutional SVI scaled by previous month's institutional SVI	Bloomberg Terminal
Log (ABSVI_City) /Log (ABSVI_Metro)	Natural logarithm of ABSVI that matches search interests of city/metropolitan statistical areas where the firm's headquarter is located	Google Trends
Attention Dummy	Indicator variable that equals one (zero) if the firm is (is not) in the attention sample	Google Trends
Log(ABSVI) Positive[29]	Indicator variable that equals one (zero) if Log(ABSVI) is (is not) positive	Google Trends
Log(ABSVI) Negative	Indicator variable that equals one (zero) if Log(ABSVI) is (is not) negative	Google Trends
HABSVIDUM	Indicator variable that equals one (zero) if ABSVI are larger than 1 for at least (less than) 6 of 12 months for any calendar years.	Google Trends
Jump	Indicator variable that equals one (zero) if the ABSVI is (is not) at the top 10 percentile	Google Trends
Fall	Indicator variable that equals one (zero) if the ABSVI is (is not) at the bottom 10 percentile	Google Trends
Fraction Positive Log(ABSVI)	Number of months that have positive Log(ABSVI) scaled by total number of months that ABSVIs are available	Google Trends
Panel B: Insider Trading and Characteristics		
Number of Shares Sold/Bought	Number of shares sold/bought by insiders, in thousands	Thomson Reuters Insider Database
Sales/Purchase Dummy	Indicator variable that equals one (zero) if firm-month is (is not) a net sale/purchase month	Thomson Reuters Insider Database
Top-level/Inside/Independent director	Indicator variable equals to one if a top-level/inside/independent director trade in a firm-month, and zero if otherwise	Thomson Reuters Insider Database
Number of Year Active	Number of years that an insider has been trading	Thomson Reuters Insider Database
Number of Trades	Numbers of trades an insider executes.	Thomson Reuters Insider Database
Panel C: Stock and Firm Characteristics		
Book-to-Market Ratio	The firm's book value scaled by its market value	CRSP, Compustat

[29] We use a similar approach to define the local ABSVI dummies.

Size	Previous year-end market value: share price times number of shares outstanding	CRSP
Log(Analysts)	Natural logarithm of 1+number of analysts covering the firm	IBES
Advertising/Sales	Advertising Expenditure scaled by sales	Compustat
Log(Price)	Natural logarithm of stock price at previous year's end	Compustat
CAR	Firm market adjusted return	CRSP
Turnover	Average monthly turnover scaled by share outstanding	CRSP
Std Market Return	Standard deviation of equally weighted market returns	CRSP
Market	Equally-weighted market return	CRSP
Excess Return	Stock return minus risk-free rate	CRSP, Fama French Data Library
Geo Dispersion	Natural logarithm of 1+number of states in which the firm operates	Compustat Segment
Poorly Governed Firms	Indicator variable that equals one (zero) if G-index is equal or larger than (less than) 12	ISS (Formerly Risk Metrics)
SA Index	Computed as (-0.737*Size) + (0.043* Size^2)-(0.040* Age), where Size is the log of inflation-adjusted book asset, and Age is the number of years the firm is listed with a non-missing stock price on Compustat. The size is capped at the log of $4.5 billion, and age is winsorized at thirty-seven years.	Compustat
KLD Index	KLD is computed by subtracting total concerns from total strength from those seven dimensions.	KLD Social Ratings Database
Product Dispersion: HHI	Herfindahl-Hirschman Index based on product sales	Compustat Product
Fortune100_DUM	Indicator variable that equals one (zero) if a firm is (is not) one of Fortune 100 best companies to work for	Fortune Magazine
Fortune100_Rank	Natural logarithm of ranks of 100 best companies to work for	Fortune Magazine
Lottery	Indicator variable that equals one (zero) if a stock is (is not) a lottery-type stock as defined in Kumar (2009)	CRSP
SUE	Actual EPS minus median forecasted EPS over those posted 90 days prior to the earnings report day scaled by the price per share	IBES, Compustat
Panel D: SEC Litigation		
Number of SEC Release	Natural logarithm of 1+number of releases of SEC litigation cases	SEC
Panel E: Macro News		
GDP Final	Indicator variable that equals one (zero) if there is (is not) an announcement on the GDP Final	Bloomberg
FOMC	Indicator variable that equals one (zero) if there is (is not) an FOMC rate decision announcement	Bloomberg

Appendix Table 1: Opportunistic Trading, ABSVI, and Future 1-month Stock Returns

This table shows the relationships of opportunistic trading, ABSVI, and future 1-month stock returns. We separate the sample into the net sales and net purchase subsamples, and we independently create quintiles based on the ABSVI and net sales and net purchase positions of each individual firm.

Net Sales\ABSVI	1 (Low)	2	3	4	5 (High)
1 (High)	1.871%	1.537%	1.347%	1.242%	0.878%
2	1.526%	1.323%	1.301%	0.968%	0.859%
3	1.416%	1.255%	1.054%	1.187%	0.746%
4	1.213%	1.125%	0.930%	0.954%	0.706%
5 (Low)	1.112%	1.129%	1.307%	0.952%	0.641%
Net Purchase\ABSVI	1 (Low)	2	3	4	5 (High)
1 (High)	3.625%	3.266%	3.356%	2.728%	1.756%
2	2.601%	2.924%	3.270%	2.102%	1.715%
3	2.568%	2.330%	2.172%	1.363%	1.600%
4	1.923%	1.948%	1.542%	1.311%	1.011%
5 (Low)	1.696%	1.284%	1.142%	1.604%	1.179%

This table reports the portfolio returns of SVI-based trading strategy. We see that future one-month returns are monotonically decreasing in the ABSVI and in net transaction positions. In particular, firms at the highest net sales and the lowest ABSVI quintile experience the highest average returns (1.871%), indicating that insiders who sell their firm's shares when investors' attention (ABSVI) is extremely low will experience the greatest opportunity cost of trading by forgoing the highest positive return in the following month. In contrast, if insiders sell at a higher ABSVI, their opportunity cost of selling will be lower. The results are similar on net insider purchase. A higher average return is realized when the ABSVI is lower; that is, insiders who buy their firm's shares when investors' attention is lower will earn higher returns. Overall, the results reinforce the argument that the ABSVI presents meaningful opportunities for profitable insider trades.

Appendix Table 2: Sub-sample Analysis

This table shows additional robustness tests. First, we split sample between earning announcement and non-earning announcement months. Second, we utilize the political regime change from the Bush to Obama Adminstration. In Columns 1 and 2, the dependent variable is Sales dummy which equals 1 only if a firm-month is a net sale month. In Columns 3 and 4, the dependent variable is the number of shares sold by all insiders (in thousands) for each firm-month observation. In Columns 5 and 6, the dependent variable is Purchase dummy which equals 1 only if a firm-month is a net purchase month. In Columns 7 and 8, the dependent variable is the number of shares bought by all insiders (in thousands) for each firm-month observation. Control variables include log(size), advertising/sales, log(BM), the equal-weighted market return, Log(Price), and Log(Turnover) defined in table 4 Two-way (Firm and month) cluster standard errors at the firm level are in parentheses. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

Only Earning Annoucement Months

	Probit Regression		Tobit Regression		Probit Regression		Tobit Regression	
	Sales Dummy		Shares Sold		Purchase Dummy		Shares Purchased	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(ABSVI)	0.154***		44.140***		-0.177***		-12.075**	
	(0.0571)		(14.319)		(0.0572)		(6.1679)	
Log(ABSVI) Positive		0.066***		17.572***				
		(0.0216)		(5.2539)				
Log(ABSVI) Negative						0.081***		6.348**
						(0.0215)		(2.5308)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	17,814	17,814	17,814	17,814	17,814	17,814	17,814	17,814
Pseudo R^2	0.070	0.069	0.003	0.003	0.069	0.069	0.016	0.017

Only Non-Earning Annoucement Months

	Probit Regression		Tobit Regression		Probit Regression		Tobit Regression	
	Sales Dummy		Shares Sold		Purchase Dummy		Shares Purchased	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(ABSVI)	0.083***		24.137**		-0.109***		-9.217**	
	(0.0311)		(9.7021)		(0.0331)		(4.6072)	
Log(ABSVI) Positive		0.041**		9.417**				
		(0.0167)		(3.7721)				
Log(ABSVI) Negative						0.033**		4.232**
						(0.0167)		(2.0857)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	32,342	32,342	32,342	32,342	32,342	32,342	32,342	32,342
Pseudo R^2	0.056	0.056	0.002	0.002	0.055	0.055	0.015	0.015

2004-2008 (Bush Administration)

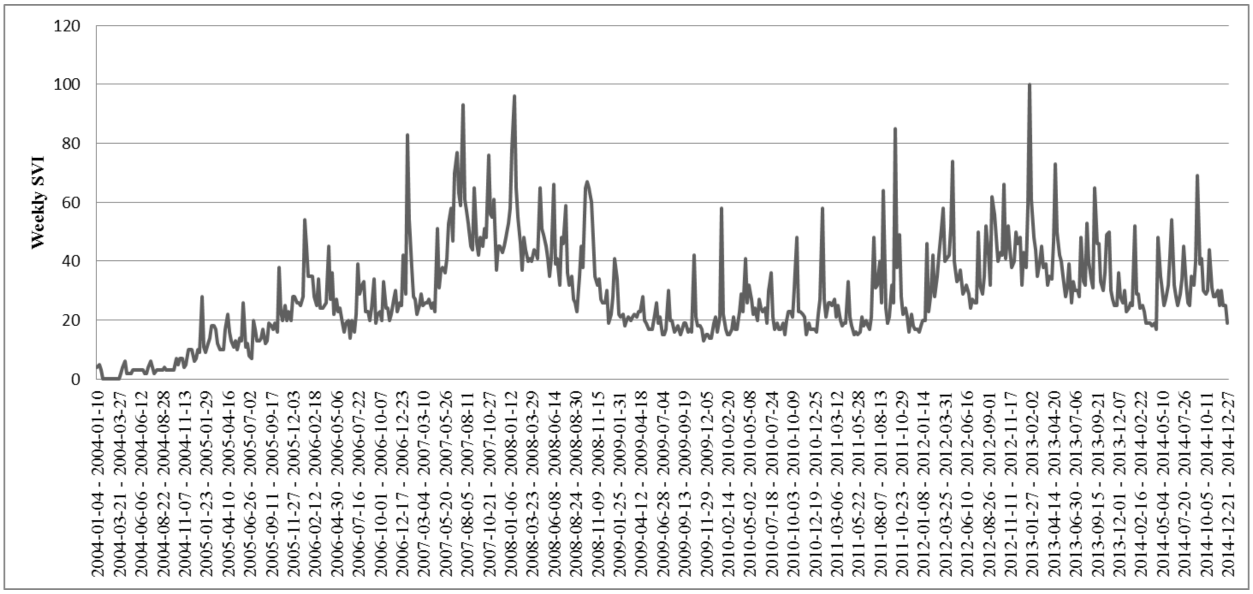
	Probit Regression		Tobit Regression		Probit Regression		Tobit Regression	
	Sales Dummy		Shares Sold		Purchase Dummy		Shares Purchased	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(ABSVI)	0.093***		18.169***		-0.124***		-8.921**	
	(0.0359)		(6.6179)		(0.0459)		(3.3655)	
Log(ABSVI) Positive		0.031**		15.831***				
		(0.0112)		(4.5049)				
Log(ABSVI) Negative						0.047**		6.052***
						(0.0192)		(2.1994)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	20,814	20,814	20,814	20,814	20,814	20,814	20,814	20,814
Pseudo R^2	0.041	0.041	0.003	0.003	0.041	0.041	0.011	0.011

2009-2014 (Obama Administration)

	Probit Regression		Tobit Regression		Probit Regression		Tobit Regression	
	Sales Dummy		Shares Sold		Purchase Dummy		Shares Purchased	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(ABSVI)	0.067***		20.970***		-0.102**		-9.973***	
	(0.0211)		(5.7894)		(0.0512)		(3.1211)	
Log(ABSVI) Positive		0.059***		17.768***				
		(0.0181)		(4.1001)				
Log(ABSVI) Negative						0.0409***		5.839**
						(0.0152)		(2.3766)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	29,342	29,342	29,342	29,342	29,342	29,342	29,342	29,342
Pseudo R^2	0.0638	0.0638	0.0021	0.0021	0.0631	0.063	0.0171	0.0170

Figure 1: Google Trends Search Index and Insider Trading

Panel A: Weekly Google Trends for Apple Inc. (AAPL)



Panel B: Monthly SVI and Insiders trading Patterns of Apple Inc. (AAPL)

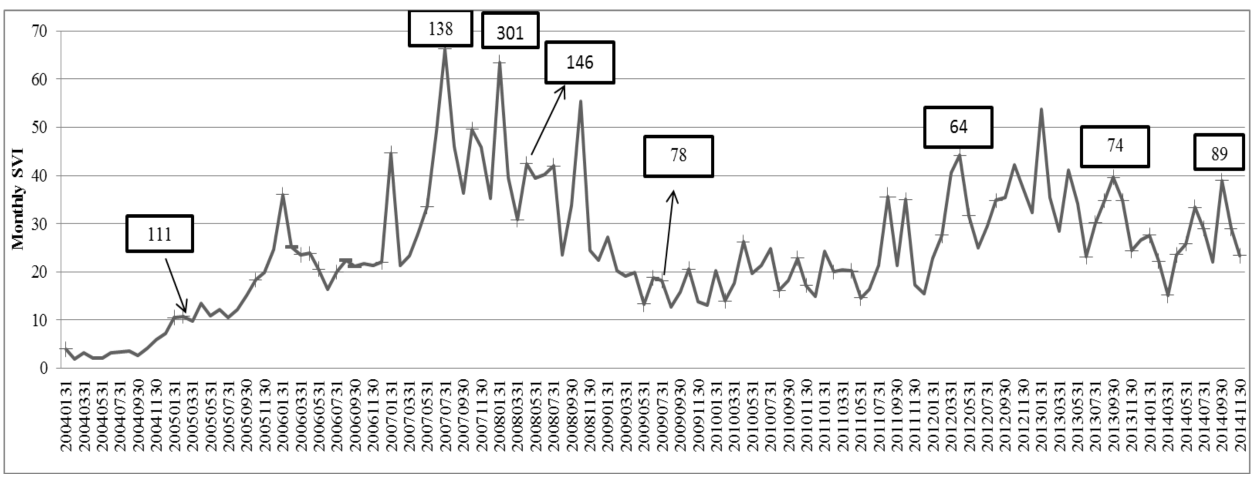
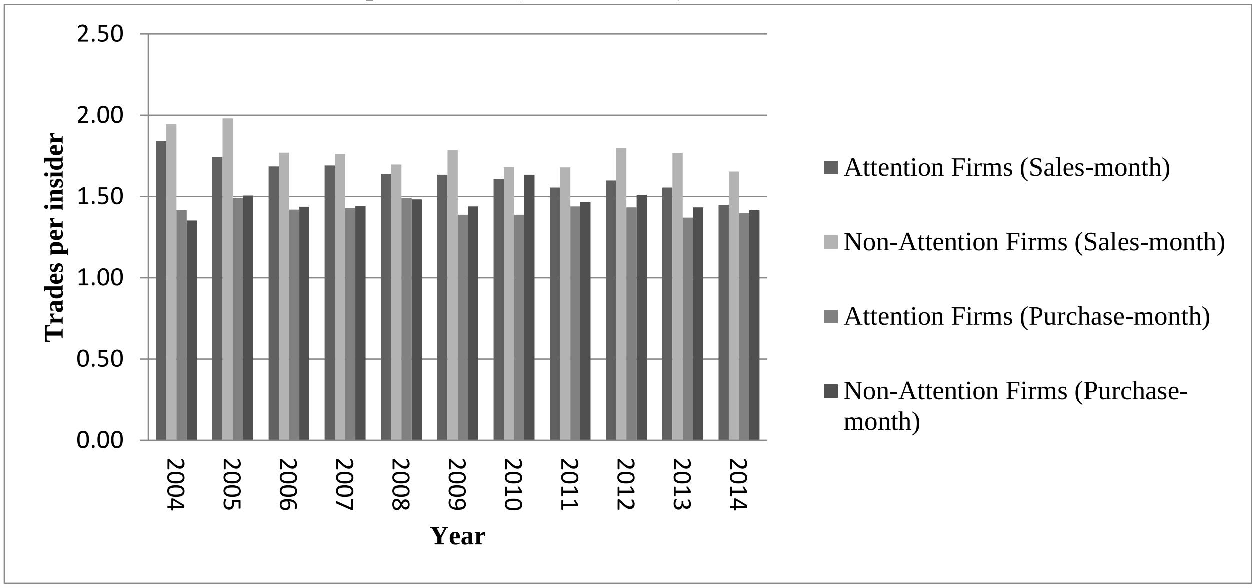


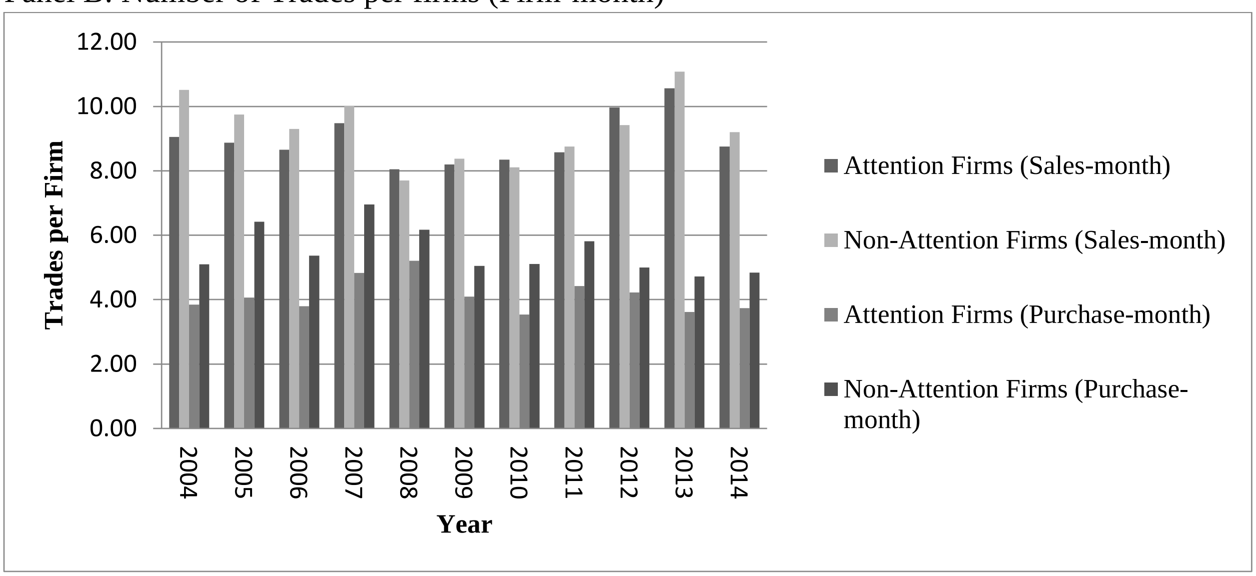
Figure 1 illustrates Google Trends search index and insider trading. Panel A displays the graphical output of Google Trends search index on Apple Inc. (ticker: AAPL). The graph plots a weekly aggregate search frequency (SVI) on "AAPL." The SVI measures the weekly search volume on "AAPL" scaled by the highest searching volume on the chart. Panel B displays insider trading patterns as related to the monthly SVI. The "+" ("-") sign refers to a net insider sale (purchase) month. Panel B only presents a trading volume greater than 50 (in thousands) shares and the number in each box is rounded to the nearest thousands.

Figure 2: Number of Trades per Insider and per Month

Panel A: Number of Trades per Insider (Firm-month)



Panel B: Number of Trades per firms (Firm-month)



In Figure 2, Panel A shows the number of trades per insider and Panel B shows the number of trades per firm in our attention firm and non-attention firm samples.

Figure 3: Insider Trading Comparison by Month

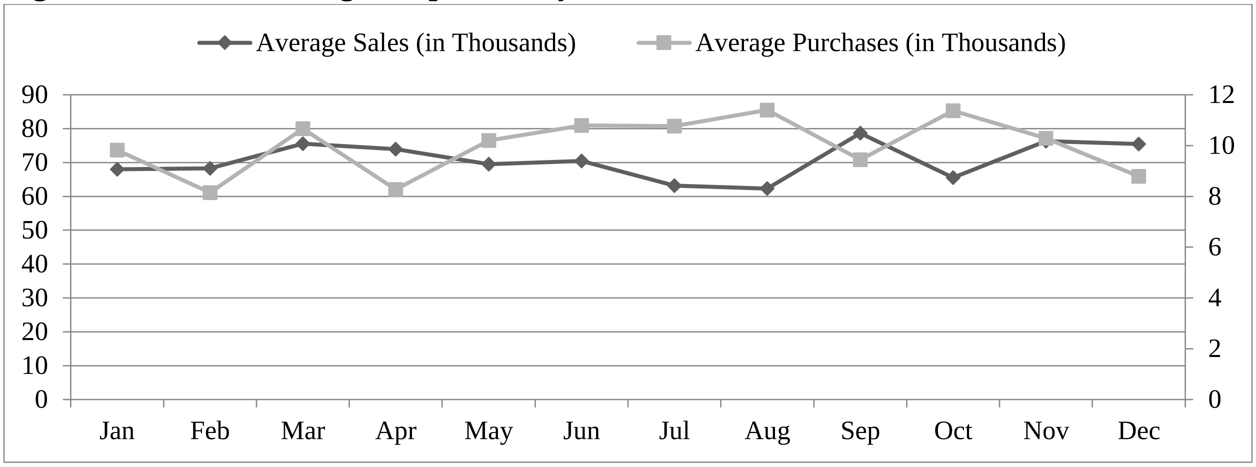


Figure 3 shows the monthly average insider sales (in thousands of shares) and purchases (in thousands of shares) in our sample.

Table 1: Summary Statistics

This table reports the summary statistics of sample firm-months for opportunistic insiders from January 2004 to November 2014. Panel A compares our sample's firm and insider characteristics with those in the insider universe. Panel B presents our attention and non-attention samples in firm-sale and firm-purchase months. Variable Size is based on the previous year-end market value (in millions of dollars). Variable BTM is the previous year-end book-to-market equity value ratio. Trades per firm-month, traders per firm month, and the number of firms per month are also reported. If a firm-month contains both an insider net sale and an insider net purchase, the observation is removed from the sample.

Non-routine Insiders (2004-2014)	Our Sample (Jan. 2004-Nov. 2014)			Whole Sample (Jan. 1986-Nov. 2014)	
Panel A: Attention Sample Vs Insider Universe	Mean	Median		Mean	Median
Size	4,599.44	923.31		4,297.72	751.96
BTM	0.56	0.47		0.57	0.47
Trades per firm-month	2.87	2.00		2.88	2.00
Traders per firm-month	1.71	1.00		1.72	1.00
Firms per month	708.66	698.00		621.79	622.00
Panel B: Decomposition of Our Sample	Mean	P25	Median	Std.	P75
SVI Firm Sales (3,096 firms, 52,477 firm-month observations)					
ABSVI	1.01	0.90	1.00	0.24	1.12
Size	6,741.29	514.10	1,457.19	15,994.14	4,604.91
BTM	0.54	0.27	0.45	0.38	0.70
Trades per firm-month	2.77	1.00	2.00	2.98	3.00
Traders per firm-month	1.70	1.00	1.00	1.15	2.00
Firms per month	399.21	318.00	381.00	120.04	492.00
Non-SVI Firm Sales (1,224 firms,15,739 firm-month observations）					
Size	1,073.19	258.65	529.43	1,947.54	1,102.51
BTM	0.49	0.24	0.42	0.36	0.64
Trades per firm-month	2.95	1.00	2.00	3.08	4.00
Traders per firm-month	1.65	1.00	1.00	1.09	2.00
Firms per month	120.15	92.00	124.00	38.27	145.00
SVI Firm Purchase (2,667 firms and 16,997 firm-month observations)					
ABSVI	0.98	0.87	0.97	0.24	1.10
Size	5,477.28	312.48	892.26	15,557.39	2,988.72
BTM	0.65	0.35	0.57	0.43	0.84
Trades per firm-month	2.17	1.00	1.00	1.99	2.00

Traders per firm-month	1.52	1.00	1.00	0.99	2.00
Firms per month	129.75	87.00	119.00	64.63	161.00
Non-SVI Firm Purchase (1,063 firms and 7,621 firm-month observations)					
Size	663.53	163.76	293.16	1,479.03	612.84
BTM	0.63	0.37	0.56	0.38	0.81
Trades per firm-month	2.44	1.00	2.00	2.11	3.00

Table 2: Industry Classification

This table reports the distribution of firms in our sample based on Fama-French 17 industry Classifications. Panel A shows the percentage of firms in each classification and the difference between our attention and non-attention samples. Panel B shows the difference of monthly Google SVI between the purchase and sale months. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Sample Distribution	**Non-attention firms**	**Attention firms**	**Difference**
Food	1.40%	2.55%	-1.16%
Mining and minerals	0.51%	1.23%	-0.73%
Oil and petro products	1.88%	5.14%	-3.26%
Textiles, apparel, and footwear	0.58%	1.56%	-0.98%
Consumer duration	0.87%	1.56%	-0.70%
Chemicals	1.08%	2.31%	-1.23%
Drugs, soap, perfume, tobacco	6.06%	3.88%	2.19%
Construction	1.73%	2.70%	-0.97%
Steel	0.79%	1.26%	-0.47%
Fabricated products	0.36%	0.57%	-0.21%
Machinery and business equipment	10.90%	12.05%	-1.14%
Automobile	0.79%	1.47%	-0.68%
Transportation	2.17%	3.30%	-1.14%
Utilities	0.65%	2.91%	-2.26%
Retail stores	4.19%	6.01%	-1.82%
Financial Institutions	27.51%	16.40%	11.11%
Other	38.56%	35.09%	3.47%
Panel B: Average Monthly ABSVI	**Purchase**	**Sales**	**Difference**
Food	0.989	1.014	-0.025**
Mining and minerals	0.960	1.032	-0.072***
Oil and petro products	0.989	1.018	-0.029**
Textiles, apparel, and footwear	0.995	1.017	-0.022
Consumer duration	0.975	1.012	-0.037**
Chemicals	1.003	1.013	-0.010
Drugs, soap, perfume, tobacco	0.979	1.012	-0.033**
Construction	0.988	1.016	-0.027**
Steel	0.993	1.024	-0.031**
Fabricated products	0.960	1.012	-0.053***
Machinery and business equipment	0.987	1.011	-0.023
Automobile	0.997	1.015	-0.018
Transportation	0.974	1.019	-0.045***
Utilities	0.984	1.018	-0.034***
Retail stores	0.988	1.003	-0.015
Financial Institutions	0.984	1.012	-0.028***
Other	0.981	1.014	-0.033***
Whole Sample	0.984	1.013	-0.029***

Table 3: Market-adjusted Returns Following Insider Trades

This table reports one-month NYSE size decile portfolio adjusted cumulative abnormal returns (CARs) following the insider trading month. CARs for trade months by insiders of attention firms are compared with those by insiders of non-attention firms. Panels A and B present the results for insider sales and purchases, respectively. In both panels, Column 1 reports results on all insiders, Column 2 on top-level officers (CEO, CFO, COO, and Chairman of the Board), Column 3 on directors in, and Column 4 on all other insiders. Standard errors are included in parentheses. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

Abnormal Returns	All Insiders	Top-level officers	Only directors	Other Insiders
	(1)	(2)	(3)	(4)
Panel A: Sales				
Attention Firms				
Size_adj CAR(%)	-0.688***	-0.930***	-0.895***	-0.497***
Standard Error	(0.093)	(0.094)	(0.099)	(0.092)
Number of Observations	52,477	16,024	20,426	24,461
Attention firms in Non-attention months				
Size_adj CAR(%)	-0.541***	-0.747***	-0.614***	-0.490***
Standard Error	(0.094)	(0.098)	(0.096)	(0.093)
Number of Observations	4,626	1,608	1,992	2,479
Difference 1	-0.147	-0.183	-0.281	-0.007
Non-Attention Firms				
Size_adj CAR(%)	-0.495***	-0.715***	-0.449***	-0.248***
Standard Error	(0.093)	(0.095)	(0.090)	(0.096)
Number of Observations	15,739	5,448	6,723	8,404
Difference 2	-0.193	-0.215	-0.446	-0.249
Panel B: Purchase				
Attention Firms				
Size_adj CAR(%)	1.010***	1.334***	0.777***	1.111***
Standard Error	(0.010)	(0.108)	(0.098)	(0.017)
Number of Observations	16,997	4,209	10,387	5,940
Attention firms in Non-attention months				
Size_adj CAR(%)	1.140***	1.878***	0.792**	1.420***
Standard Error	(0.100)	(0.109)	(0.093)	(0.109)
Number of Observations	1,786	443	1,142	597
Difference 1	-0.130	-0.544	-0.015	-0.309
Non-Attention Firms				

Size_adj CAR(%)	1.215***	1.424***	1.027***	1.625***
Standard Error	(0.115)	(0.118)	(0.109)	(0.126)
Number of Observations	7,621	2,113	4,903	2,616
Difference 2	-0.205	-0.090	-0.250	-0.514

Table 4: Return Analysis on Insider Trades

This table compares CARs following insider trades between our attention and non-attention firms. The dependent variable *Excess Ret*$_{t+1}$ is the one-month excess return % following trade month t. Attention dummy equals 1 (0) if a firm is in our attention (non-attention) sample. Log(ABSVI), Log(ABSVI Duration), Log(ABISVI) are the natural logarithm of monthly retail SVI scaled by the previous month's retail SVI, total number of months separating the trade month and the month of first valid ABSVI, and the monthly institutional SVI scaled by the previous month's institutional SVI, respectively. Other control variables include log(Analysts), log(BM), Advertising/sales, log(price), log(turnover), and CARs. Log(Analysts) is the natural logarithm of number of analysts covering the firm. Log (Size) is the natural logarithm of the previous year-end market value of firm. Log(BM) is the log of the previous year-end book-to-market equity value ratio. Advertising/Sales is the previous year-end ratio of advertisement expense to sales. Market$_{t+1}$ is the equal-weighted market return following trade month t. Log(Price) is the log of the previous year-end stock price. Log(Turnover) is the log of average monthly turnover in the previous year, where the monthly turnover is defined as the month's trading volume scaled by the number of shares outstanding: (VOL*100)/ (SHROUT*1000). CAR$_{t-3,t-1}$ is the firm's three month market adjusted return from months t-3 to t-1. CAR$_{t-12,t-1}$ is the firm's one-year market adjusted return from month t-12 to t-1. Panels A and Panel B show results on insider sales and insider purchases, respectively. Two-way Clustered standard errors at the firm level and year are in parentheses. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Insider Sales

Excess Ret$_{t+1}$%	Attention and Non-Attention firms	Attention and Non-Attention firms	Attention Firms	Attention Firms	Attention Firms	Attention Firms	Attention Firms
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-6.3011***	-2.5127	-1.9134	-3.4921	-1.7414	-1.0331	-2.7313
	(2.3902)	(4.5615)	(7.2331)	(7.6943)	(10.7317)	(0.8834)	(6.3727)
Attention Dummy		-0.2547**					
		(0.1235)					
Log(ABSVI)			-0.2123***	-0.1917***	-0.2143***	-0.2327***	0.1322
			(0.0503)	(0.0601)	(0.0614)	(0.0732)	(0.1827)
Log(SVI duration)				0.1131**	0.1937***	0.0307***	0.2139*
				(0.0534)	(0.0726)	(0.1008)	(0.1107)
Log(ABISVI)					0.0676		
					(0.2343)		
Log(Analysts)				0.0621**	0.0541**	0.0938**	0.0301
				(0.0311)	(0.0223)	(0.0443)	(0.0425)
Log(Size)	-0.3007***	-0.2003***	-0.1623***	-0.1321***	-0.4426***	-0.1003***	-0.1636***
	(0.0203)	(0.0201)	(0.0216)	(0.0323)	(0.0804)	(0.0283)	(0.0302)
Log(BM)	-0.7631***	-0.6909***	-0.5477***	-0.5313***	-0.6774***	-0.5139***	-0.5521***
	(0.1691)	(0.0947)	(0.0541)	(0.0626)	(0.0919)	(0.0694)	(0.0636)
Advertising/sales	-0.8941	-0.7317	-2.5032*	-2.3802*	-1.3727	-3.4632**	-1.3317
	(7.3129)	(1.5841)	(1.3636)	(1.3713)	(2.8351)	(1.5835)	(1.4573)
Log(Price)	0.4703***	0.5626***	0.4428***	0.4314***	0.6869***	0.4138***	0.4624***
	(0.1321)	(0.0737)	(0.0522)	(0.0515)	(0.1147)	(0.0616)	(0.0601)
Log(Turnover)	0.2491***	0.1836***	0.1443***	0.1737***	0.2324***	0.1837**	0.1725***
	(0.0134)	(0.0633)	(0.0531)	(0.0622)	(0.0661)	(0.0833)	(0.0642)

$CAR_{t-3,t-1}$	0.1347***	0.2217**	0.4591***	0.3349**	0.2425***	0.1416	0.5233***
	(0.0342)	(0.1001)	(0.1425)	(0.1451)	(0.0838)	(0.2441)	(0.1841)
$CAR_{t-12,t-1}$	2.5331***	2.8629***	2.0813***	2.6327***	3.3672***	2.7563***	2.5323***
	(0.2027)	(0.1441)	(0.4661)	(0.1036)	(0.5112)	(0.1541)	(0.1031)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	56,180	56,180	39,575	34,289	10,623	16,916	16,864
R^2	0.207	0.251	0.106	0.140	0.192	0.180	0.220

Panel B: Insider Purchase

Excess Ret_{t+1}%	Attention and Non-Attention firms	Attention and Non-Attention firms	Attention Firms	Attention Firms	Attention Firms	Attention Firms	Attention Firms
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	2.5791**	-2.2242	2.1922	-1.5743	-1.2622	13.3817	-18.9828
	(1.0327)	(1.5239)	(7.7867)	(2.1553)	(7.9434）	(29.6733)	(31.7002)
Attention Dummy		-0.3131***					
		(0.1111)					
Log(ABSVI)			-0.4737**	-1.4567**	-1.4244***	-1.7441	-2.6142**
			(0.2224)	(0.5773)	(0.4741)	(1.2832)	(1.3174)
Log(SVI duration)				-1.0741***	-1.3113**	-1.6237***	-0.7441
				(0.4004)	(0.5103)	(0.5331)	(0.6327)
Log(ABISVI)					2.3427***		
					(0.7834)		
Log(Analysts)				0.0703	0.0911	-0.0087	0.0919
				(0.1635)	(0.3543)	(0.2232)	(0.2212)
Log(Size)	-0.4534***	-0.1944**	-0.1826***	-0.3007***	-0.1638***	-0.2102	-0.5151***
	(0.0609)	(0.0791)	(0.0437)	(0.0910)	(0.0404)	(0.1321)	(0.1334)
Log(BM)	-0.6911***	-0.4919***	-0.6005***	-0.2038	-0.2426	-0.1735	-0.2032
	(0.2191)	(0.1127)	(0.1008)	(0.1714)	(0.2351)	(0.2324)	(0.2407)
Advertising/sales	-2.9423	-1.2818	-3.9222**	2.8431	2.6913	-4.3013	10.3343*
	(1.7687)	(2.1646)	(1.7711)	(4.5347)	(3.1345)	(5.5634)	(6.1541)
Log(Price)	0.6129***	0.5917***	0.4691***	-1.0263***	-1.0117***	-0.9642***	-1.0241***
	(0.2116)	(0.1431)	(0.0909)	(0.1842)	(0.2726)	(0.2544)	(0.2707)
Log(Turnover)	0.4922	0.1547	0.0243	-0.1733	0.2814	-0.5664**	0.2002
	(0.3117)	(0.1007)	(0.0736)	(0.1763)	(0.2712)	(0.2507)	(0.2501)
$CAR_{t-3,t-1}$	0.3854***	0.5733	0.2731	-1.3119*	-0.0445	-0.1013	-2.1643**
	(0.0771)	(0.4341)	(0.2522)	(0.7436)	(0.3121)	(1.0921)	(1.0818)
$CAR_{t-12,t-1}$	2.9883***	2.1877***	2.1256***	-0.6033	-0.2653	-0.3425	-0.9003
	(0.4441)	(0.1617)	(0.1516)	(0.4007)	(0.2103)	(0.5817)	(0.5727)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	15,262	15,262	10,749	8,895	2,608	4,282	4,483
R^2	0.265	0.414	0.446	0.479	0.499	0.581	0.574

Table 5: Predicting Contemporaneous Insider Trading

This table presents the results of Logit and Tobit regressions that analyze the likelihood and quantity of insider trading. In Columns 1 and 2, the dependent variable is Sales dummy which equals 1 only if a firm-month is a net sale month. In Columns 3 and 4, the dependent variable is the number of shares sold by all insiders (in thousands) for each firm-month observation. In Columns 5 and 6, the dependent variable is Purchase dummy which equals 1 only if a firm-month is a net purchase month. In Columns 7 and 8, the dependent variable is the number of shares bought by all insiders (in thousands) for each firm-month observation. Log(ABSVI) is the natural log of monthly ABSVI. Log(ABSVI) Positive (Negative) is a dummy variable which equals 1 if Log(ABSVI) is positive (negative). Control variables include log(size), advertising/sales, log(BM), the equal-weighted market return, Log(Price), and Log(Turnover) defined in table 4 Two-way (Firm and month) cluster standard errors at the firm level are in parentheses. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

	Probit Regression			Tobit Regression			Probit Regression			Tobit Regression		
	Sales Dummy			Shares Sold			Purchase Dummy			Shares Purchased		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log(ABSVI)	0.094***		0.136***	7.908***		11.968***	-0.082***		-0.071***	-3.343***		-2.850**
	(0.0341)		(0.0376)	(3.5100)		(4.1996)	(0.0242)		(0.0210)	(1.3075)		(1.1260)
Log(ABSVI) Positive		0.046***			11.619***							
		(0.0132)			(3.0348)							
Log(ABSVI) Negative								0.044***			4.164***	
								(0.0132)			(1.6034)	
Log(ABISVI)			-0.045**			-5.770**			0.031***			1.114***
			(0.0216)			(2.3581)			(0.0127)			(0.3757)
Log(Size)	0.021***	0.021***	0.017***	22.087***	20.176***	18.673***	-0.022***	-0.015***	-0.012***	-11.781***	-10.843***	-8.770***
	(0.0057)	(0.0057)	(0.0032)	(1.3472)	(1.3381)	(2.4482)	(0.0057)	(0.0057)	(0.0039)	(2.007)	(2.6577)	(1.6339)
Log(BM)	-0.109***	-0.109***	-0.136***	-26.914***	-25.472***	-26.020***	0.107***	0.106***	0.129***	9.623***	9.629***	11.850***
	(0.0102)	(0.0102)	(0.0199)	(2.5248)	(2.5376)	(3.7030)	(0.0102)	(0.0102)	(0.0198)	(1.3708)	(1.3710)	(3.0859)
Advertising/Sales	1.089***	1.092***	0.903***	401.980***	408.351***	333.960***	-1.069***	-1.101***	-0.939***	-97.832***	-98.152***	-69.474**
	(0.2248)	(0.2248)	(0.2437)	(59.2239)	(59.1672)	(63.4322)	(0.2250)	(0.2253)	(0.2124)	(29.5376)	(29.5228)	(35.4597)
$Market_t$	2.930***	2.938***	2.946***	369.999***	373.535***	311.813***	-2.912***	-2.922***	-2.917***	-296.375***	-297.794***	-205.757***
	(0.1564)	(0.1564)	(0.1700)	(36.3288)	(36.3210)	(39.7788)	(0.1566)	(0.1564)	(0.1698)	(19.1209)	(19.1323)	(53.6498)
Log(Price)	0.145***	0.144***	0.171***	-52.352***	-49.231***	-44.911***	-0.141***	-0.150***	-0.171***	-26.897***	-26.903***	-28.768***
	(0.0116)	(0.0116)	(0.0246)	(2.9071)	(2.8617)	(4.0722)	(0.0116)	(0.0114)	(0.0141)	(1.5254)	(1.5254)	(3.6359)
Log(Turnover)	0.079***	0.079***	0.061***	-4.004*	-2.883	-3.169	-0.076***	-0.080***	-0.047**	-4.814***	-4.806***	-4.770***

	(0.0099)	(0.0099)	(0.0134)	(2.3800)	(2.3756)	(4.1689)	(0.0099)	(0.0099)	(0.0233)	(1.1884)	(1.1879)	(1.3491)
Constant	-0.284**	-0.304**	-0.257*	-327.283***	-294.350***	-182.847***	0.296**	0.136	0.015	-11.727	-13.989	-18.78789
	(0.1202)	(0.1204)	(0.1486)	(27.3819)	(27.2312)	(47.2937)	(0.1205)	(0.1192)	(0.2459)	(13.568)	(13.6023)	(32.8693)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	50,156	50,156	14,115	50,156	50,156	14,115	50,156	50,156	14,115	50,156	50,156	14,115
Pseudo R^2	0.060	0.059	0.073	0.002	0.002	0.002	0.059	0.059	0.072	0.015	0.015	0.021

Table 6: Which Insiders Make Opportunistic Trades?

This table reports the results of Logit regressions that examine what types of insiders are likely to engage in opportunistic insider trades. In Columns 1, 3 and 5, the dependent variable is Sales dummy which equals 1 only if a firm-month is a net sale month. In Columns 2, 4 and 6, the dependent variable is the number of shares sold by all insiders (in thousands) for each firm-month observation. Log(ABSVI) is the natural log of monthly ABSVI. Top-level officer, Insider director, and Independent director are dummy variables equaling 1 if there is a trade in a firm-month by a top-level officer, an inside director, and an independent director, respectively. Control variables include log(size), advertising/sales, log(BM), the equal-weighted market return, Log(Price), and Log(Turnover) defined in table 4. Two-way (Firm and month) cluster standard errors at the firm level are in parentheses. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

	Top Level Officers	Top Level Officers	Independent Directors	Independent Directors	Other Insiders	Other Insiders
	Sales Dummy	shares Sold	Sales Dummy	shares Sold	Sales Dummy	shares Sold
	(1)	(2)	(1)	(2)	(5)	(6)
	Probit	Tobit	Probit	Tobit	Probit	Tobit
Log(ABSVI)	-0.035***	-16.362***	-0.020*	-10.586*	0.060***	22.1049***
	(0.0110)	(5.3293)	(0.0120)	(6.3507)	(0.0200)	(8.0164)
Log(Size)	0.083***	9.451***	0.069***	35.951***	0.073***	15.949***
	(0.0046)	(2.2155)	(0.0051)	(6.8825)	(0.0092)	(2.9781)
Log(BM)	-0.161***	-68.217***	-0.070***	-74.901***	-0.098***	-198.190***
	(0.0070)	(3.3917)	(0.0084)	(11.3929)	(0.0141)	(46.0127)
Advertising/Sales	0.315***	155.946**	0.082	195.063	2.153***	622.733 ***
	(0.1465)	(69.9265)	(0.1787)	(242.1410)	(0.2629)	(86.5563)
Market	1.075***	379.402***	1.167***	1386.044***	0.636***	1554.718**
	(0.1167)	(56.8915)	(0.1354)	(185.5708)	(0.2396)	(776.987)
Log(Price)	0.049***	-15.826***	0.109***	-43.1212***	-0.0137	-132.351**
	(0.0087)	(4.2310)	(0.0102)	(13.8312)	(0.0178)	(57.4772)
Log(Turnover)	0.099***	32.366***	0.078***	47.915***	-0.107***	-335.446***
	(0.0070)	(3.4191)	(0.0084)	(11.3749)	(0.0142)	(46.4416)
Constant	0.957***	-179.720***	0.588***	-526.594***	-0.534***	-3131.464***
	(0.0854)	(41.2153)	(0.0956)	(130.0825)	(0.1730)	(557.2777)
Obs	50,156	50,156	50,156	50,156	50156	50,156

Pseudo R^2	0.0143	0.002	0.0070	0.0005	0.0197	0.0053

Table 7: Insider Trader and Firm Characteristics

This table reports the results of Logit regressions of being non-senior-executive, non-independent insiders on a number of insider and firm characteristics during the 2004-2014 sample period. The dependent variable is a dummy at the insider level, which equals 1 only for a non-senior-executive, non-independent insider. High abnormal SVI Dummy (HABSVIDUM) is defined as equals to one if at least 6 of 12 calendar months result in ABSVI larger than one, zero otherwise.

The Other independent variables are: the number of years an insider is active; the number of years an insider has been trading; the number of states a firm has operations; a Poorly Governed Firms dummy that equals 1 if the G-index (Gompers, Ishii, & Metrick, 2003) is greater than or equal to 12; Financial Constraints-SA Index (Hadlock & Pierce, 2010); Product Sales Herfindahl index; Social Responsibility-KLD Index; and a Fortune100 dummy and rankings. All other control variables are described in Table 4. Clustered standard errors at the firm level are in parentheses. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of years active* HABSVIDUM	0.199*** (0.0134)							
Number of Trades	-0.063*** (0.0227)							
Geo Dispersion: # States * HABSVIDUM		0.157** (0.0725)						
Poorly Governed Firm (Gindex>=90 Pecentile) * HABSVIDUM			0.248*** (0.0891)					
SA Index (Financial Constraints) * HABSVIDUM				-0.012** (0.0051)				
Product Dispersion: HHI * HABSVIDUM					0.073* (0.0414)			
KLD Index * HABSVIDUM						-0.023*** (0.0075)		
FORTUNE100_DUM * HABSVIDUM							-0.281** (0.1174)	
FORTUNE100_Rank * HABSVIDUM								-0.073* (0.0424)
Log(Size)	-0.149*** (0.0182)	-0.415*** (0.0825)	-0.114*** (0.0399)	-0.164*** (0.0187)	-0.127*** (0.0220)	-0.151*** (0.0202)	-0.167*** (0.0183)	-0.126* (0.0635)

Log(BM)	-0.062*	-0.278***	-0.145**	-0.072**	-0.053*	-0.094**	-0.075***	-0.066
	(0.0321)	(0.0646)	(0.0315)	(0.033)	(0.0288)	(0.0376)	(0.0327)	(0.1824)
Advertising/Sales	-1.313**	-39.731*	-1.762	-1.354**	-1.243	-1.377*	-1.336**	-6.200*
	(0.6613)	(22.3963)	(1.4162)	(0.6540)	(0.8803)	(0.734)	(0.6497)	(3.7627)
$Market_t$	-1.116***	-2.948	-1.495	0.331	-0.316	0.325	0.447	-7.717***
	(0.3859)	(4.7163)	(2.4292)	(0.3823)	(0.4636)	(0.3992)	(0.3778)	(2.4045)
Log(Price)	-0.017	0.597***	-0.0681	0.021	-0.030	0.008	0.022	0.261
	(0.0362)	(0.2186)	(0.0751)	(0.0371)	(0.0431)	(0.0412)	(0.0367)	(0.1811)
Log(Turnover)	0.133***	0.229	0.112*	0.140***	0.151***	0.147***	0.141***	0.359**
	(0.0257)	(0.2186)	(0.0675)	(0.0371)	(0.0314)	(0.0270)	(0.0235)	(0.1808)
Past Firm Std Deviation	-0.496***	1.224	-0.417	-0.846***	-0.480***	-0.821**	-0.876***	-1.065
	(0.1137)	(1.9307)	(0.9412)	(0.2925)	(0.1807)	(0.3289)	(0.2886)	(2.0036)
Constant	3.391***	7.297**	2.408***	3.626***	3.003***	3.351***	3.684***	2.582
	(0.3637)	(2.8229)	(0.6679)	(0.3718)	(0.4453)	(0.4052)	(0.3642)	(1.5732)
Obs	74,226	683	7,877	72,643	50,927	59,241	74,226	1,407
Pseudo R^2	0.0481	0.1040	0.0196	0.0138	0.0149	0.0143	0.0191	0.0367

Table 8: Lottery-type Stocks and Insider Trades

This table reports insider trading results in the subsample of lottery-type stocks. Lottery-type stocks are those with a price in the bottom half of distribution while its volatility and skewness are both in the top half. Panel A shows mean monthly characteristics of lottery-type and non-lottery-type stocks during the 2004-2014 sample period. In Columns

1 through 4 of Panel B (C), we run Logit regressions where the dependent variable is Sales (Purchase) dummy which equals 1 if a firm-month is a net sale (purchase) month. In Columns 5 through 8, we run Tobit regressions where the dependent variable is the number of shares sold (bought) by all insiders (in thousands) for each firm-month observation. Lottery dummy takes value 1 only if firm i's stock is a lottery stock at the end of month t-1. Log(ABSVI) is the natural log of monthly ABSVI. Log(ABSVI) Positive (Negative) is a dummy variable that equals 1 if Log(ABSVI) positive (negative). Jump dummy equals 1 if ABSVI is in the top 10% of distribution, and Fall dummy equals 1 if ABSVI is in the bottom 10%. Control variables include log(size), advertising/sales, log(BM), the equal-weighted market return, Log(Price), and Log(Turnover) defined in table 4. Two-way (Firm and month) cluster standard errors at the firm level are in parentheses. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Lottery Vs Non-Lottery Stocks	Lottery Type	Non-Lottery Type
Number of Stocks	1,093	4,029
Price	6.40	23.68
Idiosyncratic Volatility	21.99	8.11
Idiosyncratic Skewness	2.10	0.29

Panel B: Sales Dummy/ Shares Sold	Probit Regression				Tobit Regression			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lottery	-0.172***	-0.282***	-0.084	-0.241***	-23.634**	-60.354***	-32.212*	-46.949***
	(0.0491)	(0.0661)	(0.0686)	(0.0549)	(11.0270)	(20.6786)	(17.6978)	(17.0659)
Log(ABSVI)	0.076**				24.023***			
	(0.0346)				(7.8233)			
Log(ABSVI)*Lottery	0.290**				186.317**			
	(0.1192)				(91.3155)			
Log(ABSVI) Positive		0.041***				10.444***		
		(0.0133)				(3.0379)		
Log(ABSVI) Positive* Lottery		0.228**				73.497**		
		(0.0937)				(31.3885)		
Log(ABSVI) Negative			-0.084***				-10.353***	
			(0.0686)				(3.0332)	

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(ABSVI) Negative*Lottery			-0.176*				-63.782**	
			(0.0935)				(31.3030)	
JUMP				0.010*				11.990***
				(0.0054)				(3.6329)
JUMP *Lottery				0.311***				109.679***
				(0.1096)				(40.4824)
Constant	-0.114	-0.133	-0.092	-0.122	-285.354***	-290.004***	-279.677***	-291.663***
	(0.1191)	(0.1192)	(0.1194)	(0.1186)	(27.0861)	(27.1271)	(27.1103)	(26.986)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	50,156	50,156	50,156	50,156	50,156	50,156	50,156	50,156
Pseudo R^2	0.060	0.059	0.059	0.060	0.002	0.002	0.002	0.002

Panel C: Purchase Dummy/ Shares Bought	Probit Regression				Tobit Regression			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lottery	0.155***	0.271***	0.056	0.225***	20.255***	30.912***	10.981***	21.655***
	(0.0493)	(0.0664)	(0.0690)	(0.0550)	(6.4558)	(8.6026)	(3.9734)	(7.5033)
Log(ABSVI)	-0.074**				-2.849**			
	(0.0346)				(1.3327)			
Log(ABSVI)*Lottery	-0.241**				-18.631**			
	(0.1211)				(9.5675)			
Log(ABSVI) Positive		-0.040***				-3.880**		
		(0.0133)				(1.6170)		
Log(ABSVI) Positive* Lottery		-0.240**				-22.533*		
		(0.0941)				(12.2631)		

Log(ABSVI) Negative			0.040***				3.756**	
			(0.0133)				(1.6155)	
Log(ABSVI) Negative*Lottery			0.199**				18.221*	
			(0.0939)				(9.2290)	
FALL				0.004				3.326*
				(0.0150)				(1.8483)
FALL*Lottery				0.227***				2.189**
				(0.1092)				(1.0729)
Constant	0.129	0.148	0.108	0.131	-15.900	-14.133	-17.937	-17.252
	(0.1193)	(0.1195)	(0.1196)	(0.1189)	(13.6363)	(13.6439)	(13.6691)	(13.5780)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	50,156	50,156	50,156	50,156	50,156	50,156	50,156	50,156
Pseudo R^2	0.059	0.059	0.059	0.058	0.015	0.015	0.015	0.015

Table 9: SEC Actions and Opportunistic Insider Trading

This table explores the link between SEC litigations and opportunistic insider trading during the 2004-2014 sample period. Panel A reports on regressions of the fraction of SVI-related sales on month t following news releases of SEC insider litigations at month t-1. The dependent variable is the number of opportunistic insider sales divided by the number of total opportunistic sales. The independent variable of interest is the Num SEC Releases in month t-1, which is the log of one plus the number of SEC releases on actions against illegal insider trading. We include control variables such as the fraction of positive Log(ABSVI) at month t and at month t-1, equally weighted market return, standard deviation of market return, and past cumulative market returns. Panel B reports the results of firm-level regressions where the dependent variables are Sales dummy (Columns 1-3) and Shares Sold (Columns 4-6). The independent variables of interest are the Num SEC Release and its interaction terms with Log(ABSVI). Panel C reports Logit regressions of SEC investigation. The observations are at the insider level and insider characteristics are constructed based on all trades and sales of each insider. SVI-relateded Sales dummy is equal to one if an insider sells in a month that has a positive Log(ABSVI), and % of SVI_induced traded (sales) dummy is equal to 1 if the number of SVI trades (sales) is more than the number of non-SVI trades (sales). Cluster standard errors are in parentheses. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Insider-level Regression	(1)	(2)	(3)	(4)	(5)	(6)
Num SEC Release	0.086***	0.055***	0.066***	0.073***	0.069***	0.073***
	(0.0217)	(0.0173)	(0.0190)	(0.0156)	(0.0188)	(0.0167)
Fraction Positive Log(ABSVI) $_t$		0.282***	0.264***	0.264***	0.265***	0.264***
		(0.0369)	(0.0329)	(0.0327)	(0.0334)	(0.0321)
Fraction Positive Log(ABSVI) $_{t-1}$			-0.078***	-0.081***	-0.080***	-0.081***
			(0.0186)	(0.0177)	(0.0175)	(0.0176)
Market Return $_{t-1}$				0.141	0.092	0.137
				(0.3099)	(0.3345)	(0.2948)
Std Market Return $_{t-1}$				3.223**	4.292*	3.069
				(1.5228)	(2.1646)	(2.6544)
Market Return $_{t-4,\ t-2}$				0.114		
				(0.2786)		
Market Return $_{t-7,\ t-2}$					0.147	
					(0.1222)	
Market Return $_{t-13,\ t-2}$						0.171
						(0 .1172)
Obs	130	130	129	129	129	129
R^2	0.039	0.547	0.585	0.594	0.595	0.594
Panel B: Firm-level Regressions		Probit Regression Sales Dummy			Tobit Regression Shares Sold	
	(1)	(2)	(3)	(4)	(5)	(6)
Num SEC Release $_{t-1}$	-0.051***	-0.065***	-0.063***	-3.232	-5.639*	-5.541*
	(0.0104)	(0.0130)	(0.0131)	(2.5189)	(3.1685)	(3.1696)
Log(Abnormal SVI) $_t$		0.081***	0.640***		27.972***	118.071***
		(0.0313)	(0.1055)		(7.4658)	(26.5771)
Log(ABSVI)$_t$ *Num SEC Release $_{t-1}$			0.326***			52.216***
			(0.0591)			(14.8172)
Constant	- 0.051	0.204	0.203	66.1598***	76.331***	76.460***
	(0.2417)	(0.2771)	(0.2764)	(13.0303)	(16.4054)	(16.4046)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	71,582	50,156	50,156	71,582	50,156	50,156
Pseudo R^2	0.027	0.031	0.032	0.001	0.001	0.001

Panel C: Probability of Being Investigated by the SEC

	(1)	(2)	(3)	(4)
SVI-Induced Sales Dummy	-0.812**	-1.456*	-0.104	-0.034
	(0.40873)	(0.7601)	(0.4493)	(0.4493)
Total Number of Insider Sales	0.434***			
	(0.1075)			
Num of SVI_Induced Trades		0.326		
		(0.2140)		
Num of Non_SVI_Induced Trades		0.336**		
		(0.1323)		
% SVI_Induced Trades Dummy			-1.307*	
			(0.6902)	
% SVI-Induced Sales Dummy				-1.125*
				(0.6802)
Obs	38,193	38,193	38,193	38,193
Pseudo R^2	0.035	0.038	0.013	0.010

Table 10: Public Information Flow or Investor Sentiment

This table reports on the effects SVI components: investor sentiment and public information on insider trading. We run following equation to decompose Log(*ABSVI*):

$Log(ABSVI)_{i,t} = \alpha_i * Log(ABISVI)_{i,t} + \beta_i * SUE_{i,Q(t)-1} + \gamma_i * \frac{Adv}{sale}_{i,Y(t)-1} + \delta_i * GDP_{Final_{t-1}} + \theta_i * FOMC_{t-1} + \vartheta_i * Earndum_{i,t} + \rho_i * Ret_{i,t-1} + \sigma_i * Vol_{i,t-1} + \tau_i * \log(Max\ price)_{i,t-1} + \varphi_i * Idiovol_{i,t-1} + Year + Industry + \varepsilon_{i,t}$, where $Log(ABISVI)_{i,t}$ is the nature logarithm of abnormal institution search volume index on the firm i at month t, $SUE_{i,Q(t)-1}$ is the previous quarter q of month t's earnings surprise for firm i. In Columns 1-3, the dependent variable is Sales (Purchase) dummy which equals 1 if a firm-month is a net sale (purchase) month. In Columns 4-6, the dependent variable is *the number of shares sold (bought)* by all insiders (in thousands) for each firm-month observation. $Adv/sale_{i,Y(t)-1}$ is the previous year-end advertising expenditure to sales ratio, GDP_Final_{t-1} and $FOMC_{t-1}$ are dummy variables that equal 1 if any macro news is release in month t-1. $Earndum_{i,t}$ is the earning dummy variable equals to 1 if a firm made an earnings announcement in month t. $Ret_{i,t-1}$ *and* $Vol_{i,t-1}$ are previous monthly return and trading volume scaled by shares outstanding, respectively. $\log(Max\ price)_{i,t-1}$ is the natural logarithm of previous month maximal price and $Idiovol_{i,t-1}$ is the previous monthly idiosyncratic volatility. We take the predicted value as the information component denoted by Log(ABSVI-Information) and the residual value as the sentiment component denoted by Log(ABSVI-Sentiment). In all specifications, control variables include Log(Size), Log(BM), equally weighted market return, Log(Price), and Log(Turnover). Definitions of these variables are in Table 4. Two-way (Firm and month) cluster standard errors at the firm level are in parentheses. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Sales	Probit Regression			Tobit Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(ABSVI-Information)	0.106		0.110	16.091		17.055
	(0.0740)		(0.0741)	(65.9780)		(64.6004)
Log(ABSVI-Sentiment)		0.133***	0.131***		22.506***	22.141***
		(0.0368)	(0.0369)		(5.6348)	(5.9866)
Constant	-0.274	-0.253	-0.273	-158.272***	-154.244***	-158.284***
	(0.2594)	(0.2595)	(0.2595)	(49.2998)	(49.2282)	(49.2897)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	12,825	12,825	12,825	12,825	12,825	12,825
Pseudo R^2	0.074	0.073	0.074	0.002	0.002	0.002

Panel B: Purchase	Probit Regression			Tobit Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(ABSVI-Information)	-0.134		-0.132	-21.634		-21.111
	(0.3694)		(0.0729)	(37.0026)		(31.0229）
Log(ABSVI-Sentiment)		-0.129***	-0.134***		-24.695***	-24.249***
		(0.0327)	(0.0369)		(6.0051)	(6.0346)
Constant	0.322	0.301	0.321	12.754	10.956	12.499
	(0.2601)	(0.2602)	(0.2602)	(15.4119)	(15.4671)	(15.4129)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	12,825	12,825	12,825	12,825	12,825	12,825

Pseudo R^2	0.074	0.073	0.074	0.0214	0.021	0.021

Table 11: Summer and Day-of-week Effect

This table reports the average abnormal SVI and insider trading patterns between Holiday and non-holiday month and the t-test.

Monthly (Firm-level)	**Summer (July & August)**	**Non-summer Months**	**Difference**
Absvi	0.9711	1.0146	-0.0435***
Shares Purchased (in Thousands)	11.1637	9.0301	2.1336***
Shares Sold (in Thousands)	62.6242	75.6622	13.0380***
Daily (Insider-Level)	**Friday**	**Other Week Days**	**Difference**
Shares Purchased (in Thousands)	5.0345	4.4317	0.6028***
Shares Sold (in Thousands)	44.9141	51.8616	-6.9475***

Table 12: IV Test[30]

This table reports the IV-test of our baseline model. Based on table 11 and figure 3, we use the summer dummy, GDP final dummy, and FOMC dummy as the instrument variables. Specifically, on the first stage, we run following equation:

$$Log(ABSVI)_{i,t} = \alpha_i * Summer_t + \beta_i * GDP_{Final_{t-1}} + \gamma_i\, FOMC_{t-1} + \theta_i * Log(size)_{i,Y(t)-1} + \vartheta_i * Log(BTM)_{i,Y(t)-1} + \rho_i * Earndum_{i,t} + \sigma_i * Ret_{i,t-1} + \tau_i * abs(Ret_{i,t-1}) + \varphi_i * Market_i + \omega_i * SUE_{i,Q(t)-1} + Year + Industry + \varepsilon_{i,t},$$

Where $Summer_t$, $GDP_{Final_{t-1}}$, and $FOMC_{t-1}$ are instrument variables, which equal to one when the months are summer months (July and August), when GDP final was announced in the previous month, when the FOMC rate decision was made in the previous month, respectively. Log(size) is the natural logarithm of previous year-end market value. Log(BTM) is the firm's book value scaled by its market value. $Earndum_{i,t}$ is the earning dummy variable equals to 1 if a firm made an earnings announcement in month t. . $Ret_{i,t-1}$ *and* $abs(Ret_{i,t-1})$ are previous monthly return and absolute return. $Market_{t-1}$ is equally-weighted market return. $log(\#\ of\ earningnews)_{t-1}$ is the natural logarithm of number of earning announcements in the previous month. $Log(\#\ of\ earningnews)_{t-1}$ is the nature logarithm of number earnings announcements released by the industry (first 2 digit sic). $SUE_{i,Q(t)-1}$is the previous quarter q of month t's earnings surprise for firm i. Two-way (Firm and month) cluster standard errors at the firm level are in parentheses in Panel A. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively. Panel B shows additional tests on our instrument variables that they need to satisfy.

Panel A	Probit Regression Sales Dummy		Tobit Regression Shares Sold		Probit Regression Purchase Dummy		Tobit Regression Shares Purchased	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(ABSVI)	1.688***		47.507***		-1.754***		-12.796**	
	(0.4898)		(10.9825)		(0.4912)		(5.7706)	
Log(ABSVI) Positive		0.399**		24.625***				
		(0.2012)		(4.8341)				
Log(ABSVI) Negative						0.467**		20.888***
						(0.2121)		(7.0826)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	43,796	43,796	43,796	43,796	43,796	43,796	43,796	43,796

30 For parsimony reason, we only report the second stage regression results.

Panel B	Log(ABSVI)	Log(ABSVI) Positive	Log(ABSVI) Negative
F Statistics (First-stage)	57.27	39.10	41.86
Cragg-Donald Walk F-Statistic	71.01	47.82	49.34
Sargan Statistic	2.610	2.208	2.479
p-value	0.271	0.332	0.290
"Rule of thumb" critical value	10	10	10
Stock Yogo Critical Value of a 5% wald test	22.30	22.30	22.30

Table 13: Portfolio Returns on SVI-based Trading Strategies

This table shows the returns of buy and sale portfolios that follow the ABSVI from 2004-2014. We first classify the sample into the positive or negative Log(ABSVI) and then create sub-groups of buy and sell portfolio samples based on the net sale or purchase positions. For example, if a firm in month t has a net sales position and encounters a positive Log(ABSVI) in month t, we group this firm into a Positive Log(ABSVI) Sells portfolio. At the end of month t+1, we rebalance the portfolio based on new firms' net positions and ABSVI. We report below the monthly percentage return on both buy and sell equally weighted as well as value weighted portfolios. Panel A presents the results of equal-weighted portfolios and Panel B shows those of value-weighted portfolios. Standard errors at the portfolio level are in parentheses. We use ***, **, and * to denote a significant difference from zero at the 1%, 5%, and 10% levels, respectively.

	Positive Log(ABSVI) Buys	Negative Log (ABSVI) Buys	L/S Buys	Positive Log(ABSVI) Sells	Negative Log(ABSVI) Sells	L/S Sells	Negative Log(ABSVI) Buys-Positive Log(ABSVI) Sells
				Panel A: Equal-Weighted			
Average Returns %	0.667	2.261	-1.594	-0.021	2.315	-2.335	2.281
Standard dev.	6.1646	5.8811	3.7997	5.4006	5.2111	3.7997	3.6811
CAPM Alpha	0.448	2.043***	-1.594***	-0.299	2.073***	-2.371***	2.341***
	(0.5469)	(0.5197)	(0.3373)	(0.4731)	(0.4565)	(0.2656)	(0.3250)
Fama-French Alpha	0.428	2.032***	-1.604***	-0.317	2.056***	-2.373***	2.349***
	(0.5393)	(0.5206)	(0.3353)	(0.4646)	(0.4503)	(0.2662)	(0.3234)
Carhart Alpha	0.455	2.064***	-1.610***	-0.269	2.081***	-2.350***	2.334***
	(0.5410)	(0.5214)	(0.3377)	(0.4618)	(0.4514)	(0.2656)	(0.3245)
5-factor Alpha	0.581	2.144***	-1.562***	-0.180	2.139***	-2.319***	2.323***
	(0.5387)	(0.5239)	(0.3391)	(0.4621)	(0.4542)	(0.2675)	(0.3280)
				Panel B: Value-Weighted			
Average Return %	0.670	1.395	-0.725	0.292	1.427	-1.135	1.103
Standard dev.	6.1397	5.5957	4.9426	4.7540	4.6496	3.1868	4.3025
CAPM Alpha	0.468	1.182**	-0.713	-0.005	1.175***	-1.168	1.177***
	(0.5442)	(0.4958)	(0.4385)	(0.4121)	(0.4055)	(0.2822)	(0.3796)
Fama-French Alpha	0.458	1.166**	-0.708	-0.012	1.162***	-1.174***	1.177***
	(0.5453)	(0.4908)	(0.4391)	(0.4036)	(0.4028)	(0.2805)	(0.3826)
Carhart Alpha	0.477	1.204**	-0.727	0.019	1.189***	-1.172***	1.188***
	(0.5477)	(0.4902)	(0.4411)	(0.4037)	(0.4031)	(0.2821)	(0.3845)
5-factor Alpha	0.5440	1.256**	-0.712	0.059	1.177***	-1.138***	1.197***
	(0.5515)	(0.4941)	(0.4459)	(0.4070)	(0.4076)	(0.2841)	(0.3887)

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