Weather-Induced Positive Sentiment and Insider Trading

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Abstract

We examine whether mood affects corporate insiders' trading behavior. Exploiting unexpected variations in sunshine exposure near insiders' locations, we find that weather-induced positive sentiment leads to higher insider purchases, albeit with lower profits. Over-optimism after experiencing unexpected favorable weather serves as the underlying mechanism. The effect is more pronounced when insider trading is more likely to be driven by their perceived private information, leading to lower price informativeness. Insiders' personal characteristics, including executive ranks, geographic distances between insiders' and headquarters' locations, and educational qualifications, also moderate the effect. Our findings highlight the overlooked yet significant influence of mood on insider trading.

Keywords: *Mood; Weather; Optimism; Insider Trading; Insider Characteristics.*

JEL Codes*:* G14; G32; G41.

“*The essential difference between emotion and reason is that emotion leads to action, while reason leads to conclusions*.” - Donald Calne, Neurologist.

1 Introduction

Emotional states have long been known to significantly shape individuals’ decision-making processes and assessments (Kaustia & Rantapuska, 2016; Autore & Jiang, 2019). A burgeoning body of literature has started exploring whether weather-induced sentiment affects market professionals’ behavior. Among others, Chhaochharia et al. (2019) find that corporate managers make greater physical and labor investments during sunnier periods. Cortés, Duchin, and Sosyura (2016) document that weather-induced mood affects managers’ subjective judgment and risk tolerance and thus influences loan approval rates. Furthermore, financial analysts’ earnings forecasts are subjected to the influence of Seasonal Affective Disorder (SAD) (Lo & Wu, 2018). Goetzmann et al. (2015) and Jiang, Norris, and Sun (2021) also find that unpleasant weather negatively affects institutional investors’ trading activities.

Although these studies confirm the relationship between weather-induced sentiment and market professionals’ actions, it is important to note that these market professionals are agents of investors, and their decisions primarily pertain to investors’ money, not their own money.[1] Institutional investors, for example, engage in trading on money they manage for their clients; management decisions prioritize the interests of shareholders, and financial analysts provide recommendations to guide investors in making investment decisions. In these cases, the immediate monetary consequences of sentiment-motivated choices are not directly and entirely borne by

[1] While these market professionals’ compensation schemes depend on their performance, they are still agents of investors and play with other people’s money after all.

market professionals themselves. When these market professionals make unwise decisions, it may be attributed to their biased assessments or their carelessness of other people's money. Thus, to provide a clearer picture of sentiment's influence on market professionals' decision-making, we utilize the context of corporate insiders, where professionals (i.e., insiders) capitalize on their own assets and their trading is directly and fully tied to their monetary benefits. Employing insider-level analysis, our investigation departs from other research and will be able to better isolate the effect of weather-induced sentiment and shed light on the role of insiders' personal characteristics.

The rationale for the impact of sentiment on insider trading is rooted in psychological and neuroscience literature. Psychological studies indicate that mood introduces bias into individual decisions, affecting future expectations, evidenced by the misattribution effect for information (Siemer & Reisenzein, 1998; Williams & Voon, 1999). Mood also impacts cognitive functions like perception, reasoning, attention, and problem-solving, which are critical for judgment and decision-making (Lewis, Haviland-Jones, & Barrett, 2010). For instance, mood influences risk preference, with anxiety favoring low-risk options and anger leaning toward high-risk seeking (Raghunathan & Pham, 1999; Lerner & Keltner, 2001).

Neuroscience literature supports the idea that mood affects decision-making, with emotional states related to the orbitofrontal cortex (OFC), cingulate cortex, and insular cortex, all pivotal in economic and financial decision-making (Damasio et al., 2000; O'Neill & Schultz, 2013; Knutson & Bossaerts, 2007). Sentiments, as subjective conditions unrelated to the decision itself, influence how we evaluate current choices by impacting our action tendencies (Phelps, Lempert, & Sokol-

Hessner, 2014). Different emotions convey distinct information and biases to decision-makers (Raghunathan & Pham, 1999).

Evidence suggests that insiders' wealth management is subject to the influence of individual characteristics and behavioral bias (Bhattacharya & Marshall, 2012; Davidson, Dey, & Smith, 2013; Hillier, Korczak, & Korczak, 2015; Akbas, Jiang, & Koch, 2020). For example, insiders' stock option exercises irrationally respond to recent stock trends and a psychological reference point (Heath, Huddart, & Lang, 1999). Optimistic executives tend to exercise an option suboptimally closer to expiration than non-optimistic executives (Sen & Tumarkin, 2015). These findings align with Bhattacharya and Marshall's (2012) proposition that latent psychological factors can explain insider trading performance. Leveraging these insights from a range of disciplines, we predict that sentiment will affect insiders' trading behavior and performance.

However, there are empirical challenges associated with investigating the relationship between sentiment and insider trading activities. First, insiders' day-to-day decisions and information sets remain unobservable and complex, posing difficulties in assessing how sentiment influences their behavior. Second, measuring sentiment accurately at the time of decision-making is challenging, as it can be confounded by other economic factors (e.g., Cortés, Duchin, & Sosyura, 2016). To overcome these challenges, we utilize the 5-digit zip codes disclosed by insiders to the Securities and Exchange Commission (SEC) to identify each insider's location.[2] By comparing these zip codes with the firms' headquarters zip codes, we find that insiders' locations often differ largely from those of their headquarters (see Appendix

[2] The Securities and Exchange Commission mandates the disclosure of their location information when insiders submit the Form 4 (See: https://www.sec.gov/about/forms/form4data.pdf). Our result qualitatively holds if removing observations with location changes or adding zip code fixed effects.

B for details)[3]. We also manually verify a random sample of insiders' residential addresses using *PeopleFinders* and confirm that the reported zip codes correspond to, or are near, their residential locations. We then employ the unexpected favorable weather nearby the insider's location as a proxy for her personal positive sentiment, given that this measure is less likely to correlate with the insiders' information set and the local economic conditions surrounding the locations of firms' headquarters.

We obtain insider-trading information from the Insider Filing Data Feed (IFDF) provided by Thomson Reuters. We focus on the number of shares traded and dollar trading volume as primary measures of insider trading activities. Additionally, we calculate the future 5-trading day profit percentage to measure their trading performance (Ali & Hirshleifer, 2017). The weather-induced positive sentiment measure is derived from unexpected variation in sunshine exposure before insider trading, which is obtained from the Integrated Surface Database (ISD) and has been widely used in prior literature (Goetzmann et al., 2015; DeHaan, Madsen, & Piotroski, 2017; Chhaochharia et al., 2019). Specifically, we focus on abnormally good weather that occurs when the 14-day rolling average of sunshine exposure before insider trading is much higher than in previous years. Such a rise in sunshine exposure in a 14-day window is more likely to be unexpected. Thus, by construction, our weather-induced positive sentiment measure is mainly random and least likely to be selected.[4]

Our baseline regression analysis shows that insiders tend to acquire more shares following unexpected abnormal sunshine exposure, albeit resulting in lower

[3] Additionally, we observe that, in most cases, insiders within the same company do not change their reported zip codes in their Form 4 fillings.
[4] In an untabulated test, we use the observations where insiders relocate and find that the likelihood of experiencing abnormally good weather does not significantly change after insiders relocate. This indicates that insiders do not appear to select locations for more sunshine exposure.

profits. Yet, we do not observe a similar pattern for insider sales. This asymmetry aligns with prior research, indicating that insider sales are primarily driven by liquidity considerations, thus being less susceptible to sentiment influences (e.g., Roulstone, 2003; Cohen, Malloy, & Pomorski, 2012; Alldredge & Cicero, 2015; Kallunki et al., 2018; Aussenegg, Jelic, & Ranzi, 2018). For the potential mechanism, we find that purchases induced by positive sentiment are larger than the scale of the insider's most recent other transactions. Moreover, the impact of positive sentiment on purchasing is more pronounced when insiders exhibit over-optimism (Malmendier & Tate, 2005). These results indicate that the rise in insider over-optimism subsequent to exceptionally favorable weather serves as the mechanism through which weather sentiment influences insider trading.

Next, we explore the effect of sentiment on different types of insider purchases. Insider purchases are divided into information-based (non-routine and sequential trading) and non-information-based transactions (routine and single trading). We also employ the informed trading measure constructed by Bogousslavsky, Fos, and Muravyev (2024) to examine insider trading informativeness. The findings suggest a more pronounced impact of positive sentiment on information-based purchases, potentially attributed to insiders' over-optimism regarding their perceived information. Their increased trading activity stems from the emotion-laden belief that their private information would result in higher returns. However, their overestimation of the informational value would finally lead to a lower profit and a lower level of informativeness of insider trading.

The further analysis investigates the influence of insiders' ranks within corporate hierarchies and the geographic distance between insiders' and the headquarters' locations. We find that behavioral biases are more evident among insiders who hold lower ranks within the firm hierarchy and who locate remotely (Cohen, Malloy, & Pomorski, 2012; Klein, Maug, & Schneider, 2017), suggesting that these insiders may lack direct access to information and are thus more susceptible to weather-induced sentiment. Also, we explore the circumstances under which insiders are particularly vulnerable to the influence of sentiment. Existing literature suggests that sentiment has a stronger impact during periods of high uncertainty (e.g., Ben-David, Graham, & Harvey, 2013; Birru & Young, 2022). We use the economic policy uncertainty index (EPU) as a proxy for market uncertainty and observe that insiders are more affected by the weather-induced positive sentiment when the market is characterized by high uncertainty.

Finally, we extend our analysis to investigate the influence of insiders' personal attributes, including age, gender, and educational qualifications. Overall, the findings suggest that insiders with lower academic qualifications, female and older insiders are more susceptible to the sentiment induced by weather conditions. This aligns with prior studies that propose a link between insiders' personal attributes (e.g., Hillier, Korczak, & Korczak, 2015; Kallunki et al., 2018) and insider trading patterns.

Our study contributes to the literature in several ways. First, it adds to the literature that supports the relationship between sentiment and stock market outcomes (e.g., Edmans, Garcia, & Norli, 2007; Chang et al., 2008; Bodoh-Creed, 2020; Dong & Tremblay, 2022) and expands the literature by exploring the connection between sentiment and market professionals' activities (Goetzmann & Zhu, 2005; Goetzmann et al., 2015; Chhaochharia et al., 2019; Jiang, Norris, & Sun, 2021). Our paper specifically examines detailed individual-level insider transaction data, highlighting sentiment's impact on corporate insiders who trade on their own assets and have information advantages over typical retail investors.

Second, our research contributes to the insider trading literature by introducing an exogenous factor to verify the impact of sentiment on insider trading behavior and performance. The conventional view that insiders are less susceptible to behavioral biases has been challenged by more recent literature (e.g., Davidson, Dey, & Smith, 2013; Hillier, Korczak, & Korczak, 2015; Alldredge & Cicero, 2015; Kallunki et al., 2018). While these studies predominantly focus on insiders' personal attributes, our empirical design identifies sources of insider trading bias through sentiment induced by an exogenous environmental factor.

Lastly, our paper provides new insight into insider trading behavior and the stock price informativeness. Prior literature on insider trading suggests that insider trading can help compound more firm-specific information into stock prices and thus enhance price informativeness (e.g., Manne, 1966; Piotroski & Roulstone, 2004), and insider buying is more informative for investors (e.g., Brochet, 2010; Piotroski & Roulstone, 2005). In contrast, we indicate that when insider trading, especially purchases, are influenced by weather-induced sentiment, such purchases reduce price informativeness. Our results highlight an interesting parallel to consumers' impulse purchase behavior and complements the existing literature on insider trading and price informativeness (e.g., Lee & Piqueira, 2019; Hsieh, Ng, & Wang, 2023).

The rest of the paper is structured as follows. The theoretical foundation and hypothesis formulation are outlined in section 2. The data and techniques used to estimate the impact of weather-induced sentiment on insider trading are described in section 3. Section 4 presents our empirical analysis, while section 5 concludes our research.

2 Literature Review and Hypothesis Development

2.1 Insider trading and their personal attributes

The insider trading literature has attracted considerable attention for decades. Prior research indicates that insiders are more cautious when pursuing profits under regulations and can still generate abnormal returns (e.g., Huddart, Ke, & Shi, 2007; Jagolinzer, 2009; Fidrmuc & Xia, 2022). Thus, studies in this area tend to explore the information content of insider trading within the confines of regulatory restrictions.

There are two broad motives behind insider trading, namely, informational-based trading and liquidity-based trading. For instance, insiders often receive equity-based compensation in the form of company stocks and options, which gives rise to diversification and liquidity motives for selling (Ali & Hirshleifer, 2017). Previous literature also finds that information-based insider trading contains more information than liquidity-based trading. For example, Cohen, Malloy, and Pomorski (2012) find that the average abnormal profit for routine traders (i.e., liquidity-based traders) is zero, while a portfolio consisting solely of opportunistic insider trades (i.e., informational-based trades) generates abnormal returns of 180 basis points per month.

Kelly (2018) confirms Cohen, Malloy, and Pomorski's (2012) findings that opportunistic sales are more indicative of negative information than routine sales. Similarly, Ali and Hirshleifer (2017) find that opportunistic traders achieve significantly higher profits than non-opportunistic traders and are associated with a higher incidence of company misconduct. Chowdhury, Mollah, and AI-Farooque (2018) establish a link between opportunistic trading and earnings manipulations, suggesting that insiders use their private information to seek personal profit in contrast to prevailing investor sentiment or belief.

Furthermore, Biggerstaff, Cicero, and Wintoki (2020) investigate insiders' trading strategies and find that insiders who report their transactions after-market hours are more likely to spread out their trading duration to conceal their intentions. Akbas, Jiang, and Koch (2020) find that insiders with short investment horizons are more likely to be informed and unexpected.

More recently, a growing strand of studies on insider trading suggests that trading performance can be affected by insiders' personal characteristics (e.g., Bhattacharya & Marshall, 2012; Davidson, Dey, & Smith, 2013; Hillier, Korczak, & Korczak, 2015; Akbas, Jiang, & Koch, 2020). Specifically, Hillier, Korczak, and Korczak (2015) find that insider's individual attributes, such as age, educational background, and gender, can explain a significant portion of insiders' trading performance. Akbas, Jiang, and Koch (2020) show that opportunistic traders are more likely to hold MBA qualifications and are more likely to be male. Kallunki et al. (2018) suggest that strategic insider selling is related to insider's wealth. Davidson, Dey, and Smith (2013) find that executives who tend towards less frugality are more likely to pursue personal profits through insider trading compared to other executives in the same firm.

Insiders' stock option exercise can also be affected by behavioral bias. Heath, Huddart, and Lang (1999) show that insiders' stock option exercise is not purely rational and is influenced by the current stock price trends and a psychological reference point. Sen and Tumarkin (2015) suggest that executives' optimism affects their optimal option exercise strategies. Optimistic executives exercise their options closer to expiration than non-optimistic executives. They also retain a portion of the stock from exercising instead of selling all shares.

2.2 Sentiment and market professionals' behavior

A series of studies in finance and accounting have documented the influence of sentiment on professional behavior. For instance, numerous research document the relationship between sentiment and aggregate stock market outcomes (e.g., Loughran & Schultz, 2004; Edmans, Garcia, & Norli, 2007; Bodoh-Creed, 2020).

Goetzmann and Zhu (2005), being the pioneering one, find limited evidence linking individual investor stock trading activity to local weather conditions, prompting a shift in focus towards market makers. Since then, researchers have started to investigate the impact of mood on market participants' behavior. Specifically, several studies attribute the influence of sentiment on professionals' decision-making to the level of mood-induced optimism and pessimism. Notably, Goetzmann et al. (2015) introduce a cloud-cover-based measure of institutional investors' mood. They use de-seasonalized cloud cover as a proxy for mood and find that institutional investors exhibit higher levels of optimism on sunnier days and are more willing to buy because they perceive less overpricing in the market.

Relatedly, DeHaan, Madsen, and Piotroski (2017) find that analysts experiencing unpleasant weather respond slower than analysts experiencing pleasant weather due to pessimism and reduced activity. Jiang, Norris, and Sun (2021) show that unpleasant weather affects the efficiency and timeliness of institutional investors when processing information, leading to delayed market responses. Lo and Wu (2018) focus on the influence of seasonal affective disorder (SAD) on financial analysts' performance by examining their quarterly earnings forecasts. They find that financial analysts with SAD exhibit reduced accuracy and increased pessimism during winter months. Chhaochharia et al. (2019) suggest that managerial decisions can also be affected by weather-induced mood through its impact on managerial economic expectations.

Another string of literature examines the influence of sentiment on market professionals' subjective judgment by affecting their risk preferences. For example, Bassi, Colacito, and Fulghieri (2013) conduct a series of experiments to study the effect of weather on individuals' risk aversion. They find that a negative mood increases risk aversion, whereas a positive mood promotes risk-taking behavior. Further, Cortés, Duchin, and Sosyura (2016) examine mortgage brokers' risk assessment and decision-making in sunny periods. Specifically, local sunshine is associated with higher loan approval rates, and vice versa. Drawing on these empirical studies, Bodoh-Creed (2020) proposes the concept of mood-congruent memory to model the association between mood and financial decision-making, suggesting that individuals are more inclined to recall information consistent with their current mood, resulting in a biased selection of recalled information.

While the studies mentioned above confirm the link between weather-induced sentiment and the actions of market professionals, it is crucial to recognize that these actions are primarily intended to serve the interests of others, not the interests of professionals. In such instances, the immediate consequences of these imperfect decisions are not directly and fully borne by the professionals themselves. Thus, it remains unclear whether such sentiment can affect insiders' trading decisions, particularly concerning matters directly and fully tied to their personal benefits, given their informational advantages.

We argue that unexpected variation in local sunshine exposure may work as a driver of an insider's positive sentiment. Sunshine has been shown in social psychology, medicine, and neurobiology as the most influential environmental factor that substantially and consistently impacts mood (Prasko, 2008; Spindelegger et al., 2012). For example, Bassi, Colacito, and Fulghieri (2013) provide direct evidence that positive mood induced by sunshine and good weather promotes individual risk-taking behavior. Goetzmann et al. (2015) find that sunshine-induced optimism increases institutional investors' propensities to buy. Cortés, Duchin, and Sosyura (2016) show that local sunshine is associated with higher credit approval rates. More recently, Chhaochharia et al. (2019) suggest that small business managers exhibit more optimistic expectations following a relatively sunnier period, positively affecting firm-level hiring and investment decisions.

Drawing from the literature on insider trading, weather-induced sentiment effects, and the idea proposed by Bhattacharya and Marshall (2012) that latent psychological factors can elucidate insider trading performance, we propose the following hypothesis:

Hypothesis: Positive sentiment induced by exceptionally good weather conditions leads to more insider purchases but lower trading profit.

3 Sample and Variable Construction

3.1 Data and sample

According to Section 16 of the Securities Exchange Act of 1934, all insiders are required to disclose their transactions to the SEC. An insider is defined as a person who is a direct or indirect beneficial owner of more than 10% of any class of any equity securities or a director or officer of the issuer of those equity securities (Section 16(a) (1) of the Securities Exchange Act of 1934). The SEC requires insiders to file on Form 4 if there has been a change in their ownership. Especially, insiders are required to report their trades within two business days after August 29, 2002 (SEC Rule 16a-(2)(C)), while they can report within 10 days after the end of each calendar month in which the transaction occurred before the adoption of SEC Rule 16a-(2) (C). Therefore, we select the year 2003 as the start of our sample period since the accuracy of the insider transaction date is significantly improved due to the adoption of SEC Rule 16a-(2)(C). The data for insider trading is obtained from the Insider Filing Data Feed (IFDF) provided by Thomson Reuters from 2003 to 2015. The sample period ends in 2015 due to the significant amount of missing data on insiders' locations (over 75% of zip code data are missing after 2016, whereas 3% to 5% are absent during our sample period).

Following Cohen, Malloy, and Pomorski (2012), we include all open market purchases and sales, and exclude private transactions and options exercises. Specifically, we drop transactions whose acquisition flags are not "A" or "D". We also require transactions in the sample to have available information on the transaction price, number of shares traded, stock identification (i.e., CUSIP6), as well as the insider's zip code. Further, firms from financial (SIC codes between 6000 and 6999) and utility industry (SIC codes between 4900 and 4999) are excluded from the sample because of the heavy regulations imposed. We also drop companies for which book value of equity and prior fiscal year book-to-market ratio are missing and firms with daily stock prices of less than $2 to reduce measurement errors.

Following existing literature (e.g., Skaife, Veenman, & Wangerin, 2013; Chowdhury, Mollah, & AI-Farooque, 2018), we aggregate transactions conducted by the same insider on the same stock on the same day at the same zip code to calculate their net purchase or net sales per day. The final sample comprises 503,849 insider-day observations for the period 2003-2015, including 78,203 insider-day net purchase observations and 425,646 insider-day net sales.

3.2 Measuring weather-induced positive sentiment

We collect hourly data of all U.S. weather stations from the Integrated Surface Database (ISD) from 1998 to 2015. The cloud cover measure ranges from 0 (clear sky) to 8 (full sky cloud cover).[5] We exclude observations with quality control indicators being classified as suspect or erroneous. Following DeHaan, Madsen, and Piotroski (2017), we obtain hourly weather data from 6 am to 6 pm each day. We also require a minimum of 4 hours of data availability per day. Next, we aggregate hourly data to daily data by calculating the daily average for each weather station.

Following Goetzmann et al. (2015), we merge the locations of insiders with those of weather stations by considering the geographical distance between these two points. Specifically, we use the 5-digit zip code of each insider, merge it with corresponding coordinates, and then calculate the distance between each insider and all weather stations using the *haversine* distance formula. The daily sky cloud cover at the zip code level is computed as the daily average value from all weather stations within a 50 km radius of an insider's zip code coordinates. To capture the average weather conditions preceding an insider trading day, we transform the daily cloud cover into a 14-day rolling average measure, as suggested by Goetzmann et al. (2015), and require a minimum of 10 calendar days with available data for accurate calculation.

Due to the seasonal effect of weather conditions, we also calculate the cloud cover on the same day within the same zip code of the prior five years as a benchmark for seasonality (Goetzmann et al., 2015; Chhaochharia et al., 2019). Then, we subtract the seasonal benchmark from the RSCC to obtain the de-seasonalized sky cloud cover (DSCC). Finally, to examine the impact of optimism arising from an abnormal

[5] Note that higher sky cloud cover means lower sunshine exposure.

weather scenario, we create a dummy variable called *the abnormally good weather indicator (AbnGood).* This variable takes the value of one if the de-seasonalized cloud-cover measure (DSCC) ranks in the bottom 10th percentile of the entire sample, and zero otherwise. Notably, *AbnGood* captures the highest-percentile variation in sunshine exposure within a short-term window after de-seasonalization. Thus, *AbnGood* is largely unexpected and random.

3.3 Measuring insider trading activity and performance

As noted by Brochet (2010), volumes of insider trading could be influenced by their information advantage. We construct two direct measures to capture insider trading behavior. The first measure (*LnNum)* is the natural logarithm of one plus the number of shares traded by an insider in a day. The second measure (*LnDolVol)* represents the natural logarithm of one plus the total dollar volume traded by an insider in a day. The second measure incorporates the actual dollar value, offering a comprehensive perspective on the insider's consideration.

Building on previous literature (e.g., Skaife, Veenman, & Wangerin, 2013; Chen et al., 2023), we define insider profitability as the unrealized capital gain after purchase and the losses avoided by sales (i.e., *Profit Percentage*). Specifically, as suggested by previous literature, the impact of sentiment on managerial expectation is short-lived (Chhaochharia et al., 2019), and a longer window could capture more profitability but would also introduce more noise (Ali & Hirshleifer, 2017). Therefore, we choose to calculate a buy-and-hold market-adjusted abnormal return over a span of 5 trading days, commencing from the day following an insider's transaction. Next, we multiply this abnormal return with the product of the number of shares traded and their respective trading prices, and then divide the unrealized capital gains by the daily market value of the company. This result is multiplied by 100 to express the measure as a percentage, and then further multiplied by 100 to ensure consistency with the magnitude of other measures.

3.4 Other Variable Definitions

In relation to firm-level variables, we control for various variables in the regressions, following Cohen, Malloy, and Pomorski (2012), which includes prior one-month stock returns (*Return*), prior one-month stock volatility (*Volatility*), firm size (*Size*), and book-to-market ratios (*BTM*). Data are obtained from Compustat and Center for Research in Security Prices (CRSP). Appendix A summarizes the definition of all variables. All continuous variables are winsorized at the top 1% and bottom 99% levels.

3.5 Summary statistics

Table 1 reports descriptive statistics of these variables. In terms of insider purchase, the average profit percentage for each insider is 0.164 (i.e., 0.00164%). The average sale profit percentage is 0.017 (i.e., 0.00017%). This observation is consistent with existing literature that insider sales are less informative than purchases (e.g., Jagolinzer, Larcker, & Taylor, 2011; Alldredge & Cicero, 2015; Kallunki et al., 2018). The number of shares and daily dollar trading volume of an insider in a day on average is 4,100 and $41,232, respectively. In terms of the sentiment proxy, 7.5% of insiders in the purchase sample experienced abnormally good weather before the transaction, while 10.5% of insiders in the sale sample experienced abnormally good weather before the transaction.

Table 2 presents the Pearson correlation matrix among these variables. We also divided the full sample into purchases and sales. Table 2 shows a negative relationship between insider trading profit and weather proxy in purchases, but a positive relationship between insider trading profit and weather proxy in sales. The correlation between *LnNum* (i.e., the number of shares traded by an insider) and weather proxy is -0.004 for purchase, while it is 0.011 for sales. However, dollar trading volume shows a positive and significant correlation with the weather proxy for purchases, while it shows a negative and significant correlation with the weather proxy for sales.

4 Empirical Results

4.1 Baseline result

To examine whether abnormally good weather affects insider trading activities, we estimate the following regression model:

$$Insider\ trading\ activities_{j,t} = \beta_1\ AbnGood_{j,t} + Z_{j,t-1} + Fixed\ Effects + e_{i,t}\ . \quad (1)$$

In Model (1), three dependent variables are used to measure insider trading activities: the number of trading shares (*LnNum*), dollar trading volume (*LnDolVol*), and trading profit (*Profit Percentage*). Our main interested variable, $AbnGood_{j,t}$, is a proxy for abnormally good weather, which equals one if an insider is experiencing abnormally good weather in the 14 days preceding the trade. $Z_{j,t-1}$ is a vector of control variables. For fixed effects, we include year and month fixed effects to control for time-related patterns in insider trading. The insider fixed effect is also included to mitigate potential omitted variable bias associated with insider time-invariant characteristics. The standard errors of all estimates are clustered at the firm level.[6]

Table 3 reports the baseline results of our regression model. Specifically, the first three columns present the results based on the insider purchase sample, while the last three present insider sales results. In the insider purchase sample, the coefficients of $AbnGood$ are positive when the dependent variables are the $LnNum$ and $LnDolVol$. However, the coefficient for $AbnGood$ turns negative when $Profit\ Percentage$ serves as the dependent variable. These coefficients are all significant, at least at 5% level.[7] Specifically, the findings in Column 1 (2) reveal a 9.88% (11.2%) increase in the number of shares traded by insiders (the dollar trading volume) when these insiders were exposed to unusually favorable weather conditions before executing a transaction. However, the trading profitability of these transactions is reduced (Column 3), resulting in a loss.

The results from the insider sales are presented in Columns 4, 5, and 6, which suggests that the $AbnGood$ yields no impact on insiders' selling activities. The asymmetry observed in our findings between insider purchases and sales aligns with existing literature, suggesting that diverse motivations may influence insider sales and are generally less informative. For instance, insider sales could be motivated by

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[6] We acknowledge the possibility that insiders might choose to relocate to areas with favorable weather conditions, which could potentially bias our findings. To address these concerns, we conduct several untabulated robustness tests. Firstly, we use the observations where insiders relocate and directly examine whether insider relocation correlates with the likelihood of experiencing exceptionally favorable weather conditions. Yet, we find no significant relationship. Secondly, we exclude observations where insiders relocate during our sample period. Thirdly, we incorporate zipcode fixed effects. Fourthly, we also compare insiders located in North-East versus South of the USA and find that the abnormal good weather has similar impacts on insiders' purchase activities. All these support the robustness of our result. Our results remain robust even after clustering the standard error by firm and by month.

[7] It is possible that unexpected bad weather may affect insider trading behavior and performance as well. In an untabulated test, we observe that such weather is associated with reduced numbers and dollar volumes of share purchases, albeit without affecting trading profits. As trading profits are not affected by unexpected bad weather, such insider trading suggests a weak link to behavioral bias. Thus, our investigation focuses on the positive sentiment induced by unexpected good weather.

liquidity needs, consumption reasons, or portfolio rebalancing (Roulstone, 2003). Alldredge and Cicero (2015) show that insiders face significant litigation risk when they sell stock, leading to a reduction in the amount of private information embedded in such transactions. In addition, existing research investigating the role of insiders' personal characteristics mainly focuses on insider purchases, given the greater diversity in selling behavior among insiders (e.g., Roulstone, 2003; Hillier, Korczak, & Korczak, 2015; Dai et al., 2016; Cohen, Malloy, & Pomorski, 2012).

In sum, the results in Table 3 are consistent with our hypothesis and suggest that after experiencing unusually good weather, insiders show increased confidence in the profitability of their purchases, leading them to acquire more shares, albeit with a lower profit[8].

4.2 The mechanism: Insider over-optimism

This section examines whether optimism serves as the driving force behind the observed relation between weather sentiment and trading behavior.[9] Existing literature suggests that market professionals tend to be more optimistic on sunnier days (Goetzmann et al., 2015; Chhaochharia et al., 2019; Cortés, Duchin, & Sosyura, 2016). Moreover, psychological studies establish a connection between over-optimism and the overestimation of desirable outcomes. This indicates that individuals' decision-making often involves "wishful thinking", defined as the

[8] We acknowledge that our measure of insiders' trading profitability over five trading days could potentially capture an announcement effect on the market reaction to the disclosure of the insiders' transactions. To address this concern, we first examine the relationship between abnormal good weather and the one- and two-day market reactions. We find no significant relationship. Secondly, we observe that insider purchases typically induce a positive market reaction, while our measure shows a negative effect. Therefore, the observed effect would likely be even stronger if we control for the announcement effect.

[9] From this section onward, our analysis centers on insider purchases. This choice is based on the results in Table 3, which indicate that weather-induced sentiment has no discernible impact on insider sales.

inclination to overestimate the likelihood of a desired outcome (De Bondt & Thaler, 1995). Malmendier and Tate (2005) construct a *NetPurchase* measure for CEOs' over-optimism. They argue that only when CEOs are over-optimistic about their firm prospects would they purchase additional shares, irrespective of their increased exposure to firm-specific risk. In this context, insiders would be more influenced by weather-induced positive mood if they were optimistic about the firm's future prospects.

To explore this mechanism, we first test whether weather-induced sentiment affects the level of insiders' optimism by examining the changes in their purchasing behavior. As the average number of purchases per insider in a given year and firm is 2.46, we create an indicator, *GreaterBuy*, which equals one if the current buy volume is larger than the most recent two purchases by the same insider for the same stock, and zero otherwise. Column (1) of Table 4 reports the results. Consistent with the prediction that insiders exhibit greater optimism following exceptionally good weather, their buying volumes significantly exceed those of their prior transactions.

Next, to measure over-optimism for insiders, we follow Malmendier and Tate (2005) and calculate the total number of shares bought and sold in the 12 months preceding the month an insider executes a trade. Then, we define an indicator variable, *NetBuyer*, which equals one if the total number of shares purchased by an insider over the past 12 months surpasses the total number of shares sold over the same window, and zero otherwise. There are 49,817 insider-day purchases can be mapped into the over-optimism classification, where 43,603 of them are classified as over-optimism, and 6,214 of them are not.

We perform our baseline regression analysis separately within two samples. In line with our prediction, as demonstrated in Table 4, insiders display an increased tendency to be influenced by abnormally good weather and engage in excessive trading, receiving less trading profit only when they express over-optimism about their firms' future performance (Columns 2, 4, and 6). Conversely, they are not affected by weather-induced sentiment when they are not optimistic (Columns 3, 5, and 7). In sum, these findings imply that the underlying cause for the excessive insider purchases is the over-optimism induced by the abnormally good weather conditions.

4.3 Information-based and Liquidity-based trading

Having established that weather-induced optimism influences insiders' trading behavior and performance, we now conduct subsample analysis to further explore the potential mechanisms. In this section, we examine whether the effect of weather-induced sentiment differs between information-based and liquidity-based trading, and then explore the information content these transactions carry.

Prior research shows that information-based insider trading conveys more valuable information than liquidity-driven trading (Cohen, Malloy, & Pomorski, 2012; Ali & Hirshleifer, 2017). Given that sentiment can shape professionals' subjective judgment and behavior (Chhaochharia et al., 2019; Cortés, Duchin, & Sosyura, 2016), we predict that insiders' information-driven purchase decisions are more susceptible to the influence of sentiment. In contrast, routine trades with regular patterns are less likely to be affected by sentiment.

Information-based insider trades are identified by Cohen, Malloy, and Pomorski (2012). Insiders are categorized as routine traders if they have executed at least one transaction in the same month for the past three consecutive years; otherwise, they are labelled as opportunistic traders. Following such an identification approach, our sample of insider purchases is divided into two categories. The first group comprises routine transactions, including those driven by non-informational factors. The remaining transactions are categorized as non-routine transactions.

Next, we apply the baseline regression separately for the routine and non-routine samples. Regarding insider trading behavior (i.e., *number of shares* and *dollar trading volume*), Columns (1) and (3) of Table 5 present the results based on non-routine transactions, whereas Columns (2) and (4) present findings of routine transactions. We find that the estimated coefficients of *AbnGood* are positive and significant in the non-routine transaction sample, while being insignificant for the routine trading sample. In terms of insider trading profit, Column (5) of Table 5 shows a negative relationship between weather-induced positive mood and non-routine insiders' trading profit percentage. Consistent with our findings on insider sales, the impact of sentiment on routine purchases is insignificant, as shown in Column (6).

However, we notice that the number of routine trades is only 1,920, a much smaller figure than the 76,283 non-routine trades. To ensure the robustness of our findings, we adopt an alternative method to classify information-based transactions. Biggerstaff, Cicero, and Wintoki (2020) investigate insider trading patterns and find that opportunistic insiders spread their trades over a long period of time if they possess long-liven private information, which suggests that information-based insiders tend to break their trades into sequence rather than trade at one time.

We follow Klein, Maug, and Schneider (2017) to define a trading sequence as a series of transactions executed by the same insider in the same direction within a seven-day window. A new sequence starts if two transactions in the same direction are interrupted by a transaction in the opposite direction. In total, 52,086 net insider-day purchases can be categorized into sequential classifications. Among these, 38,305 are classified as single transactions, while 13,781 are identified as sequential transactions. Then, we perform the baseline analysis within two samples: a sequential and a single transaction sample. The results are reported in Columns 7-12 of Table 5. Consistent with the classification method results of Cohen, Malloy, and Pomorski (2012), abnormally good weather exhibits a positive and statistically significant impact on insider trading behavior only for sequential transactions (Columns 7 and 9). The sequential traders, who experience abnormally good weather before trades, face poor trading performance (Column 11). In contrast, such impacts disappear within the single trade sample (Columns 8, 10 and 12).

Then, we employ a new measure of informed trading developed by Bogousslavsky, Fos, and Muravyev (2024) to provide further evidence on how sentiment-induced insider trading affects trader performance. Specifically, the measure of informed insider trading is *ITI(insider)* is trained on historical opportunistic insider trades following the classification method of Cohen, Malloy, and Pomorski (2012). This measure provides insights into liquidity conditions and can effectively detect different levels of informed trading compared to traditional liquidity measures. A trader is more likely to be an informed trader if the ITI is higher.

The final sample includes 19,250 net insider-day purchases. Then, we regress the abnormal good weather indicator on *ITI(insider)*. The results are reported in Column 13 of Table 5. Consistent with the results of opportunistic trading performance (Columns 5 and 11), the *ITI(insider)* measure is negatively associated with the abnormal good weather indicator. This implies that less private information is reflected in stock prices if opportunistic insiders experience abnormally good weather prior to their transactions. This supports the notion that insider trading influenced by weather sentiment is less likely to be informative.

In sum, the findings in this section indicate that traders relying on information are more susceptible to weather-induced positive sentiment than non-informational-based traders. When exposed to abnormally good weather, these information-based traders tend to overestimate the impact of their perceived information, resulting in aggressive trading. However, this trading behavior ultimately leads to poor trading profitability and lower levels of price informativeness.

4.4 The impact of insiders' executive ranks and locations

Insiders' organizational roles significantly influence their access to and timing of material information (Feng et al., 2012; Klein, Maug, & Schneider, 2017; Davis et al., 2021; Lambe, Li, & Qin, 2022). Information from less influential insiders tends to be delayed and limited compared to key insiders. Therefore, it is reasonable to predict that the behavioral bias resulting from abnormal weather conditions would have a more pronounced impact when insiders have limited access to crucial information. We employ two measures to serve as proxies for insiders' access to crucial information: insiders' exeutive ranks within the corporate hierarchy and the geographic distance between the insiders' and the headquarters' locations.

First, we partition the sample by important insiders and non-important insiders, following the top executive classification by Malmendier, Pezone, and Zheng (2023). The important insiders include the CEO, CFO, chairman, vice chairman, chief investment officer, chief operating officer, chief technology officer, president, executive vice president, and general counsel (Goldman & Ozel, 2023).

The non-important sample consists of the remaining individuals in our baseline sample.

Table 6 reports the results. We observe a positive relation between the number of shares acquired, insider dollar trading volume, and the positive sentiment induced by weather for both non-important insiders and important insiders (Columns 1, 2, 3, and 4). However, non-important insiders' trading profits are significantly lower when they experience abnormally good weather before their transactions (Column 5). In contrast, important insiders do not experience a negative impact on their trading profits due to such weather-induced sentiment (Column 6). The finding is consistent with our prediction that the quality of private information possessed by non-important insiders is relatively lower compared to that of important insiders. This distinction renders non-important insiders more susceptible to the influence of sentiment.

Second, building on the findings of Cohen, Malloy, and Pomorski (2012) that non-local insiders have less direct access to quality private information, we employ a distance-based metric to classify our baseline sample and distinguish the value of their information sets (Seasholes & Zhu, 2010; Anand et al., 2011). Specifically, we categorize insiders as local if they are located within a 100km radius of their firm headquarters; otherwise, they are classified as remote. We expect remote insiders would suffer more from weather-induced transactions.

Table 7 shows that local insiders significantly increase share purchases after experiencing abnormally good weather before trading, with no impact on trading profits (Columns 2, 4, and 6). In contrast, remote insiders experience a significant reduction in trading profits under abnormally good weather conditions before trading (Column 5). This finding is consistent with our previous results in Table 6, where important insiders increase their trading during favorable weather conditions without influencing their trading profits. In contrast, less important insiders face a more adverse effect on their trading profit.

Similarly, we also categorize insiders into two groups: financial center insiders and non-financial center insiders[10]. Insiders situated near financial hubs may possess greater access to valuable information than those outside these hubs. Specifically, insiders are labeled as financial center insiders if they conduct trades while located in New York, Los Angeles, Washington, San Francisco, or Chicago; otherwise, they are categorized as non-financial center insiders.

Table 8 presents the findings for financial center insiders and non-financial center insiders. Consistent with our prediction, the results in Table 8 show that non-financial center insiders significantly increase share purchases after experiencing abnormally good weather conditions before trading, albeit reducing their trading profit (Columns 1, 3, and 5). In contrast, financial center insiders are not affected by such weather-induced sentiment (Columns 2, 4, and 6). These robustness tests confirm that the sentiment effect is more pronounced for insiders with less quality information access.

In sum, the findings in this section suggest that transactions by both non-important insiders and remote insiders are prone to over-optimism due to abnormal favorable weather conditions. This results in reduced trading profits, as their information content is considered less reliable when compared to important or local insiders.

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[10] In an untabulated test, we further divide insiders into insiders located in urban and rural areas. We observe that urban insiders tend to increase share purchases following unusually favorable weather conditions, with no impact on trading profits. Conversely, rural insiders encounter a notable decrease in trading profits due to such weather conditions. The possible explanation is that insiders located in cities are more likely to have in-person interaction during good weather and thus good weather may have a stronger impact on urban insiders.

4.5 The effect of economic policy uncertainty

Then, we test the impact of weather-induced sentiment on insiders' behavior during periods of heightenedeconomic policy uncertainty. Economic uncertainty creates conditions where psychological factors, including weather-induced sentiment, can have an outsized impact on decision-making due to reduced reliance on clear fundamental signals and increased susceptibility to emotional influences (e.g., Ben-David, Graham, & Harvey, 2013; Birru & Young, 2022). Among market participants, insiders are especially sensitive to business conditions and are highly responsive to the signs of uncertainty (Lambe, Li, & Qin, 2022). Consequently, weather-induced positive sentiment is likely to have a stronger influence on insiders during periods of high market uncertainty.

We use the economic policy uncertainty (EPU) index as a proxy for market uncertainty (Baker, Bloom, & Davis, 2016). Specifically, our baseline sample is segmented based on the median EPU index level, and the results are presented in Table 9. Columns (1), (3), and (5) show insider behavior and performance under high economic policy uncertainty, while Columns (2), (4), and (6) are under low economic policy uncertainty. We find that insider trading activity, as measured by the number of stocks traded and dollar-trading volume, significantly increases under high economic uncertainty when insiders experience abnormally good weather conditions before transactions. This suggests that insiders tend to place more reliance on and have higher expectations regarding the favorable outcomes derived from their perceived private information when market uncertainty is relatively high.

4.6 The impact of insiders' personal characteristics

Existing studies on insider trading suggest that trading performance can be affected by insiders' personal characteristics (e.g., Bhattacharya & Marshall, 2012; Davidson, Dey, & Smith, 2013; Hillier, Korczak, & Korczak, 2015; Akbas, Jiang, & Koch, 2020). Thus, we explore the impact of weather-induced positive sentiment on insider behavior and profits across various subsamples based on insiders' personal attributes.

Specifically, inspired by Hillier, Korczak, and Korczak (2015), who classify insiders based on age, gender, and education, we similarly divide our baseline sample into subsets based on these observed attributes. Prior research suggests that men are more vulnerable to sentiment-driven effects in significant corporate decisions compared to women (Huang & Kisgen, 2013). As such, we divide our sample by gender, with the male subset comprising all male insiders and the female subset comprising all female insiders. For age, the older (younger) subset includes transactions by insiders whose ages fall within the top (bottom) 10th percentile of the entire sample at the time of the trade, capturing extreme variations in age during the sample period. Given that age-related cognitive decline negatively affects firm performance (Waelchli & Zeller, 2013), we predict that older insiders are more vulnerable to sentiment effects.

Regarding special qualifications, we merge the insider with the BoardEx database and designate transactions as part of the special qualification subset if an insider possesses an educational background in science, finance, law, or engineering. Additionally, the special qualification subset includes transactions by insiders holding a Ph.D. qualification. These qualifications involve logical analysis, suggesting that the impact of weather-induced positive sentiment may be less pronounced among those insiders (Chou, Chung, & Yin, 2013; Pham, 2020).

Table 10 presents the findings for age and gender, whereas Table 11 analyses the subsamples based on special qualifications. The results in Table 10 reveal that weather-induced sentiment affects both young (female) and old (male) insiders. However, the results in Table 11 indicate a significant increase in insider trading activities for non-special qualification insiders due to abnormally good weather conditions (Columns 1 and 3). In contrast, no such increase is observed for insiders with special qualifications (Columns 2 and 4), aligning with our predictions.

The results in this section, especially findings related to insiders with special qualifications, add a valuable dimension to existing research that suggests insiders' personal academic attributes may help reduce behavioral bias associated with the weather-induced sentiment (e.g., Hillier, Korczak, & Korczak, 2015; Kallunki et al., 2018).

5 Conclusion

This paper examines whether sentiment affects insiders' investment decisions, which are directly related to their own monetary benefits. Using unexpected variation in sunshine exposure of insiders' locations as a proxy of sentiment, we find that weather-induced positive mood affects insider purchases. Specifically, we discover that insiders significantly increase the number of shares and dollar trading volume they purchase when experiencing abnormally good weather conditions. However, these sentiment-motivated transactions result in lower trading profits.

Consistent with the existing literature documenting that individuals are more likely to be optimistic during sunnier days, we also find that sunshine exposure leads to an increase in insiders' over-optimism, and information-driven transactions are more vulnerable to the influence of abnormally good weather, resulting in lower price informativeness. Further, our findings become more pronounced when insiders are more likely to be optimistic about firms' future prospects and have limited access to quality private information. Our results suggest that insiders exhibit over-optimism in the value impact of their private information after experiencing sunnier times, prompting them to over-react and increase share purchases, albeit with lower profits and price informativeness.

Our study offers insight into the effect of local weather conditions on insider trading and has important implications. It emphasizes the impact of sentiment on market professionals' decisions, extending beyond their career choices to include decisions with personal assets and benefits involved. In the context of stock price informativeness, a clear lesson from our findings is that although insider purchase conveys information, it is important for investors to be attentive of the impact of weather-induced sentiment on the relative informativeness of these trades. Further research is needed to broaden our understanding and delve deeper into the effects arising from insiders' characteristics together with local environmental conditions.

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Appendix A Variable Definitions

Variables	Definitions
Profit%	Aggregate profitability of each insider over a 5-trading day window measured as a percentage of market value of equity at transaction day.
LnNum	The natural logarithm of one plus number of shares traded by an insider in a particular transaction day.
LnDolVol	The natural logarithm of one plus total dollar trading profit traded by an insider in a day.
RSCC	A 14-days rolling average of the ZIP code-level sky cloud cover.
SCC	An average 14-days rolling average for the same day of the prior five years.
DSCC	The difference between RSCC and SCC.
AbnGood	An abnormally good weather indicator, based on DSCC ranking over the whole sample. It takes the value of one if the DSCC measure ranks in the bottom 10^{th} of the entire sample.
GreaterBuy	An indicator equals to one if the current purchase volume is larger than the most recent two purchases by the same insider for the same stock, zero otherwise.
NetBuyer	An indicator equals to one if total number of shares purchased by an insider over the past 12 months surpasses the total number of shares sold over the same window, zero otherwise.
Routine	An indicator equals to one if an insider has executed at least one transaction in the same month for the past three consecutive years, zero otherwise.
Sequential	An indicator equals to one at the first day of a trading sequence, zero otherwise.
ITI(insider)	An informed trading measure constructed by Bogousslavsky, Fos, and Muravyev (2024).
Important	An indicator equals to one if an insider is CEO, CFO, chairman, vice chairman, chief investment officer, chief operating officer, chief technology officer, president, executive vice president, or general counsel, zero otherwise.
Local	An indicator equals to one if the distance between an insider is situated within a 100km radius of her firm headquarter when she trades, zero otherwise.
Urban	An indicator equals to one if an insider is located in the urban areas according to the 200 census.
FinCenter	An indicator equals to one if an insider is located in New York, Los Angeles, Washington, San Francisco, or Chicago.
High EPU	An indicator equals to one if the economic policy uncertainty index (EPU) in the insider trading month is above its median over the sample period, zero otherwise.
Older	An indicator equals to one if an insider's age falls within the top 10th percentile of the entire sample at the time of the trade, zero otherwise.
Younger	An indicator equals to one if an insider's age falls within the bottom 10th percentile of the entire sample at the time of the trade, zero otherwise.
Female	An indicator equals to one if an insider is female, zero otherwise.
Male	An indicator equals to one if an insider is male, zero otherwise.
Special	An indicator equals to one if an insider possesses an educational background in science, finance, law, engineering, or if an insider holds a Ph.D., zero otherwise.
Size	The natural logarithm of one firm's market capitalization of the prior fiscal year.
BTM	The ratio of book value to market value of total assets of the prior fiscal year.
Return	The prior month buy-and-hold market-adjusted abnormal returns, measured by one-month period accumulative abnormal return ending one day before an insider conducts a transaction.
Volatility	The standard deviation of a firm's prior one-month return.

Appendix B: Insiders' Zip Codes and their Headquarters' Zip Codes Comparision

Zip code Digits	#. Insider Zip Codes	% of the Same
Total	63,817	-
Five digit	29,324	45.95%
Four digit	32,136	50.36%
Three digit	38,515	60.35%
Two digit	44,664	69.99%
One digit	49,975	78.31%

Table 1: Summary Statistics – Full Sample

	Purchases						Sales					
	No.	Mean	SD	Q1	Median	Q3	No.	Mean	SD	Q1	Median	Q3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Dependent Variables												
Profit %	78,203	0.164	0.848	-0.014	0.006	0.115	425,646	0.017	0.584	-0.028	0.001	0.039
LnDolVol	78,203	10.627	2.068	9.230	10.534	11.883	425,646	12.222	1.845	11.041	12.259	13.442
LnNum	78,203	8.319	1.976	6.909	8.324	9.568	425,646	8.986	1.647	7.968	8.987	10.016
Panel B: Explanatory Variables												
AbnGood	78,203	0.075	0.263	0.000	0.000	0.000	425,646	0.105	0.306	0.000	0.000	0.000
Return	78,203	-0.029	0.147	-0.116	-0.031	0.045	425,646	0.038	0.117	-0.029	0.026	0.091
Volatility	78,203	0.034	0.020	0.019	0.029	0.044	425,646	0.025	0.014	0.016	0.022	0.031
Size	78,203	5.780	1.777	4.463	5.633	6.896	425,646	7.073	1.742	5.954	6.938	8.141
BTM	78,203	0.614	0.448	0.280	0.507	0.824	425,646	0.424	0.326	0.206	0.342	0.546

This table reports the summary statistics of all variables in the baseline regression. The aggregate sample includes insider transactions obtained from the Insider Filling Data Feed (IFDF) provided by Thomson Reuters for an aggregate total of 503,849 insider-per-day observations for the period 2003-2015. All variables are defined in the Appendix.

Table 2: Correlation Matrix

Variables	Purchases								Sales							
	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
Profit %	1								1							
LnDolVol	0.220***	1							0.038***	1						
LnNum	0.258***	0.891***	1						0.049***	0.890***	1					
AbnGood	-0.008**	0.015***	-0.004	1					0.007***	-0.033***	0.011***	1				
Return	-0.026***	-0.006*	-0.034***	-0.013***	1				0.018***	0.065***	0.057***	0.016***	1			
Volatility	0.067***	-0.037***	0.141***	-0.051***	-0.156***	1			0.043***	-0.161***	0.007***	0.059***	0.240***	1		
Size	-0.042***	0.367***	0.068***	-0.003	-0.093***	-0.159***	1		-0.020***	0.469***	0.191***	-0.076***	-0.099***	-0.383***	1	
BTM	0.004	-0.172***	-0.057***	-0.032***	0.101***	0.040***	-0.355***	1	0.003*	-0.204***	-0.057***	0.064***	0.049***	0.093***	-0.367***	1

This table reports the Pearson correlation coefficients for the sample of aggregate insider purchases and sales (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table 3: Weather-induced Sentiment: Insider Trading Behavior and Performance

	Purchases			Sales		
	LnNum	*LnDolVol*	*Profit%*	*LnNum*	*LnDolVol*	*Profit%*
	(1)	(2)	(3)	(4)	(5)	(6)
AbnGood	0.0988**	0.1120***	-0.0356**	0.0131	0.0356***	0.0051
	(0.0391)	(0.0395)	(0.0179)	(0.0094)	(0.0103)	(0.0045)
Return	-0.3890***	0.1280	-0.3710***	0.6780***	1.2900***	0.0961***
	(0.0947)	(0.0924)	(0.0598)	(0.0315)	(0.0335)	(0.0200)
Volatility	8.4000***	1.7980**	1.5360***	2.0890***	-0.8340*	1.0040***
	(0.729)	(0.720)	(0.431)	(0.3870)	(0.4380)	(0.198)
Size	0.0543**	0.4000***	-0.0483***	0.1040***	0.4420***	0.0132***
	(0.0268)	(0.0250)	(0.0100)	(0.0154)	(0.0171)	(0.0042)
BTM	0.0642	-0.0682	0.0154	0.0457	-0.2380***	-0.0045
	(0.0748)	(0.0727)	(0.0218)	(0.0334)	(0.0389)	(0.0149)
Insider FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-sq	2.2%	4.9%	0.6%	0.8%	6.4%	0.1%
# of observations	78,203	78,203	78,203	425,646	425,646	425,646

This table presents the baseline regression result of weather-induced sentiment on insider behavior and performance for purchases and sales, respectively. The dependent variable in Columns 1 and 4 is the number of shares purchased (sold) by an insider (*LnNum*). The dependent variable in Columns 2 and 5 is the dollar trading volume purchased (sold) by an insider (*LnDolVol*). The dependent variable in Columns 3 and 6 is insider trading profitability (*Profit%*). The key independent variable is *AbnGood.* Control variables include Return, Volatility, Size, and BTM. All regressions include insider fixed effects, year-fixed effects, and month-fixed effects. Variable definitions are presented in the Appendix. Continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: The Mechanism: Insiders' Over-optimism

	GreaterBuy	*LnNum*		*LnDolVol*		*Profit%*	
		Over-optimism	*Non-over-optimism*	*Over-optimism*	*Non-over-optimism*	*Over-optimism*	*Non-over-optimism*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AbnGood	0.0193***	0.1020***	0.0006	0.1060***	-0.0498	-0.0491**	-0.0334
	(0.0074)	(0.0374)	(0.0887)	(0.0388)	(0.0847)	(0.0194)	(0.0370)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insider FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-sq	1.1%	1.6%	3.5%	4.5%	2.9%	0.7%	1.9%
# of observations	78,203	43,603	6,214	43,603	6,214	43,603	6,214

This table shows what drives the changes in insider behavior and performance. We follow Malmendier and Tate (2005) to calculate the *NetPurchase* as a measure of over-optimism. Detailed construction procedures are described in Section 4.2. The sample includes insider trades between 2003 and 2015. The dependent variable in Column 1 is the *GreaterBuy* indicator. The dependent variable in Columns 2 and 3 are the number of shares purchased by an insider (*LnNum*). The dependent variable in Columns 4 and 5 is the dollar trading volume purchased by an insider (*LnDolVol*). The dependent variable in Columns 6 and 7 is insider trading profitability (*Profit%*). The key independent variable is *AbnGood*. Control variables include Return, Volatility, Size, and BTM. All regressions include insider fixed effects, year-fixed effects, and month-fixed effects. Variable definitions are presented in the Appendix. Continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Weather-induced Sentiment: Opportunistic and Informed Trading

	Routine VS Non-routine						Sequential VS Single						Informed Trading
	LnNum		*LnDolVol*		*Profit%*		*LnNum*		*LnDolVol*		*Profit%*		*ITI*
	Non-Routine	*Routine*	*Non-Routine*	*Routine*	*Non-Routine*	*Routine*	*Sequential*	*Single*	*Sequential*	*Single*	*Sequential*	*Single*	*(Insider)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
AbnGood	0.0904***	0.0988	0.1080***	0.1140	-0.0389**	-0.0047	0.1940***	0.0084	0.1950***	0.0305	-0.1010**	-0.0373	-0.0119**
	(0.0219)	(0.101)	(0.0411)	(0.102)	(0.0183)	(0.0670)	(0.0710)	(0.0315)	(0.0697)	(0.0312)	(0.0475)	(0.0287)	(0.00586)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insider FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-sq	-27.9%	-7.1%	4.7%	2.4%	0.6%	3.8%	3.6%	4.2%	7.7%	3.4%	1.4%	0.4%	1.2%
#of observations	76,283	1,920	76,283	1,920	76,283	1,920	13,781	38,305	13,781	38,305	13,781	38,305	19,250

This table shows how weather-induced sentiment disproportionately affects information-based trading compared to liquidity-based trading, and its impact on price informativeness. Columns 1-6 follow Cohen, Malloy, and Pomorski (2012) to classify insider transactions based on their past trading history. Columns 7-12 follow Klein, Maug, and Schneider (2017) to classify insider transactions based on their trading pattern. Detailed construction procedures are described in Section 4.3. The sample includes insider trades between 2003 and 2015. The dependent variable in Columns 1, 2, 7, and 8 are the number of shares purchased by an insider (*LnNum*). The dependent variable in Columns 3, 4, 9, and 10 is the dollar trading volume purchased by an insider (*LnDolVol*). The dependent variable in Columns 5, 6, 11 and 12 is insider trading profitability (*Profit%*). The dependent variable in Column 13 is an informed insider trading intensity measure provided by Bogousslavsky, Fos, and Muravyev (2024). The key independent variable is *AbnGood.* Control variables include Return, Volatility, Size, and BTM. All regressions include insider fixed effects, year-fixed effects, and month-fixed effects. Variable definitions are presented in the Appendix. Continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively

Table 6: Weather-induced Sentiment: Insiders' Executive Ranks

	LnNum		*LnDolVol*		*Profit%*	
	Non-important	*Important*	*Non-important*	*Important*	*Non-important*	*Important*
	(1)	(2)	(3)	(4)	(5)	(6)
AbnGood	0.0993**	0.1130**	0.1130**	0.1180**	-0.0454**	-0.0026
	(0.0457)	(0.0559)	(0.0458)	(0.0566)	(0.0227)	(0.0211)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Insider FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-sq	2.2%	2.2%	4.6%	4.8%	0.6%	0.6%
# of observations	59,826	18,377	59,826	18,377	59,826	18,377

This table shows how insiders' executive ranks affect the weather-induced sentiment for insider trading. We follow Malmendier, Pezone, and Zheng (2023) and Goldman and Ozel (2023) to classify top executives and construct important insider sample and non-important insider sample. Detailed construction procedures are described in Section 4.4. The sample includes insider trades between 2003 and 2015. The dependent variable in Columns 1 and 2 are the number of shares purchased by an insider (*LnNum*). The dependent variable in Columns 3 and 4 is the dollar trading volume purchased by an insider (*LnDolVol*). The dependent variable in Columns 5 and 6 is insider trading profitability (*Profit%*). The key independent variable is *AbnGood.* Control variables include Return, Volatility, Size, and BTM. All regressions include insider fixed effects, year-fixed effects, and month-fixed effects. Variable definitions are presented in the Appendix. Continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Weather-induced Sentiment: Insiders' Locations

	LnNum		*LnDolVol*		*Profit%*	
	Remote	*Local*	*Remote*	*Local*	*Remote*	*Local*
	(1)	(2)	(3)	(4)	(5)	(6)
AbnGood	0.0734	0.1020**	0.0831*	0.1130**	-0.0680**	0.0021
	(0.0450)	(0.0429)	(0.0453)	(0.0438)	(0.0334)	(0.0160)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Insider FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-sq	1.8%	2.7%	5.2%	4.2%	0.8%	0.6%
# of observations	34,526	43,124	34,526	43,124	34,526	43,124

This table shows how insiders' locations affect the weather-induced sentiment for insider trading. We divide the sample using a distance-based measure following Seasholes and Zhu (2010). Detailed construction procedures are described in Section 4.4. The sample includes insider trades between 2003 and 2015. The dependent variable in Columns 1 and 2 are the number of shares purchased by an insider (*LnNum*). The dependent variable in Columns 3 and 4 is the dollar trading volume purchased by an insider (*LnDolVol*). The dependent variable in Columns 5 and 6 is insider trading profitability (*Profit%*). The key independent variable is *AbnGood.* Control variables include Return, Volatility, Size, and BTM. All regressions include insider fixed effects, year-fixed effects, and month-fixed effects. Variable definitions are presented in the Appendix. Continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Financial Center and Non-financial Center Insiders

	LnNum		*LnDolVol*		*Profit%*	
	Non-FinCenter	*FinCenter*	*Non-FinCenter*	*FinCenter*	*Non-FinCenter*	*FinCenter*
	(1)	(2)	(3)	(4)	(5)	(6)
AbnGood	0.113***	0.0891	0.127***	0.102	-0.0455**	0.0448
	(0.0226)	(0.0628)	(0.0450)	(0.0757)	(0.0188)	(0.0574)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Insider FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-sq	-30.4%	-13.6%	5.0%	5.9%	0.6%	1.1%
# of observations	64,208	13,193	64,208	13,193	64,208	13,193

This table shows additional robustness checks on how insiders' locations affect the weather-induced sentiment for insider trading. We divide the sample into financial center insiders and non-financial centers insiders. Detailed construction procedures are described in Section 4.4. The sample includes insider trades between 2003 and 2015. The dependent variable in Columns 1 and 2 are the number of shares purchased by an insider (*LnNum*). The dependent variable in Columns 3 and 4 is the dollar trading volume purchased by an insider (*LnDolVol*). The dependent variable in Columns 5 and 6 is insider trading profitability (*Profit%*). The key independent variable is *AbnGood.* Control variables include Return, Volatility, Size, and BTM. All regressions include insider fixed effects, year-fixed effects, and month-fixed effects. Variable definitions are presented in the Appendix. Continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Weather-induced Sentiment: Market Uncertainty

	LnNum		*LnDolVol*		*Profit%*	
	High EPU	*Low EPU*	*High EPU*	*Low EPU*	*High EPU*	*Low EPU*
	(1)	(2)	(3)	(4)	(5)	(6)
AbnGood	0.1290**	0.0293	0.1320**	0.0454	-0.0577	-0.0409*
	(0.0588)	(0.0305)	(0.0582)	(0.0312)	(0.0365)	(0.0216)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Insider FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-sq	1.6%	1.8%	4.3%	4.4%	0.5%	0.9%
# of observations	38,698	39,505	38,698	39,505	38,698	39,505

This table shows the influence of weather-induced sentiment under market uncertainty. We adopted a new-based measure of the monthly economic policy uncertainty index (EPU) to construct my samples. Detailed construction procedures are described in Section 4.5. The sample includes insider trades between 2003 and 2015. The dependent variable in Columns 1 and 2 are the number of shares purchased by an insider (*LnNum*). The dependent variable in Columns 3 and 4 is the dollar trading volume purchased by an insider (*LnDolVol*). The dependent variable in Columns 5 and 6 is insider trading profitability (*Profit%*). The key independent variable is *AbnGood.* Control variables include Return, Volatility, Size, and BTM. All regressions include insider fixed effects, year-fixed effects, and month-fixed effects. Variable definitions are presented in the Appendix. Continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10: Weather-induced Sentiment: Insiders' Personal Attributes

	Age						*Gender*					
	LnNum		*LnDolVol*		*Profit%*		*LnNum*		*LnDolVol*		*Profit%*	
	Older	*Younger*	*Older*	*Younger*	*Older*	*Younger*	*Female*	*Male*	*Female*	*Male*	*Female*	*Male*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
AbnGood	0.2230**	0.1330	0.2380**	0.1800**	0.0151	-0.0165	0.2150**	0.0861**	0.2850**	0.1010***	-0.0485	-0.0095
	(0.0975)	(0.1040)	(0.0975)	(0.0870)	(0.0439)	(0.0477)	(0.1060)	(0.0361)	(0.1140)	(0.0352)	(0.0540)	(0.0149)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insider FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-sq	5.1%	5.3%	9.8%	3.1%	1.7%	1.6%	8.8%	2.4%	6.9%	4.9%	2.7%	0.8%
# of observations	6,118	4,552	6,118	4,552	6,118	4,552	2,538	41,676	2,538	41,676	2,538	41,676

This table shows how insiders' personal attributes affect the weather-induced sentiment for insider trading. Detailed construction procedures are described in Section 4.6. The sample includes insider trades between 2003 and 2015. The dependent variable in Columns 1, 2, 7, and 8 is the number of shares purchased by an insider (*LnNum*). The dependent variable in Columns 3, 4, 9, and 10 is the dollar trading volume purchased by an insider (*LnDolVol*). The dependent variable in Columns 5, 6, 11, and 12 is insider trading profitability (*Profit%*). The key independent variable is *AbnGood.* Control variables include Return, Volatility, Size, and BTM. All regressions include insider fixed effects, year-fixed effects, and month-fixed effects. Variable definitions are presented in the Appendix. Continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11: Weather-induced Sentiment: Insider's Special Qualifications

	LnNum		*LnDolVol*		*Profit%*	
	Non-special	*Special*	*Non-special*	*Special*	*Non-special*	*Special*
	(1)	(2)	(3)	(4)	(5)	(6)
AbnGood	0.1240***	0.0301	0.1330***	0.0668	-0.0070	-0.0243
	(0.0439)	(0.0527)	(0.0425)	(0.0506)	(0.0172)	(0.0239)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Insider FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-sq	2.6%	3.2%	5.5%	4.3%	0.8%	1.0%
# of observations	29,624	14,590	29,624	14,590	29,624	14,590

This table shows how insiders' educational qualifications affect the weather-induced sentiment for insider trading. Detailed construction procedures are described in Section 4.6. The sample includes insider trades between 2003 and 2015. The dependent variable in Columns 1 and 2 is the number of shares purchased by an insider (*LnNum*). The dependent variable in Columns 3 and 4 is the dollar trading volume purchased by an insider (*LnDolVol*). The dependent variable in Columns 5 and 6 is insider trading profitability (*Profit%*). The key independent variable is *AbnGood.* Control variables include Return, Volatility, Size, and BTM. All regressions include insider fixed effects, year-fixed effects, and month-fixed effects. Variable definitions are presented in the Appendix. Continuous variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively