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Insider trading and climate disasters

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ABSTRACT

Climate disasters are increasing in frequency and severity. While a large body of research has shown that extreme climate affects various economic decisions, how climate events influence investment decisions remains largely under-investigated. This paper examines whether, and to what extent, climate disasters influence insider transactions, which are important investment decisions that attract increasing attention from both corporate management and policymakers. We find that the monthly value of insider trades increases markedly in firms headquartered in counties with a climate disaster. Climate-induced insider trading holds in general but is stronger when investors are distracted and less prevalent when insiders face higher litigation risk. Climate disasters trigger uncertainty about short-term firm fundamentals, and insiders benefit by selling prior to this being priced. Insiders living in disaster counties do not trade more than those in unaffected counties, which does not support a personal liquidity motivation. Our paper documents a new way through which climate impacts investor behavior and financial markets.

1. Introduction

We document a new determinant of insider trading. Our results show that climate disasters, such as hurricanes and floods, in the county of a firm's headquarters cause a material increase in the level of insider trading in that firm. There are two plausible motivations for insiders to trade more in periods when climate disasters impact firms. First, they may ascertain the impact of the disaster on the firm more quickly and accurately than outside investors, and time their trades to earn larger returns than they would if the disaster information were fully reflected in prices. Second, insiders may trade because the disaster impacts them personally. Insiders in disaster-impacted counties may experience increased fear and anxiety or need to realize funds to cover personal property losses, which could lead to stock trading, mainly selling.

We present evidence that supports the informational advantageous explanation and indicates against the personal impact explanation. Climate disasters trigger uncertainty about short-term firm fundamentals. We show that firm sales growth declines in the quarter following disasters. In addition, stock return volatility increases in the month following disasters. Moreover, insiders who sell following climate disasters earn increased short-term returns. We do not have insiders' asset data or information on the impact of climate disasters on these assets. However, an indication that personal impact is the driver of climate-induced insider trading would be given by evidence of greater trading from insiders who live within climate disaster counties than from those outside these counties. We

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find no evidence of less trading of outside county insiders during climate disaster periods.

The climate-induced insider trading increase is large. We show that the insider trading value is more than double in firms with headquarters in counties that are impacted by a climate disaster that month. Furthermore, trading by insiders is higher when the damage caused by disasters is larger. This result withstands a myriad of robustness checks. It is evident when the number and volume of insider trades are used as insider trading proxies. Our finding does not change in county-level and firm-level analysis. It also exists when we use other determinants of insider trading as control variables. While the result is evident in the sample of all insider transactions, it is more prevalent in opportunistic transactions than in routine ones.

Our results indicate several factors impact the climate disaster–insider trading relation (hereafter climate-induced insider trading). Insiders who trade face litigation risk (e.g., Kim & Skinner, 2012). Other investors could launch private securities litigation if they have lost money due to insider trading. Huddart, Ke, and Shi (2007) show insiders sometimes do not participate in profitable insider trading opportunities to avoid litigation risk, which suggests the importance of this risk to insiders. Our results indicate less climate-induced insider trading in stocks with higher litigation risk.

Climate disasters increase anxiety and stress (e.g., Clayton, 2020). Individuals can be expected to become concerned about their health and that of their family members and their physical possessions. Given the increased focus on these factors and the fact that there are limits to attention (e.g., Kahneman, 1973), it seems reasonable to expect that investors, in general, will be less focused on their investments in climate disaster periods. We follow Da, Engelberg, and Gao (2011) and use Google search volumes as investor attention and distraction proxies. We find fewer searches about stocks during climate disaster periods, consistent with investor distraction, and more searches for climate-related words. Moreover, climate-induced insider trading is greater when investors are more distracted. Finally, climate-induced insider trading is impacted by the information environment, firm monitoring, and environmental, social, and governance (ESG) performance. It is more prevalent in firms with higher information asymmetry, lower analyst coverage, lower institutional ownership, and lower ESG ratings.

Our results do not necessarily imply that insiders are exploiting undisclosed private material information. Alldredge and Cicero (2015) find that insiders are better than other investors at understanding the implications of public information and profiting from it. They suggest that this effect is stronger when there is lower outside investor attention. The fact that we find that climate-induced insider trading is more common in firms with a more opaque information environment at a time when investors are more distracted is consistent with the notion of insiders benefiting from being better able to interpret public information.[1]

In the segment of insider trading literature to which we contribute, we identify our work as most closely aligned with the research initiated by Alldredge and Cicero (2015) who show that some profitable insider trading can be attributed to insiders using the earnings announcements of their major customers. Other work in this area includes Bowen, Dutta, Tang, and Zhu (2018) who find that private in-house meetings between insiders, investors, and analysts are informative to insiders and allow them to time their trades to earn larger profits. Duellman, Guo, Zhang, and Zhou (2018) find that financial experts who serve on audit committees earn larger returns from insider purchases compared to non-experts. However, our work is distinct from the above studies by highlighting a new insider trading determinant.

Some existing papers document that insiders make use of information that other investors do not have. Zhang and Zhang (2018) show that opportunities for insider trading cause insiders to reduce the supply of firm-performance information to outsiders. Ryan, Tucker, and Zhou (2016) find insiders sell before reporting nonperforming securitized loans and the write-downs of securitization-related assets. Cheng and Lo (2006) show that managers time their trades around negative news releases. Furthermore, Jagolinzer, Larcker, Ormazabal, and Taylor (2020) find evidence of a positive relation between informed trading and political connections when Troubled Assets Relief Fund funds were distributed. Another strand of literature documents deterrents to insider trading. For instance, Davidson and Pirinsky (2022) show that insiders trade a significantly lower number of shares per insider trade and earn lower abnormal insider trading profits, if they are exposed to an SEC insider trading enforcement action of an insider that they have an association with.[2]

The second part of the literature our paper results are related to is climate finance. There is growing evidence of the effect of climate events on firms and financial markets (e.g., Hong, Karolyi, & Andrew, and Scheinkman, Jose A., 2020). However, as Nordhaus (2019) notes, many questions regarding the financial implications of climate change remain unanswered.[3] The three papers most closely related to ours appear to be those of Dessaint and Matray (2017), Rehse, Riordan, Rottke, and Zietz (2019), and Alok, Kumar, and Wermers (2020). Dessaint and Matray (2017) show that managers make the mistake of increasing cash levels following hurricanes, which imposes a cost on the firm. We show that insiders also focus on themselves following disasters and take the opportunity to engage in insider trading. Rehse et al. (2019) find climate disasters can impact liquidity, with reduced trading and heightened bid-ask spreads in real estate investment trusts affected by Hurricane Sandy.[4] Our results indicate that, while outside investors may trade less during climate disasters, insiders trade more. Alok et al. (2020) show fund managers overreact to disasters by selling stocks in disaster zones during the quarter of the disaster which results in underperformance. This result is consistent with ours if insiders sell quickly

[1] We thank an anonymous referee to highlighting this point.

[2] The interested reader should also consider the excellent literature review in Amiram et al. (2018).

[3] See Hong et al. (2020) and Giglio, Kelly, and Stroebel (2021) for excellent reviews.

[4] Other climate papers include those of Schüwer, Lambert, and Noth (2020), who find independent banks in the disaster area increased their capital following Hurricane Katrina. Krueger, Sautner, and Starks (2020) suggest that surveyed institutional investors feel climate risk to be an important consideration in their investing. Peress and Schmidt (2020) identify climate disasters as a form of sensational news that distracts investors and include four climate disasters in their sample of 68 new events that distract noise traders.

(within the month of the disaster) and fund managers continue to sell over the disaster quarter. However, Alok et al. (2020) do not provide monthly analysis, so it is not possible to be definitive on this point.

This paper is organized as follows: The data are described in Section 2. Section 3 contains the method and empirical results. The results and possible explanations for the insider trading–climate disaster relation we observe are discussed in Section 4. Our conclusions are in Section 5.

2. Data

We source insider trading data from the Thomson Reuters insider filings database. Insiders are defined as directors, officers, directors, and those who are beneficial owners of more than 10% of a company's stock. Under U.S. law, insiders must report their open market trades to the U.S. Securities and Exchange Commission (SEC). Before 2002, filing had to occur within ten days of the end of the calendar month during which the trade occurred. Since 2002, trades have had to be reported within two working days. Moreover, as noted by Rogers, Skinner, and Zechman (2016), in June 2003, the SEC began requiring insider transaction filings to be conducted via its online Electronic Data Gathering, Analysis, and Retrieval system (EDGAR), which has increased the accessibility of the information for other investors. Following the literature (e.g., Dai, Parwada, & Zhang, 2015; Frankel & Li, 2004; Gao, Lisic, & Zhang, 2014), we include the purchases and sales of common stocks (SHRCD = 10 or 11) in the Center for Research in Security Prices (CRSP) database and exclude the following transactions: (i) transactions with prices outside of the daily high–low price range in the CRSP database, (ii) transactions with numbers of shares traded higher than the total daily trading volume in the CRSP database, and (iii) transactions with trading prices of less than $2 or fewer than 100 shares.[5] Following Fidrmuc, Goergen, and Renneboog (2006) and Ali and Hirshleifer (2017), we group multiple trades made by the same insider on a given day into one trade and classify it as a buy (or sell) if the number of shares bought is greater (smaller) than the number of shares sold by the insiders.[6]

We obtain data from CRSP and Compustat to calculate variables such as firm returns and book-to-market equity. We then allocate firms to counties based on their headquarters data. We use climate data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS).[7] These county-level disaster data record the direct property and crop losses, injuries, and fatalities from fog, hail, coastal disasters, drought, flooding, hurricanes, tornados, wildfires, wind, severe storms, and winter weather.[8] SHELDUS data have been used extensively in the literature on climate disasters,[9] including Dessaint and Matray (2017), who consider whether managers overreact to salient risks, based on SHELDUS hurricane data, and Barrot and Sauvagnat (2016) and Hsu, Lee, Peng, and Yi (2018), who examine the impact of natural disasters on several corporate outcomes. SHELDUS reports the value of crop damage and property damage by county. We sum these two quantities and focus our analysis on what we refer to as climate damage, which consists of, over the entire sample, 80% property damage, and 20% crop damage. We follow Barrot and Sauvagnat (2016) and consider disasters that last for less than 30 days and focus on major disasters only for meaningful interpretations (Baker, Bloom, & Terry, 2020). We define a county exposed to a major disaster if the total estimated damage to that county in a given month is $50 million or more in 2016 constant dollars. Our final firm-level sample consists of 1,287,154 firm–month observations spanning 1986–2016. Our county-level sample consists of 171,982 county–month observations over the same period.

Fig. 1 presents the frequency of major climate disasters for each county in the U.S. mainland over the sample period. The hardest-hit counties include San Bernardino County and San Diego County in California, Miami-Dade County and Volusia County in Florida, and Lubbock County in Texas.

3. Baseline results and additional analyses

This section examines insider trading around Hurricane Katrina, considered one of the most devasting hurricanes ever recorded to make landfall in the United States.[10] One prominent example is not indicative of a broader relation, but the lack of relation in such a major disaster would cast doubt on other results. We also present baseline results and a range of additional robustness checks.

3.1. Hurricane Katrina

Hurricane Katrina is one most significant disasters during the last 20 years, so we consider the level of insider trading in the counties impacted by Katrina[11] before and after August 2005, when it hit. Fig. 2 shows that the average insider trading value in stocks headquartered in counties affected by Katrina increased from an average of $66 million in June and July to $91 million in August, before declining to an average of $40 million in September and October. Moreover, the ratio of insider trading to total trading value

[5] Our findings remain unchanged if we include small trades (i.e., transactions with trading prices of less than $2 or fewer than 100 shares).

[6] We do so to avoid double-counting insider transactions, since same-day trades are likely to be executed based on similar information. Our results (not tabulated in the paper for brevity but available upon request) are robust if we treat each insider trade as an independent transaction.

[7] See https://cemhs.asu.edu/sheldus.

[8] SHELDUS also covers data on geophysical disasters such as earthquakes, landslides, volcanoes, and tsunamis. These disasters occur at a much lower frequency and represent just 5% of its total number of disasters.

[9] See https://cemhs.asu.edu/sheldus/applications.

[10] See https://www.nhc.noaa.gov/outreach/history/#katrina.

[11] These include counties within Alabama, Florida, Georgia, Indiana, Kentucky, Louisiana, Mississippi, Ohio, and Tennessee.

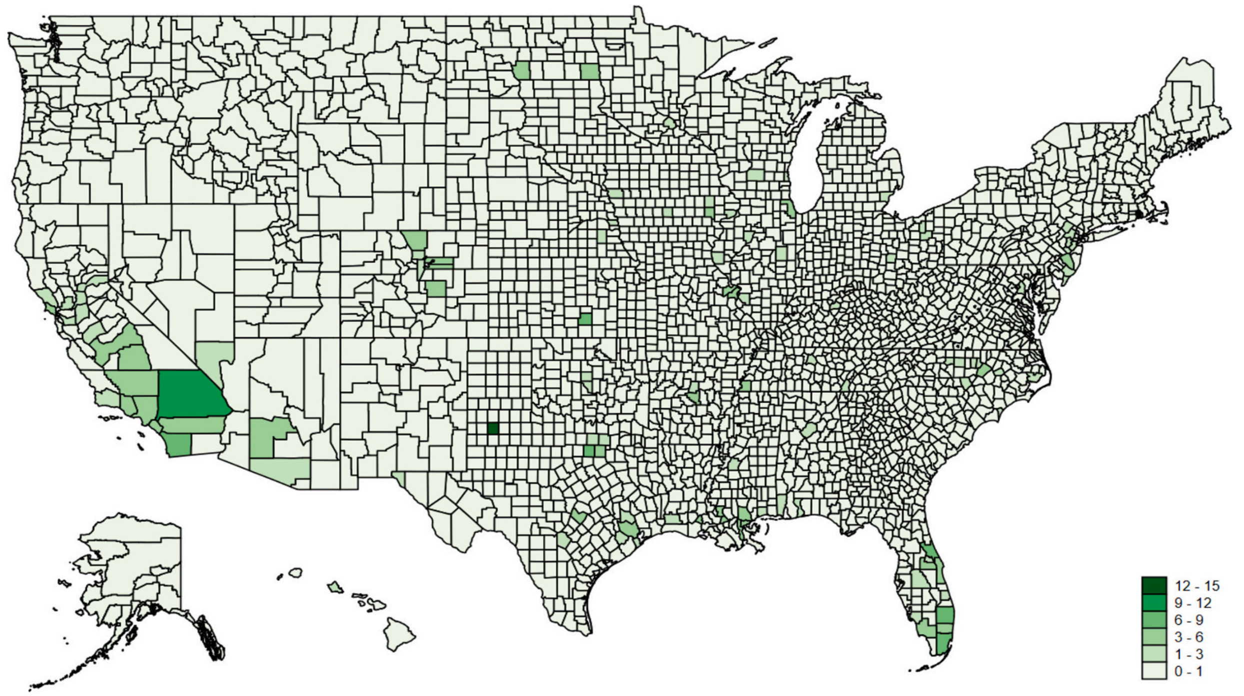

Fig. 1. Climate Disaster Frequency by U.S. County.
This map presents the number of major climate disasters for each county in the U.S. mainland over the sample period. For each county–month, we define a county as exposed to major disaster if the total estimated damage caused by climate disasters to that county in a given month is $50 million or more in 2016 constant dollars.

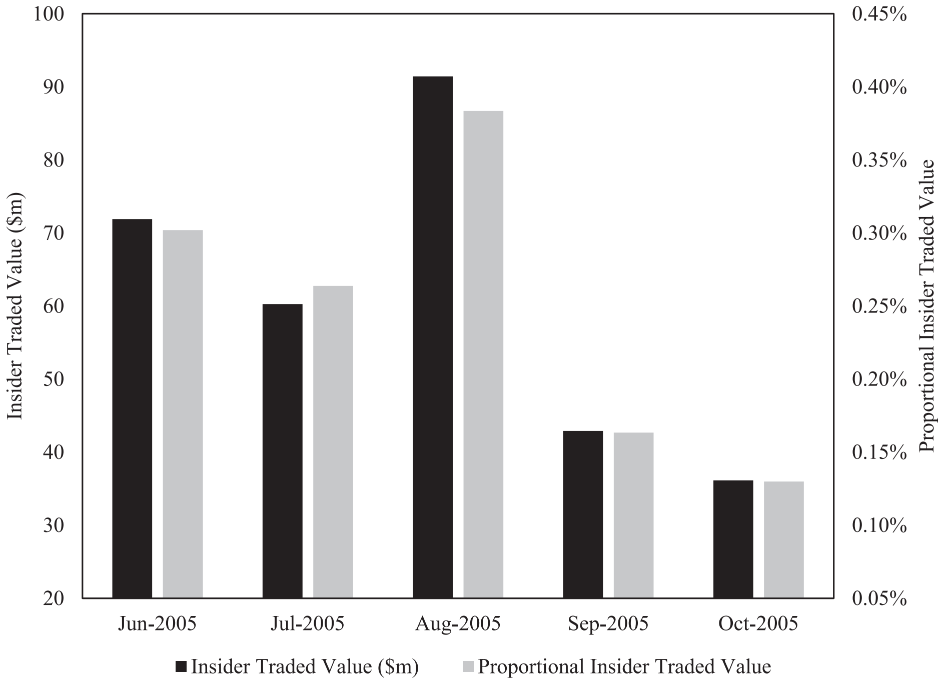

Fig. 2. Insider Trading in Counties Affected by Hurricane Katrina in 2005.
This figure plots the level of insider trading and the proportion of insider trading to total trading in the stocks of companies headquartered in counties impacted by Hurricane Katrina. The plot is based on trading values, in millions of dollars, in the month of Hurricane Katrina (August 2005) and for the counties two months before and after.

follows a similar pattern. Despite this pronounced pattern of insider trading, the aggregate trading of shares headquartered in the affected states shows no such pattern.[12]

3.2. Summary statistics and baseline results

We apply the natural logarithmic transformation of our insider trading variables for empirical analyses. Specifically, we define *TVALUE* as the logarithm of one plus the insider trading value, *TVOLUME* as the logarithm of one plus the insider trading volume, and *#TRADE* as the logarithm of one plus the number of insider trades.

Table 1 presents the mean numbers of *#TRADE*, *TVALUE*, and *TVOLUME* for disaster and non-disaster months and two subsamples for the 31 years. The entire sample covers 171,982 county–month observations. There is a clear and consistent pattern of *TVALUE*, *TVOLUME,* and *#TRADE,* all being larger in firms located in counties during months impacted by disasters than in counties during months without disasters. The mean differences are statistically significant at the 1% level. The average insider trading value and volume are 208% and 169% higher,[13] respectively, in disaster months, while the number of insider trades is 37% higher. The differences are slightly less pronounced in the most recent subsample; however, they remain sizable. The value, volume, and number of insider trades are over 166%, 138%, and 33% larger and statistically significant in disaster months, respectively.

We report the regression results for both firm- and county-level analyses. Our firm-level model is expressed as:

$$INSTRD_{it} = \beta\, CLIMATE_{it} + \gamma_t + \delta_k + \tau_c + \varepsilon_{it} \tag{1}$$

where $INSTRD_{it}$ represents one of the three firm-level insider trading measures (*TVALUE*, *TVOLUME,* and *#TRADE*), and $CLIMATE_{it}$ is our climate disaster proxy, measured by either *CLIMATE_DUMMY* or *CLIMATE_DAMAGE*. The baseline firm-level specification includes year-month fixed effects, γ_t, industry fixed effects (based on two-digit Standard Industrial Classification codes), δ_k, and county fixed effects, τ_c, to account for time-, industry-, and county-variant factors, respectively, that could be associated with insider transactions. Robust standard errors are clustered simultaneously by firm and year dimensions (Gow, Ormazabal, & Taylor, 2010; Petersen, 2009; Thompson, 2011). The variables *TVALUE*, *TVOLUME*, and *#TRADE* are the firm–month observations of insider trading value, insider trading volume, and the number of insider trades, respectively.[14] The variable *CLIMATE_DUMMY* is a dummy that equals one if there is a major climate disaster in the county of a firm's headquarters during a given month, and zero otherwise, and *CLIMATE_DAMAGE*, calculated as the natural logarithm of the sum of crop and property damages, measures the magnitude of a climate disaster. The baseline county-level specification is the same, except that *TVALUE*, *TVOLUME*, and *#TRADE* are the county–month observations of insider trading value, insider trading volume, and the number of insider trades, respectively. Our empirical methodology builds on recent studies that employ exogenous shocks that vary by time and location for identification to make casual inferences (e.g., Bertrand, Duflo, & Mullainathan, 2004; Bertrand & Mullainathan, 2003; Bourveau, Lou, & Wang, 2018). The coefficient β is our difference-in-differences estimate, which captures the average effect of disasters for the treatment group relative to the control group. We report the results of our baseline analyses in Panels A and B of Table 2.

The firm-level results in Panel A of Table 2 reveal a consistently strong positive relation between the climate disaster dummy variable and climate damage and insider trading activity. There is clear evidence of increased insider trading activity for firms headquartered in the counties and months of a climate disaster. The coefficients on *CLIMATE_DUMMY* and *CLIMATE_DAMAGE* are statistically significant at the 1% level across the three insider trading measures. On average, the value, volume, and number of insider trades are 8.7%, 6.8%, and 1.1% higher, respectively, during climate disaster months than during non-disaster months.[15] There is also evidence of a strong positive connection between the impact of the disaster, in terms of the size of the climate damage, and insider trading activity. The county-level results in Panel B are consistent with their firm-level counterparts. There is a positive relation between the climate dummy and each insider trading metric. Moreover, there is a strong positive relation between the magnitude of the climate disaster and insider trading activity.[16]

3.3. Robustness checks

Our baseline results withstand a myriad of robustness checks. The results in Table 3 indicate they hold after controlling for firm characteristics. There is more insider trading in larger and growth firms (Lakonishok & Lee, 2001; Rozeff & Zaman, 1998), but climate-

[12] We also plot the number of insider trades and trading volume and find that the pattern (untabulated) is broadly like the insider trading profile in Fig. 2.

[13] These percentage changes are calculated based on log differences in insider trading value and volume. For example, the change in insider trading value is calculated as 7.015–4.936 = 208%.

[14] If a firm has no trades in a given month, it is coded as zero.

[15] Since these dependent variables for insider trading activity are in natural logarithmic form, we take the exponential of the climate variables to derive their impact on the dependent raw values. For example, the coefficient of 0.0836 for *CLIMATE_DUMMY* means an 8.7% (= $e^{0.0836}$–1) increase in the insider trading value.

[16] We also generate results using property and crop damages rather than climate damage as a measure of the magnitude of the climate disaster. Property damage is the most important component of climate damage (around 80%), whereas crop damage is of lesser importance. We find the property damage results are consistent with those for climate damage, whereas there is no statistically significant link between crop damage and insider trading.

Table 1
Summary Statistics.

	Disaster Months (A)		Non-Disaster Months (B)		Difference (A – B)
	Obs.	Mean	Obs.	Mean	Mean
Panel A: Full Sample (1986–2016)					
TVALUE	518	7.015	171,464	4.936	2.079***
TVOLUME	518	5.509	171,464	3.815	1.694***
#TRADE	518	1.028	171,464	0.661	0.366***
Panel B: First Subsample (1986–2001)					
TVALUE	233	4.671	90,918	2.867	1.805***
TVOLUME	233	3.687	90,918	2.223	1.464***
#TRADE	233	0.683	90,918	0.383	0.299***
Panel C: Second Subsample (2002–2016)					
TVALUE	285	8.930	80,546	7.272	1.659***
TVOLUME	285	6.999	80,546	5.613	1.385***
#TRADE	285	1.309	80,546	0.975	0.334***

This table presents the means of three measures of county-level insider trading, namely, *TVALUE*, *TVOLUME*, and *#TRADE*, in disaster and non-disaster months for the entire sample period (Panel A) and for two equal subsamples (Panels B and C). The variable *TVALUE* is the logarithm of one plus the insider trading value, *TVOLUME* is the logarithm of one plus the insider trading volume, and *#TRADE* is the logarithm of one plus the number of insider trades. In the final column, we examine the statistical significance of mean differences using a *t*-test. *** indicates the significance level of 1%.

induced insider trading is additional. Other controls include leverage, research and development (R&D), and sales (Aboody & Lev, 2000; Denis & Xu, 2013).[17]

In a recent paper, Engle, Giglio, Kelly, Lee, and Stroebel (2020) construct a climate risk series based on the correlation between *The Wall Street Journal* text content and climate change words, on the basis that climate change is typically discussed in the media when there are concerns about it. As an alternative measure of climate risk, we estimate the climate change news beta, β^{News}, for each stock from the monthly rolling regression of stock excess returns on innovations in the monthly climate change news index over a 36-month window, with a minimum of 24 valid monthly return observations for each stock i in each month t (e.g., Huynh & Xia, 2021).[18] We then include the climate change news beta, β^{News}, as our climate risk proxy in the firm-level baseline regression, instead of *CLIMATE_DUMMY* or *CLIMATE_DAMAGE*. The results in Appendix A1, Panel A, indicate a consistent relation between this climate risk proxy and *TVALUE*, *TVOLUME*, and *#TRADE* that is statistically significant at the 1% level.

As an alternative measure of insider trading, we use *INSIDER_DUMMY*, a dummy that equals one if there is any insider transaction in a firm–month, and zero otherwise. We use the same specification as eq. (1) and logit regressions for these analyses. We present these results in Appendix A1, Panel B. The results show that the probability of insider trading is higher in climate disaster months and increases with the damage caused by climate disasters.

In Appendix A2, we present results for different regression specifications. First, we use Fama and MacBeth (1973) cross-sectional regression framework and Newey and West (1987) adjusted *t*-statistics. Second, we account for the possibility of different levels of insider trading across firms in various industries by measuring *TVALUE*, *TVOLUME*, and *#TRADE* as the industry mean-adjusted variables. Third, we use an alternative specification of industry based on the Fama–French 48 industry classifications. Fourth, we consider whether the relation between climate disasters and insider trading holds in the post-2002 period. In 2002, the Sarbanes–Oxley Act, which mandated financial reporting changes, was passed. Furthermore, from 2002 onward, the insider trade reporting window was reduced from five to two working days, and in 2003 insider trading information became easier to obtain for other investors with the SEC requiring insider transaction filings to be conducted via its online EDGAR system. There is consistent evidence of climate insider trading across each robustness check. Ali and Hirshleifer (2017) observe more insider trading around quarterly earnings announcements, while Wang, Wang, Wei, Zhang, and Zhou (2022) show that the threat of selling short negatively impacts opportunistic insider selling. In Panel E, we present results that indicate climate insider trading is evident after controlling for earnings announcements and firm-level short interest (e.g., Ali & Hirshleifer, 2017; Wang et al., 2022).[19]

In Appendix A3, we adopt alternative definitions of a major climate disaster. In our results, we define a county exposed to a major

[17] It is important to ensure it is the climate disaster rather than some other information that an insider has in advance that is driving the insider trading. We also rerun our baseline result controlling for the abnormal return in the three-month period following the insider trading. We measure abnormal return as the disaster firm's three-month return adjusted for same industry, same size non-disaster firm returns. Overall, our insider trading result is robust to this control.

[18] We thank Engle et al. (2020) for making their data available for academic research.

[19] To account for earnings announcements, we create an indicator variable to denote whether there is an earnings announcement date in a given month. We follow Bao et al. (2019) and measure firm-level short interest using the short interest available at the end of each quarter scaled by the number of shares outstanding.

Table 2
Climate Disaster and Insider Trading.

Panel A: Firm-Level Analysis

	TVALUE	*TVOLUME*	*#TRADE*
CLIMATE_DUMMY	0.0836***	0.0657***	0.0113***
	(2.82)	(2.90)	(2.84)
Industry fixed effects	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes
Adjusted R-squared	0.1292	0.1268	0.1121
Observations	1,287,154	1,287,154	1,287,154
CLIMATE_DAMAGE	0.0045***	0.0035***	0.0006***
	(2.96)	(3.06)	(2.98)
Industry fixed effects	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes
Adjusted R-squared	0.1292	0.1268	0.1121
Observations	1,287,154	1,287,154	1,287,154

Panel B: County-Level Analysis

	TVALUE	*TVOLUME*	*#TRADE*
CLIMATE_DUMMY	0.4973**	0.3952**	0.0675*
	(2.35)	(2.49)	(1.94)
Year–month fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
S.E. clustered by county & year	Yes	Yes	Yes
Adjusted R-squared	0.4810	0.4850	0.5371
Observations	171,982	171,982	171,982
CLIMATE_DAMAGE	0.0269**	0.0213**	0.0036*
	(2.38)	(2.51)	(1.94)
Year–month fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
S.E. clustered by county and year	Yes	Yes	Yes
Adjusted R-squared	0.4810	0.4850	0.5371
Observations	171,982	171,982	171,982

In Panel A, we regress firm-level insider trading measures on two measures of climate disasters, namely, *CLIMATE_DUMMY* and *CLIMATE_DAMAGE*. We report the county-level regression results in Panel B. The variable *CLIMATE_DUMMY* is a dummy that equals one in the county–months in which there is a major climate disaster, and zero otherwise; *CLIMATE_DAMAGE* measures the magnitude of the climate disaster in a given county–month; and *TVALUE*, *TVOLUME*, and *#TRADE* are three measures of insider trading, where *TVALUE* is the logarithm of one plus the insider trading value, *TVOLUME* is the logarithm of one plus the insider trading volume, and *#TRADE* is the logarithm of one plus the number of insider trades. We control for all models for industry, county, and year–month fixed effects. The *t*-statistics, computed using standard errors robust to heteroscedasticity and clustered simultaneously on firm and year dimensions (Petersen, 2009), are reported in parentheses. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

disaster if the total estimated damage to that county in a given month is $50 million or more. In Panels A to F of Appendix A3, we define a county exposed to a major disaster if the total estimated damage to that county in a given month is at least $10 million, $20 million, $30 million, $40 million, $60 million or $100 million, respectively. We find our results are robust.

Cohen, Malloy, and Pomorski (2012) show that insider trading can be classified as either routine or opportunistic. Some insider trading occurs at the same time of year, as insiders look to realize remuneration received as stocks into cash or reinvest cash bonuses into stocks. This trading is not driven by an informational advantage and is not informative about a firm's prospects. On the other hand, opportunistic insider trading occurs intermittently but is highly informative about firm prospects. We follow Cohen et al. (2012) approach and define routine insider trading. Specifically, we define a routine trader as an insider who placed a trade in the same calendar month for at least three consecutive years. Non-routine, or opportunistic, insiders are the remaining insiders. In Appendix A4, we show our result is predominantly evident in opportunistic insider trading.

Furthermore, we consider alternative measures of insider trading. Specifically, we employ the ratio of insider trading to total trading volume. *TVALUE / TVOL*, *TVOLUME / TVOL*, and *#TRADE / TVOL* are three alternative measures of insider trading, where

Table 3
Climate Disaster and Insider Trading: Additional Analyses.

Panel A: Climate Dummy	*TVALUE*	*TVOLUME*	*#TRADE*
CLIMATE_DUMMY	0.0849**	0.0665**	0.0115**
	(2.05)	(2.08)	(2.41)
LOG(MARKET_SIZE)	0.6283***	0.4418***	0.0494***
	(10.12)	(9.91)	(9.31)
MTB	0.2117***	0.1541***	0.0234***
	(7.60)	(7.43)	(7.04)
LEVERAGE	−0.0665	−0.0191	−0.0160
	(−0.61)	(−0.24)	(−1.44)
RD_DUMMY	0.0077	0.0402	0.0059
	(0.13)	(0.87)	(0.94)
LOG(SALES)	0.0139	0.0068	0.0016
	(0.54)	(0.35)	(0.55)
Industry fixed effects	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes
Adjusted R-squared	0.1880	0.1769	0.1518
Observations	1,180,330	1,180,330	1,180,330

Panel B: Climate Damage	*TVALUE*	*TVOLUME*	*#TRADE*
CLIMATE_DAMAGE	0.0046**	0.0037**	0.0006**
	(2.18)	(2.23)	(2.55)
LOG(MARKET_SIZE)	0.6283***	0.4418***	0.0494***
	(10.12)	(9.91)	(9.31)
MTB	0.2117***	0.1541***	0.0234***
	(7.60)	(7.43)	(7.04)
LEVERAGE	−0.0665	−0.0191	−0.0160
	(−0.61)	(−0.24)	(−1.44)
RD_DUMMY	0.0077	0.0402	0.0059
	(0.13)	(0.87)	(0.94)
LOG(SALES)	0.0139	0.0068	0.0016
	(0.54)	(0.35)	(0.55)
Industry fixed effects	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes
Adjusted R-squared	0.1880	0.1769	0.1518
Observations	1,180,330	1,180,330	1,180,330

This table reports the regression results of insider trading activities after controlling for a range of firm characteristics. We regress firm-level insider trading measures *(#TRADE*, *TVALUE*, *TVOLUME*) on two proxies for climate disasters, *CLIMATE_DUMMY* and *CLIMATE_DAMAGE,* and control variables. The variables *LOG(MARKET_SIZE)*, *MTB*, and *LEVERAGE* are the natural logarithm of market capitalization, the market-to-book ratio, and leverage, respectively; *RD_DUMMY* controls for firm-level R&D expenditures; and *LOG(SALES)* is the natural logarithm of total sales. We control all models for industry, county, and year–month fixed effects. The *t*-statistics, computed using standard errors robust to heteroscedasticity and clustered simultaneously on firm and year dimensions (Petersen, 2009), are reported in parentheses. *** and ** indicate the significance levels of 1% and 5% respectively.

TVALUE is the logarithm of one plus the insider trading value, *TVOLUME* is the logarithm of one plus the insider trading volume, *#TRADE* is the logarithm of one plus the number of insider trades, and *TVOL* is the logarithm of total trading volume. Appendix A5 reports the results for these analyses. We find our results are robust to alternative measures of insider trading.

4. Determinants of the degree of climate insider trading

This section documents a range of variables that influence the relation between climate disasters and insider trading.

4.1. Litigation risk

Litigation risk is an essential consideration for insiders determining whether they should trade. As Billings and Cedergren (2015) note, class action lawsuits brought under Rule 10b-5 of the Securities Exchange Act of 1934 typically allege that managers either made deceptive statements or neglected to reveal material adverse information in a timely manner. Lawsuits generally involve investors who purchased stock during this period and subsequently lost money as the release of negative news resulted in a stock price drop.

Ali and Hirshleifer (2017) suggest that insiders consider the value of their insider information versus the risk of enforcement action when deciding whether to trade before quarterly earnings announcements. Huddart et al. (2007) show profitable insider trading opportunities are sometimes passed up by insiders to avoid litigation risk, which indicates the importance of this risk to insiders.

We consider whether overarching concerns about litigation risk influence climate insider trading. We measure firm-level litigation risk using Kim and Skinner (2012) approach.[20] Specifically, we first collect data on filings of securities class action lawsuits from the Stanford Law School Securities Class Action Clearinghouse.[21] We then construct a firm-level litigation risk measure as follows:

$$SUED_t = \beta_0 + \beta_1\, FPS_t + \beta_2\, LNASSET_{t-1} + \beta_3\, SALE\_GROWTH_{t-1} + \beta_4\, RETURN_{t-1} + \beta_5\, SKEWNESS_{t-1} + \beta_6\, STD_{t-1} + \beta_7\, TURNOVER_{t-1} + \varepsilon_t \tag{2}$$

where $SUED_t$ is a dummy that equals 1 if a class lawsuit filling occurs during the year and 0 otherwise; FPS_t is a dummy that equals 1 if the firm is in the biotech (SIC codes 2833–2836 and 8731–8734), computer (SIC codes 3570–3577 and 7370–7344), electronics (SIC codes 3600–3674), or retail (SIC codes 5200–5960) industry, and 0 otherwise; $LNASSET_{t-1}$ is the natural logarithm of total assets at the end of year *t-1; $SALE\_GROWTH_{t-1}$* is year *t-1* sales less year *t-2* sales scaled by the beginning of year *t-1* total assets; $RETURN_{t-1}$, $SKEWNESS_{t-1}$, and STD_{t-1} are market-adjusted stock return, skewness, and standard deviation of the firm's 12-month returns, respectively; and *TURNOVER* is trading volume accumulated over the past 12 months.

We consider the influence of litigation risk using the following regression specification:

$$INSTRD_{it} = \beta_1 CLIMATE_{it} + \beta_2 LITIGATION\_RISK_{it} + \beta_3 CLIMATE_{it} \times LITIGATION\_RISK_{it} + \gamma_t + \delta_k + \tau_c + \varepsilon_{it} \tag{3}$$

The variables in this equation are as in eq. (1), and *LITIGATION_RISK* is the firm-level litigation risk measured following Kim and Skinner (2012) approach.[22]

Table 4 indicates less climate-induced insider trading in firms with greater litigation risks. This result holds for each measure of insider trading and both the *CLIMATE_DUMMY* and *CLIMATE_DAMAGE* proxies. Litigation risk influences insider trading, but our results show that it does not subsume the climate insider trading relation.

4.2. *Investor distraction*

We measure investor distraction using Google Search Volume Index (SVI) data, *SVI*.[23] Since company names can be searched for reasons other than investment, we follow Da et al. (2011) and obtain search data according to company tickers.[24] Some tickers, such as *DNA*, can have a generic meaning, so we only include ticker searches for CRSP stocks that are not deemed to have "noisy names."[25]

For each stock, the *ASVI* variable is defined as:

$$ASVI_{i,t} = log(1 + SVI_{i,t}) - log\left[1 + \text{mean}(SVI_{i,t-1}, \dots, SVI_{i,t-6})\right] \tag{4}$$

where, for stock *i*, $\log(1 + SVI_{i,t})$ is the logarithm of *SVI* during month *t*, and $\log[1 + \text{mean}(SVI_{i,t-1}, \dots, SVI_{i,t-6})]$ is the logarithm of the average value of *SVI* during the prior six months.[26] For ease of interpretation, we create a distraction measure, *DISTRACTION*, as minus one multiplied by the stock's *SVI* value (denoted $-1 \times \log(1 + SVI)$). The higher the value of *DISTRACTION*, the more investors are distracted away from monitoring stocks. We construct two distraction measures for both *SVI* and *ASVI* and compare distraction measures between months when there is a climate disaster in a county and months when no climate disaster is reported.

The results presented in Table 5, Panel A, show that the *CLIMATE_DUMMY* coefficient is positive and statistically significant at the 1% level. This finding indicates that investors are more distracted in months with climate disasters. The *CLIMATE_DAMAGE* coefficient is positive, suggesting more distraction from stock investments in months when climate disasters inflict more property and crop damage than in months with less damage. There is strong evidence that climate disasters distract investors from monitoring stock investments. As a robustness check, we measure distraction based on firm-level EDGAR searches from the SEC (e.g., Ben-Rephael, Da, & Israelsen, 2017; DeHaan, Shevlin, & Thornock, 2015). The results in Appendix A6 indicate more distraction in climate disaster periods based on this proxy. We also obtain *SVI* data for climate keywords, including *climate disaster, hurricane, storm, tornado, flooding, drought, winter, weather,* and *wildfire*. The climate SVI data are monthly for the period 2004–2016. The results in Appendix A7 indicate more Google search activity for these words during climate disaster periods.

In Panel B of Table 5, we consider whether the degree of distraction influences climate insider trading. We run a regression similar to eq. (3), except that we replace *LITIGATION_RISK* with *DISTRACTION*. We find strong evidence of more climate-induced insider

[20] They identify that firms in specific industries, such as biotech, computers, electronics, and retail, experience more litigation risk, and firm-specific variables such as size, growth opportunities, and return volatility are also related to this risk.

[21] The lawsuits database begins in 1996, so our analysis on litigation risk covers the period of 1996 to 2016.

[22] The sample for litigation risk data begins in 1996, since this is the first year when the data on securities class action lawsuits became available from the Stanford Securities Class Action Clearinghouse.

[23] The SVI data begin in 2004, since it is the first year the Google SVI was available.

[24] Search is a revealed attention measure, and if a person searches for a company ticker on Google, this person is undoubtedly paying attention to it (Da et al., 2011). The stock ticker SVI values are nationwide.

[25] We thank Da et al. (2011) for providing us the list of noisy tickers.

[26] Our results are robust to alternative lengths (i.e., four months, eight months, and 10 months) used to calculate *ASVI*.

Table 4
Litigation Risk.

Panel A: Climate Dummy			
	TVALUE	*TVOLUME*	*#TRADE*
CLIMATE_DUMMY	0.1710**	0.1274**	0.0216**
	(2.31)	(2.13)	(2.57)
CLIMATE_DUMMY × LITIGATION_RISK	−7.2660***	−4.9905**	−0.6451**
	(−2.88)	(−2.34)	(−2.58)
LITIGATION_RISK	1.9760	1.6708	0.0408
	(1.21)	(1.46)	(0.24)
Industry fixed effects	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes
Adjusted R-squared	0.0527	0.0511	0.0488
Observations	862,656	862,656	862,656

Panel B: Climate Damage			
	TVALUE	*TVOLUME*	*#TRADE*
CLIMATE DAMAGE	0.0090**	0.0067**	0.0012**
	(2.40)	(2.22)	(2.68)
CLIMATE DAMAGE × LITIGATION_RISK	−0.3777***	−0.2586**	−0.0335**
	(−2.84)	(−2.29)	(−2.56)
LITIGATION_RISK	1.9756	1.6704	0.0408
	(1.21)	(1.46)	(0.24)
Industry fixed effects	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes
Adjusted R-squared	0.0527	0.0511	0.0488
Observations	862,656	862,656	862,656

This table presents the results on the influence of litigation risk on the relation between climate disasters and insider trading. We measure firm-level litigation risk, *LITIGATION_RISK*, using Kim and Skinner (2012) approach. The variable *CLIMATE_DUMMY* is a dummy that equals one in the county–months in which there is a climate disaster, and zero otherwise. The variable *CLIMATE_DAMAGE* measures the magnitude of the climate disaster, and *TVALUE*, *TVOLUME*, and *#TRADE* are three measures of insider trading, where *TVALUE* is the logarithm of one plus the insider trading value, *TVOLUME* is the logarithm of one plus the insider trading volume, and *#TRADE* is the logarithm of one plus the number of insider trades. We control all models for industry, county, and year–month fixed effects. The *t*-statistics, computed using standard errors robust to heteroscedasticity and clustered simultaneously on firm and year dimensions (Petersen, 2009), are reported in parentheses. *** and ** indicate the significance levels of 1% and 5% respectively.

trading with greater distraction, evident for each insider trading proxy and *CLIMATE_DUMMY* and *CLIMATE_DAMAGE*.

4.3. Other determinants

In this section, we consider the impact of information asymmetry, corporate governance, and ESG performance on climate-induced insider trading, given that these factors are significant determinants of insider transactions (e.g., Aboody & Lev, 2000; Gao et al., 2014; Jagolinzer, Larcker, & Taylor, 2011). We use the regression setup in eq. (3) but replace *LITIGATION_RISK* with the variables of interest and run separate regressions for each moderating variable. The variable *HIGH_ALYST_COVERAGE* is a dummy variable that equals one if a firm's analyst coverage belongs to the top tercile each year, and zero otherwise; *HIGH_INST_INVESTOR* is a dummy variable that equals one if the number of institutional investors in each year quarter belongs to the top tercile, and zero otherwise; and *INFORMATION_ ASYMMETRY*, which accounts for stock volume and return autocorrelation, is the market-based information asymmetry measure based on the metric proposed by Llorente, Michaely, Saar, and Wang (2002).

We source ESG data from MSCI/KLD database and follow Servaes and Tamayo (2013) and Lins, Servaes, and Tamayo (2017) to construct the firm-level ESG measure. Specifically, the MSCI/KLD database rates companies using different ESG categories such as environment, employee relation, community, diversity, and human rights. For each of the five categories, we consider the data on both strengths and concerns, and construct a net ESG measure that adds strengths and subtracts concerns (Lins et al., 2017). As the number of strengths and concerns for each ESG category varies over time, we follow Servaes and Tamayo (2013) and scale the strengths (concerns) for each category by dividing the number of strengths (concerns) for each firm-year by the maximum number of strengths (concerns) possible for each category year. The net ESG index per each category, measured by subtracting the concerns index from the strength index, ranges from −1 to +1. We then combine the net ESG indices for the five categories into an aggregate measure of firm-level ESG, denoted *ESG_SCORE*. The value of *ESG_SCORE* ranges from −5 to +5. This *ESG_SCORE* provides a comprehensive and

Table 5
Climate-Induced Distraction.

Panel A: Climate Disasters-Induced Distraction

	Distraction ($-1 \times \log(1 + SVI)$)	Distraction ($-1 \times ASVI$)	Distraction ($-1 \times \log(1 + SVI)$)	Distraction ($-1 \times ASVI$)
	(1)	(2)	(3)	(4)
CLIMATE_DUMMY	0.0270***	0.0159***		
	(47.65)	(81.42)		
CLIMATE_DAMAGE			0.0015***	0.0007***
			(48.36)	(58.48)
Industry fixed effects	Yes	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes	Yes
Adjusted R-squared	0.1540	0.0717	0.1540	0.0717
Observations	181,697	161,668	181,697	161,668

Panel B: Climate Disaster, Distraction, and Insider Trading

	TVALUE	*TVOLUME*	*#TRADE*
CLIMATE_DUMMY	1.0520***	0.7782***	0.1042***
	(3.86)	(3.55)	(3.71)
CLIMATE_DUMMY × *DISTRACTION*	0.2702***	0.1989**	0.0261***
	(3.27)	(3.05)	(4.74)
DISTRACTION	−0.1667***	−0.1185***	−0.0139***
	(−3.40)	(−3.30)	(−3.11)
Industry fixed effects	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes
Adjusted R-squared	0.0722	0.0684	0.0700
Observations	181,697	181,697	181,697
CLIMATE_DAMAGE	0.0561***	0.0415***	0.0056***
	(4.12)	(3.79)	(4.10)
CLIMATE_DAMAGE × *DISTRACTION*	0.0145***	0.0106***	0.0014***
	(3.58)	(3.32)	(6.33)
DISTRACTION	−0.1667***	−0.1185***	−0.0139***
	(−3.40)	(−3.30)	(−3.11)
Industry fixed effects	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes
Adjusted R-squared	0.0722	0.0684	0.0700
Observations	181,697	181,697	181,697

In Panel A, we present the panel regressions results of investor distraction on our proxies for climate disasters, including *CLIMATE_DUMMY* and *CLIMATE_DAMAGE*, where *CLIMATE_DUMMY* is a dummy variable set to one in the county–months with a major climate disaster, and zero otherwise. The variable *CLIMATE_DAMAGE* measures the magnitude of the climate disaster, and *TVALUE*, *TVOLUME*, and *#TRADE* are three measures of insider trading, where *TVALUE* is the logarithm of one plus the insider trading value, *TVOLUME* is the logarithm of one plus the insider trading volume, and *#TRADE* is the logarithm of one plus the number of insider trades. We follow Da et al. (2011) and collect data on Google searches for company tickers to directly measure investor attention to a firm (denoted $\log(1 + SVI)$). We also measure the stock abnormal *SVI*, denoted *ASVI*, as the logarithm of one plus the stock *SVI* value during the current month, minus the logarithm of one plus the average value of the stock *SVI* value during the previous six months. The results are for the period 2004–2016, as the SVI data start in 2004. In Panel B, we examine whether the degree of distraction influences the climate disaster–insider trading relation, where *DISTRACTION* is defined as −1 multiplied by the stock *SVI* value ($-1 \times \log(1 + SVI)$). We control all models for industry, county, and year–month fixed effects. The *t*-statistics, computed using standard errors robust to heteroscedasticity and clustered simultaneously on firm and year dimensions (Petersen, 2009), are reported in parentheses. *** and ** indicate the significance levels of 1% and 5% respectively.

conservative measure of firm-level ESG performance. To address possible trends in the ESG measures, we follow Pástor, Stambaugh, and Taylor (2022) and use the indicator *HIGH_ESG*, which equals one if a firm belongs to the top tercile of the sample's ESG values each year, and zero otherwise. We report the results for each of the moderating variables in rows (1) to (4) and (5) to (8) in Table 6. For brevity, we report the results for the interaction terms only as they capture the moderating effects of interest.

Our results indicate that climate insider trading is more prevalent in firms with higher information asymmetry, consistent with the

Table 6
Other Influences.

Panel A: Climate Dummy			
	TVALUE	*TVOLUME*	*#TRADE*
[1] *CLIMATE_DUMMY* × *INFORMATION_ASYMMETRY*	0.1133**	0.0831**	0.0105**
	(2.07)	(2.08)	(2.07)
[2] *CLIMATE_DUMMY* × *HIGH_ALYST_COVERAGE*	−0.4228*	−0.3020*	−0.0396*
	(−1.91)	(−1.88)	(−1.91)
[3] *CLIMATE_DUMMY* × *HIGH_INST_INVESTOR*	−0.4115**	−0.2879**	−0.0380**
	(−2.07)	(−2.05)	(−2.06)
[4] *CLIMATE_DUMMY* × *HIGH_ESG*	−0.0529***	−0.0404***	−0.0049***
	(−4.75)	(−4.65)	(−4.01)
Panel B: Climate Damage			
	TVALUE	*TVOLUME*	*#TRADE*
[5] *CLIMATE DAMAGE* × *INFORMATION_ASYMMETRY*	0.0058**	0.0042**	0.0005**
	(2.06)	(2.07)	(2.07)
[6] *CLIMATE DAMAGE* × *HIGH_ALYST_COVERAGE*	−0.0225*	−0.0160*	−0.0021*
	(−1.92)	(−1.89)	(−1.95)
[7] *CLIMATE DAMAGE* × *HIGH_INST_INVESTOR*	−0.0216**	−0.0150**	−0.0020**
	(−2.03)	(−2.00)	(−2.03)
[8] *CLIMATE DAMAGE* × *HIGH_ESG*	−0.0529***	−0.0404***	−0.0049***
	(−4.75)	(−4.65)	(−4.01)

This table uses the regression setup in eq. (3) but replaces *LITIGATION_RISK* with the variables of interest, and runs separate regressions for each moderating variable. The variable *INFORMATION_ASYMMETRY* is the market-based information asymmetry measure based on the metric proposed by Llorente et al. (2002); *HIGH_ALYST_COVERAGE* is a dummy variable that equals one if a firm's analyst coverage belongs to the top tercile each year, and zero otherwise; and *HIGH_INST_INVESTOR* is a dummy variable that equals one if the number of institutional investors in each year–quarter belongs to the top tercile, and zero otherwise. We follow Lins et al. (2017) to construct the ESG measure and use an indicator, *HIGH_ESG*, that equals one if a firm belongs to the top tercile of the sample variable each year, and zero otherwise. We control all models for industry, county, and year–month fixed effects. The *t*-statistics, computed using standard errors robust to heteroscedasticity and clustered simultaneously on firm and year dimensions (Petersen, 2009), are reported in parentheses. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

work of Aboody and Lev (2000), who suggest more insider trading in firms with more opaque information environments. There is also more climate-induced insider trading in firms with lower analyst coverage and lower institutional ownership. These two groups enhance the information environment and serve as important monitors (Armstrong, Core, Taylor, & Verrecchia, 2011; Dai, Fu, Kang, & Lee, 2016). Gao et al. (2014) show a lower incidence of insider trading in firms committed to social good via ESG activities. We find less climate-induced insider trading in these companies.[27]

5. Motivations for climate insider trading

This section considers two possible motivations for the increased insider trading we note during climate disaster months. We investigate if the increase is due to insiders earning larger returns than they would have made by delaying their trades until the impact of the climate disaster is fully reflected in prices or whether the trading is motivated by a need to raise funds for personal liquidity reasons.

5.1. Returns

Insiders may trade during climate disaster periods because they can earn larger returns than they would by delaying their trades. There could be market mispricing due to other investors being distracted by the climate disaster or simply not understanding the impact of the climate disaster on the firm. Cohen and Frazzini (2008) show that investors have limited ability to understand the full effect of public information, which leads to return predictability. Alldredge and Cicero (2015) find that insiders can trade profitably on

[27] Another potential determinant of insider trading is the degree to which firms are financially and operationally hit by disasters. It is however empirically challenging to address this point due to several reasons. First, data on production facilities and their locations are not readily available. Second, even if such data can be obtained, we may remain unable to i) identify which production facilities are the most important, and ii) decide how to estimate the weight that each production facility contributes to the whole firm's production, i.e., whether production capacity, number of employees, or number of insiders located within the same geographical area of the facility should be used. Having said that, we conduct several additional tests by including Tobin's Q, return-on-asset (ROA), and return-on-equity (ROE) to capture firm financial fundamentals. We find no significant decline in short-term fundamentals following a climate disaster, which suggests that our main findings are not entirely driven by the financial or operational consequences of the disaster. We thank an anonymous referee for raising this point.

publicly available information due to their ability to better understand the implications of this information for the firm than outside investors.

To test this explanation, we calculate the returns from insider trading in climate disaster and non–climate disaster months. Following Jagolinzer et al. (2011), Gao et al. (2014), and Dai et al. (2015), we calculate the returns from insider trading as the average risk-adjusted return for each transaction over 30 days following the transaction and relative to the Fama and French (1993) and Carhart (1997) four-factor models.[28] The trade-specific risk-adjusted return is defined as

$$R_i – R_f = \alpha + \beta_1 \left(R_{mkt} – R_f\right) + \beta_2 SMB + \beta_3 HML + \beta_4 UMD + \varepsilon \tag{5}$$

where R_i is the daily return to firm i; R_f and R_{mkt} are the daily risk-free interest rate and market return, respectively; *SMB*, *HML*, and *UMD* are the size, book-to-market, and momentum factors of Fama and French (1993) and Carhart (1997); and α ($-\alpha$) is the average daily risk-adjusted return to insider purchases (sales).[29]

We then regress these risk-adjusted returns on the *CLIMATE_DUMMY* and *CLIMATE_DAMAGE* variables. This allows us to measure whether the 30-day risk-adjusted returns for trades during climate disaster months are greater than those in other months. We follow the insider trading literature and control for a set of firm-level variables related to insider trading. Specifically, we follow Seyhun (1986), Lakonishok, Shleifer, and Vishny (1994), Rozeff and Zaman (1998), Lakonishok and Lee (2001), and Skaife, Veenman, and Wangerin (2013) and control for firm size, the book-to-market ratio, leverage, the earnings-to-price ratio, sale growth, and turnover. We include R&D expenses since Aboody and Lev (2000) find higher insider trading profits among firms with intensive R&D activities. We follow Aboody and Lev (2000) and Gao et al. (2014) and use a dummy variable, *R&D*, that equals one if a firm has positive R&D expenses, and zero otherwise. We follow Frankel and Li (2004) and Huddart and Ke (2007) and include analyst coverage to account for a firm's information environment and external monitoring. We control for a firm's negative earnings, *LOSS*, since Huddart and Ke (2007) and Brochet (2010) find that *LOSS* is related to insider trading intensity. We also include stock return volatility, since Ravina and Sapienza (2010) find it related to insider trading profits. We winsorize all continuous variables at the first and 99th percentiles to mitigate the effect of outliers.

Table 7 examines whether climate disasters trigger uncertainty about firm fundamentals, and whether insider trading activities and returns reflect these short-term profit opportunities. Panel A shows that short-term firm fundamentals, as proxied by sales growth, decline in the quarter following climate disasters. The short-term decline in firm sales growth is consistent with the results of Barrot and Sauvagnat (2016), and Hsu et al. (2018). We find the sales growth of an affected firm falls by 1% in the quarter following a climate disaster. In addition, in Appendix A8, we find that stock return volatility increases in the month following disasters, which might lead to short-term profit opportunities for insiders.

It is documented that insiders tend to sell more than they buy (e.g., Lakonishok & Lee, 2001). Our sample is dominated by insider sales, with about 70% of all transactions being sales. We investigate whether climate insider trading varies across sell and buy trades by creating a new variable, *SELL/BUY*, measured as the ratio of the number of insider sells over the number of insider purchases. The results in Table 7, Panel B, indicate that this sell-to-buy ratio increases in periods of climate disasters, indicating more sell than buy transactions.

In Panel C of Table 7, we show that the 30-day returns from climate-induced sell trades are larger than those in non-climate disaster months. There is no evidence of a difference in returns from climate-induced insider purchases. The results are consistent with the view that insiders benefit from their insight into the adverse impact of climate disasters on firm fundamentals through the sale of their holdings.

5.2. Personal impact

Another possible explanation for climate-induced insider trading is the personal impact of disasters on insiders. An insider who lives in counties impacted by a disaster can experience increased fear and anxiety. Furthermore, insiders may need to realize funds to cover costs incurred as the disaster impacts their assets. Testing this personal impact explanation is challenging, due to data availability. We do not have access to data on insiders' assets or the impact of climate disasters on these. However, we have insiders' addresses, enabling us to differentiate insiders who live in the same county as the affected firm from those who reside in counties unaffected by the disaster. We suggest that evidence of less climate insider trading by out-of-county investors would support the personal impact explanation.

To test the personal impact explanation, we run a regression specification similar to eq. (3) but replace *LITIGATION_RISK* with an *OUT_OF_COUNTY* variable that equals one if the insider lives out of the county, and zero otherwise. The interaction coefficients of *OUT_OF_COUNTY* and climate disaster variables are statistically insignificant in both Panels A and B of Table 8, suggesting that the increased insider trading activities in the disaster month are not driven by the potential negative impact on insiders' assets.

[28] As Jagolinzer et al. (2011) note, this approach of estimating trading profitability comes with two important benefits. First, estimating average daily abnormal returns reduces the biases in statistical tests of long-run buy-and-hold returns. Second, computing trade-day specific risk-adjusted returns allows us to control for differences in risk across transactions and, hence, provides a trade-specific measure of insider trading profitability.

[29] In untabulated results, we find the average trade-specific risk-adjusted returns following insiders' transactions is 0.01% and significant at the 1% level, suggesting that insiders generally earn abnormal profits, which is largely consistent with the literature (e.g., Dai et al., 2015; Jagolinzer et al., 2011; Lakonishok & Lee, 2001).

Table 7
Climate Insider Trading Returns.

Panel A: Uncertainty About Short-Term Fundamentals

	SALES_GROWTH (T + 1)	*SALES_GROWTH* (T + 1)	*SALES_GROWTH* (T + 2)	*SALES_GROWTH* (T + 1)	*SALES_GROWTH* (T + 1)	*SALES_GROWTH* (T + 2)
	(1)	(2)	(3)	(4)	(5)	(6)
CLIMATE_DUMMY	−0.0102**	−0.0090**	−0.0060			
	(−2.16)	(−2.14)	(−1.00)			
CLIMATE_DAMAGE				−0.0005**	−0.0004*	−0.0003
				(−2.14)	(−1.95)	(−0.89)
SALES_GROWTH	−0.1213***	−0.1891***	−0.0669***	−0.1213***	−0.1515***	−0.0669***
	(−14.66)	(−28.23)	(−7.57)	(−14.66)	(−24.96)	(−7.57)
LOGSIZE		−0.0094***	−0.0056***		−0.0058***	−0.0056***
		(−5.72)	(−6.25)		(−6.12)	(−6.25)
BTM		−0.0274***	−0.0255***		−0.0318***	−0.0255***
		(−9.25)	(−11.89)		(−11.30)	(−11.89)
R&D		−0.0061	−0.0036		−0.0007	−0.0036
		(−1.13)	(−1.34)		(−0.24)	(−1.34)
LOSS		0.0106***	0.0254***		0.0330***	0.0254***
		(4.25)	(10.48)		(11.28)	(10.48)
ANALYST COVERAGE		−0.0013***	−0.0006***		−0.0005**	−0.0006***
		(−4.74)	(−2.93)		(−2.22)	(−2.93)
RETVOL		0.0676***	0.0893***		0.1072***	0.0893***
		(4.49)	(4.89)		(5.65)	(4.89)
TURNOVER		−0.0168*	0.0407***		0.0446***	0.0407***
		(−1.75)	(4.13)		(4.29)	(4.13)
EARNINGS_PRICE		0.0175***	0.0159***		0.0221***	0.0159***
		(3.25)	(3.56)		(4.29)	(3.56)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
S.E. clustered	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
Adjusted R-squared	0.0370	0.0971	0.0246	0.0370	0.0495	0.0246
Observations	1,222,498	1,037,706	1,035,318	1,222,498	1,037,755	1,035,318

Panel B: Sell and Buy Trades

	SELL/BUY	*SELL/BUY*	*SELL/BUY*
	(1)	(2)	(3)
CLIMATE_DUMMY	0.0616**		
	(2.49)		
CLIMATE_DAMAGE		0.0033**	
		(2.57)	
CLIMATE_RISK			0.0006**
			(2.05)
Industry fixed effects	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes
Adjusted R-squared	0.0489	0.0488	0.0488
Observations	1,067,644	1,067,644	1,067,644

Panel C: Short-Term Returns

	Return (t + 30)		Return (t + 30)	
	Buy	Sell	Buy	Sell
	(1)	(2)	(3)	(4)
CLIMATE_DUMMY	−0.0332	0.0418**		
	(−0.79)	(1.99)		
CLIMATE_DAMAGE			−0.0018	0.0023**
			(−0.79)	(1.98)

(*continued on next page*)

Table 7 (*continued*)

Panel C: Short-Term Returns

	Return (t + 30)		Return (t + 30)	
	Buy	Sell	Buy	Sell
	(1)	(2)	(3)	(4)
LOGSIZE	−0.0085*	0.0053*	−0.0085*	0.0053*
	(−1.75)	(1.71)	(−1.75)	(1.71)
BTM	0.0024	−0.0116	0.0024	−0.0116
	(0.21)	(−1.42)	(0.21)	(−1.42)
R&D	0.0247	−0.0112*	0.0246	−0.0112*
	(1.54)	(−1.79)	(1.54)	(−1.79)
LOSS	−0.0125	0.0127	−0.0125	0.0127
	(−1.13)	(1.26)	(−1.13)	(1.26)
ANALYST COVERAGE	0.0003	−0.0010*	0.0003	−0.0010*
	(0.27)	(−1.88)	(0.27)	(−1.88)
RETVOL	0.6864***	0.0013	0.6864***	0.0014
	(9.38)	(0.02)	(9.38)	(0.02)
TURNOVER	−0.0208	0.0290	−0.0208	0.0290
	(−0.32)	(1.02)	(−0.32)	(1.02)
EARNINGS_PRICE	−0.0844*	−0.0670*	−0.0844*	−0.0670*
	(−1.87)	(−1.94)	(−1.87)	(−1.94)
SALES_GROWTH	−0.0019	0.0001	−0.0019	0.0001
	(−0.74)	(0.07)	(−0.74)	(0.07)
Industry fixed effects	Yes	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes	Yes
Adjusted R-squared	0.0164	0.0032	0.0164	0.0032
Observations	63,355	155,957	63,355	155,957

In Panel A, we show the impact of climate disasters on sales growth in the quarter following disasters, after controlling for firm size (*LOGSIZE*), the book-to-market ratio (*BTM*), R&D expenses (*R&D*), negative earnings (*LOSS*), analyst coverage (*ANALYST_COVERAGE*), return volatility (*RETVOL*), turnover (*TURNOVER*), and the earnings-to-price ratio (*EARNINGS_PRICE*). In Panel B, we examine whether climate insider trading varies across sell and buy trades. We construct a sell-to-buy ratio, *SELL/BUY*, defined as (1 + number of sells)/(1 + number of buys). Panel C presents the short-term returns for insider purchases and sales. We follow Jagolinzer et al. (2011) and compute trade-specific returns as the average risk-adjusted return for each transaction calculated over periods over 30 days following the transaction and relative to the Fama and French (1993) and Carhart (1997) four-factor models. We control all models for industry, county, and year–month fixed effects. The *t*-statistics, computed using standard errors robust to heteroscedasticity and clustered simultaneously on firm and year dimensions (Petersen, 2009), are reported in parentheses. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

6. Conclusions

We show that insider trading activity is influenced by climate disasters. We match disasters with firms headquartered in the same county and show that monthly insider trading value is over 200% higher in disaster county firm–months than in other months. The financial impact of the disaster is important. Insider trading is more prevalent when disasters inflict more damage. The result holds after controlling for several determinants of insider trading. It is prevalent in the entire sample of insider trades but stronger in opportunistic trades than in routine trades.

Although the result is evident, on average, there is variation in the cross section. There is less climate disaster-induced insider trading in firms whose insiders face greater litigation risk. Moreover, the insider trading we document is influenced by investor distraction, and the greater the distraction caused by the climate disaster, the higher the level of insider trading. We also find that the information environment and firm ESG performance influence the degree of insider trading in climate disaster periods. It is stronger in firms with higher information asymmetry, lower analyst coverage, lower institutional ownership, and lower ESG performance.

There are two plausible explanations for climate-induced insider trading. Insiders might benefit from their superior knowledge of the firm and the impact of the disaster on the firm to earn larger returns from climate-induced trading than from transactions in other periods. Alternatively, insiders may be personally impacted by the disaster and need to sell stock to cover personal expenses. We find evidence to support the return explanation and no evidence to support the personal liquidity explanation. Short-term firm fundamentals decline following disasters, and insiders earn larger than normal returns from their insider sales. This finding suggests that insiders correctly judge the impact of the climate disaster on the firm and benefit from this. There is no evidence of increased insider trading from insiders who live in the county impacted by the climate disaster compared to out-of-county insiders, which points against the personal liquidity explanation.

CRediT authorship contribution statement

Rui Ma: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal

Table 8
Location of Insiders.

Panel A: Climate Dummy			
	TVALUE	*TVOLUME*	*#TRADE*
CLIMATE_DUMMY	0.0901***	0.0706***	0.0121***
	(2.62)	(2.62)	(2.79)
CLIMATE_DUMMY × *OUT_OF_COUNTY*	−0.0303	−0.0228	−0.0039
	(−0.22)	(−0.20)	(−0.20)
OUT_OF_COUNTY	0.7674***	0.6183***	0.1034***
	(3.90)	(3.90)	(3.95)
Industry fixed effects	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes
Adjusted R-squared	0.1930	0.1970	0.2232
Observations (firm–month)	1,287,154	1,287,154	1,287,154

Panel B: Climate Damage			
	TVALUE	*TVOLUME*	*#TRADE*
CLIMATE_DAMAGE	0.0047**	0.0037***	0.0006***
	(2.58)	(2.60)	(2.78)
CLIMATE_DAMAGE × *OUT_OF_COUNTY*	−0.0009	−0.0006	−0.0001
	(−0.12)	(−0.10)	(−0.11)
OUT_OF_COUNTY	0.7673***	0.6182***	0.1034***
	(3.90)	(3.90)	(3.95)
Industry fixed effects	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes
Adjusted R-squared	0.1930	0.1970	0.2232
Observations (firm–month)	1,287,154	1,287,154	1,287,154

This table considers the impact of insider locations on the climate disaster–insider trading link. The variable *OUT_OF_COUNTY* is a dummy variable that equals one if the insider lives out of the county, and zero otherwise. We control all models for industry, county, and year–month fixed effects. The variable *CLIMATE_DUMMY* is a dummy that equals one in the county–months in which there is a climate disaster, and zero otherwise. The variable *CLIMATE_DAMAGE* measures the magnitude of the climate disaster, and *TVALUE*, *TVOLUME*, and *#TRADE* are three measures of insider trading, where *TVALUE* is the logarithm of one plus the insider trading value, *TVOLUME* is the logarithm of one plus the insider trading volume, and *#TRADE* is the logarithm of one plus the number of insider trades. The *t*-statistics, computed using standard errors robust to heteroscedasticity and clustered simultaneously on firm and year dimensions (Petersen, 2009), are reported in parentheses. *** and ** indicate the significance levels of 1% and 5% respectively.

analysis, Data curation, Conceptualization. **Ben R. Marshall:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hung T. Nguyen:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nhut H. Nguyen:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nuttawat Visaltanachoti:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Appendix

Appendix A1
Other climate risk and insider trading measures.

Panel A: Climate Risk			
	TVALUE	*TVOLUME*	*#TRADE*
CLIMATE_RISK	0.0027***	0.0019***	0.0002***
	(3.37)	(3.26)	(3.11)
Industry fixed effects	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes
Adjusted R-squared	0.1335	0.1308	0.1154
Observations	1,067,644	1,067,644	1,067,644

Panel B: Insider Trading Dummy Variable		
	INSIDER_DUMMY	*INSIDER_DUMMY*
CLIMATE_DUMMY	0.0502**	
	(2.31)	
		0.0025***
CLIMATE_DAMAGE		(2.97)
Industry fixed effects	Yes	Yes
Year–month fixed effects	Yes	Yes
County fixed effects	Yes	Yes
S.E. clustered by firm and year	Yes	Yes
Observations	1,121,218	1,121,218

This table reports the impact of climate disasters on insider trading based on alternative climate and insider trading measures. In Panel A, as an alternative measure of climate risk, we estimate the climate change news beta from the monthly rolling regression of stock excess returns on innovations in the monthly Engle–Giglio–Kelly–Lee–Strobel (2020) climate change news index over a 36-month window, with a minimum of 24 valid monthly return observations for each stock *i* in each month *t*. In Panel A, we include these climate risk proxies in the firm-level regression instead of *CLIMATE_DUMMY* or *CLIMATE_DAMAGE*. In Panel B, we use an alternative measure of insider trading, *INSIDER_DUMMY*, a dummy that equals one if there are any insider transactions in a firm–month, and zero otherwise. We use the same specification as eq. (1) and the logit regressions for Panel B. We control all models for industry, county, and year–month fixed effects. The *t*-statistics, computed using standard errors robust to heteroscedasticity and clustered simultaneously on firm and year dimensions (Petersen, 2009), are reported in parentheses. *** and ** indicate the significance levels of 1% and 5% respectively.

Appendix A2
Climate Disaster and Insider Trading: Additional Results.

Panel A: Fama–MacBeth (1973) Cross-Sectional Regression						
	TVALUE	*TVOLUME*	*#TRADE*	*TVALUE*	*TVOLUME*	*#TRADE*
	(1)	(2)	(3)	(4)	(5)	(6)
CLIMATE_DUMMY	0.7933***	0.5877***	0.0759***			
	(3.18)	(3.07)	(3.15)			
CLIMATE_DAMAGE				0.0328***	0.0247***	0.0032***
				(2.61)	(2.63)	(2.80)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
County dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,287,154	1,287,154	1,287,154	1,287,154	1,287,154	1,287,154

(*continued on next page*)

Appendix A2 (*continued*)

Panel A: Fama–MacBeth (1973) Cross-Sectional Regression						
	TVALUE	*TVOLUME*	*#TRADE*	*TVALUE*	*TVOLUME*	*#TRADE*
	(1)	(2)	(3)	(4)	(5)	(6)

Panel B: Alternative Measure of Insider Trading (Industry-Adjusted Insider Transaction)						
	ADJ_TVALUE	*ADJ_TVOLUME*	*ADJ_#TRADE*	*ADJ_TVALUE*	*ADJ_TVOLUME*	*ADJ_#TRADE*
	(1)	(2)	(3)	(4)	(5)	(6)
CLIMATE_DUMMY	0.0174***	0.0180***	0.0222***			
	(2.93)	(2.99)	(2.90)			
CLIMATE_DAMAGE				0.0009***	0.0010***	0.0012***
				(3.04)	(3.12)	(3.03)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.1256	0.1233	0.1090	0.1256	0.1233	0.1090
Observations	1,287,142	1,287,142	1,287,142	1,287,142	1,287,142	1,287,142

Panel C: Alternative Industry Classification (Fama–French 48 Industries)						
	TVALUE	*TVOLUME*	*#TRADE*	*TVALUE*	*TVOLUME*	*#TRADE*
	(1)	(2)	(3)	(4)	(5)	(6)
CLIMATE_DUMMY	0.0835***	0.0658***	0.0113***			
	(2.82)	(2.89)	(2.84)			
CLIMATE_DAMAGE				0.0045***	0.0036***	0.0006***
				(2.96)	(3.05)	(2.98)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.1288	0.1264	0.1118	0.1288	0.1264	0.1118
Observations	1,287,154	1,287,154	1,287,154	1,287,154	1,287,154	1,287,154

Panel D: Subsample Analysis (Post-Sarbanes–Oxley Act)						
	TVALUE	*TVOLUME*	*#TRADE*	*TVALUE*	*TVOLUME*	*#TRADE*
	(1)	(2)	(3)	(4)	(5)	(6)
CLIMATE_DUMMY	0.1236*	0.1098**	0.0198***			
	(1.84)	(2.24)	(2.75)			
CLIMATE_DAMAGE				0.0065*	0.0058**	0.0011***
				(1.91)	(2.32)	(2.90)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.0549	0.0528	0.0507	0.0549	0.0528	0.0507
Observations	580,753	580,753	580,753	580,753	580,753	580,753

Panel E: Additional Control Variables						
	TVALUE	*TVOLUME*	*#TRADE*	*TVALUE*	*TVOLUME*	*#TRADE*
	(1)	(2)	(3)	(4)	(5)	(6)
CLIMATE_DUMMY	0.0939***	0.0733***	0.0121***			
	(2.60)	(2.64)	(2.66)			
CLIMATE_DAMAGE				0.0051***	0.0040***	0.0007***
				(2.72)	(2.77)	(2.77)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

(*continued on next page*)

Appendix A2 (*continued*)

Panel E: Additional Control Variables

	TVALUE	*TVOLUME*	*#TRADE*	*TVALUE*	*TVOLUME*	*#TRADE*
	(1)	(2)	(3)	(4)	(5)	(6)
Year–month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.1340	0.1314	0.1150	0.1340	0.1314	0.1150
Observations	1,301,282	1,301,282	1,301,282	1,301,282	1,301,282	1,301,282

This table presents the results for a myriad of sensitivity analyses. In Panel A, we use Fama and MacBeth (1973) cross-sectional regression framework and Newey and West (1987) adjusted *t*-statistics. In Panel B, we account for the possibility of different levels of insider trading across firms in different industries by measuring *TVALUE, TVOLUME,* and *#TRADE* as the industry-adjusted variables. In Panel C, we use an alternative specification of industry based on the Fama–French 48 industry classifications. In Panel D, we consider whether the relation between climate disasters and insider trading holds in the post-2002 period. In Panel E, we rerun our baseline models, eq. (1), after controlling for earnings announcements and firm-level short interest. To account for earnings announcement, we create an indicator indicating if there is an earnings announcement date in a given month. We source earnings announcements dates from Compustat. We follow Bao, Kim, Mian, and Su (2019) and measure firm-level short interest using the short interest available at the end of each quarter scaled by the number of shares outstanding. We control all models for industry, county, and year–month fixed effects, except in Panel A. The *t*-statistics, computed using standard errors robust to heteroscedasticity and clustered simultaneously on firm and year dimensions (Petersen, 2009), are reported in parentheses. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

Appendix A3

Alternative Definitions of Major Climate Disasters.

	Disaster Months (A)		Non-Disaster Months (B)		Difference (A – B)
	Obs.	Mean	Obs.	Mean	Mean
Panel A: Total damage to a county-month of at least $10 million					
TVALUE	54,486	5.224	117,496	4.811	0.413***
TVOLUME	54,486	4.047	117,496	3.715	0.332***
#TRADE	54,486	0.721	117,496	0.635	0.086***
Panel B: Total damage to a county-month of at least $20 million					
TVALUE	954	6.674	171,028	4.933	1.741***
TVOLUME	954	5.237	171,028	3.813	1.424***
#TRADE	954	0.993	171,028	0.661	0.333***
Panel C: Total damage to a county-month of at least $30 million					
TVALUE	717	6.656	171,265	4.935	1.721***
TVOLUME	717	5.240	171,265	3.814	1.426***
#TRADE	717	0.988	171,265	0.661	0.327***
Panel D: Total damage to a county-month of at least $40 million					
TVALUE	600	6.618	171,382	4.936	1.681***
TVOLUME	600	5.196	171,382	3.816	1.381***
#TRADE	600	0.967	171,382	0.661	0.306***
Panel E: Total damage to a county-month of at least $60 million					
TVALUE	443	7.000	171,539	4.937	2.063***
TVOLUME	443	5.493	171,539	3.816	1.676***
#TRADE	443	1.007	171,539	0.662	0.345***
Panel F: Total damage to a county-month of at least $100 million					
TVALUE	319	7.273	171,663	4.938	2.336***
TVOLUME	319	5.725	171,663	3.817	1.908***
#TRADE	319	1.073	171,663	0.662	0.411***

This table presents the means of three measures of county-level insider trading, namely, *TVALUE*, *TVOLUME*, and *#TRADE*, in disaster and non-disaster months for the entire sample period (1986–2016). The variable *TVALUE* is the logarithm of one plus the insider trading value, *TVOLUME* is the logarithm of one plus the insider trading volume, and *#TRADE* is the logarithm of one plus the number of insider trades. In Panels A to F, we define a county exposed to a major disaster if the total estimated damage to that county in a given month is of at least $10 million, $20 million, $30 million, $40 million, $60 million or $100 million, respectively. In the final column, we examine the statistical significance of mean differences using a *t*-test. *** indicates the significance level of 1%.

Appendix A4
Opportunistic versus Routine Insider Trading.

	Opportunistic Trading			Routine Trading		
	#TRADE	*TVALUE*	*TVOLUME*	*#TRADE*	*TVALUE*	*TVOLUME*
CLIMATE_DUMMY	0.0125***	0.0876***	0.0679***	0.0048**	0.0373	0.0288
	(2.99)	(2.84)	(2.87)	(2.12)	(1.57)	(1.60)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.0982	0.1161	0.1138	0.0374	0.0421	0.0413
Observations (firm–month)	1,207,169	1,207,169	1,207,169	1,207,169	1,207,169	1,207,169
CLIMATE_DAMAGE	0.0007***	0.0047***	0.0037***	0.0003**	0.0019	0.0015
	(3.14)	(2.99)	(3.03)	(2.13)	(1.51)	(1.53)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.0982	0.1161	0.1138	0.0374	0.0421	0.0413
Observations (firm–month)	1,207,169	1,207,169	1,207,169	1,207,169	1,207,169	1,207,169

This table reports the impact of climate disasters on different types of insiders. We follow Cohen et al. (2012) approach and define opportunistic and routine insider trading. Specifically, we define a routine trader as an insider who placed a trade in the same calendar month for at least three consecutive years. Non-routine, or opportunistic, insiders are the remaining insiders. The variable *CLIMATE_DUMMY* is a dummy that equals one in the county–months in which there is a climate disaster, and zero otherwise. The variable *CLIMATE_DAMAGE* measures the magnitude of the climate disaster, and *TVALUE*, *TVOLUME*, and *#TRADE* are three measures of insider trading, where *TVALUE* is the logarithm of one plus the insider trading value, *TVOLUME* is the logarithm of one plus the insider trading volume, and *#TRADE* is the logarithm of one plus the number of insider trades. We control for industry, county, and year–month fixed effects in all models, except in Panel A. The *t*-statistics, computed using standard errors robust to heteroscedasticity and clustered simultaneously on firm and year dimensions (Petersen, 2009), are reported in parentheses. *** and ** indicate the significance levels of 1% and 5% respectively.

Appendix A5
Alternative Measures of Insider Trading.

	TVALUE / TVOL	*TVOLUME / TVOL*	*#TRADE / TVOL*
CLIMATE_DUMMY	0.0062***	0.0048***	0.0008***
	(2.76)	(2.72)	(2.62)
Industry fixed effects	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes
Adjusted R-squared	0.1271	0.1242	0.1090
Observations	1,236,645	1,236,645	1,236,645
CLIMATE_DAMAGE	0.0003***	0.0003***	0.0000***
	(2.91)	(2.89)	(2.76)
Industry fixed effects	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes
Adjusted R-squared	0.1271	0.1242	0.1090
Observations	1,236,645	1,236,645	1,236,645

The table reports the results when alternative measures of insider trading are employed. The variable *CLIMATE_DUMMY* is a dummy that equals one in the county–months in which there is a major climate disaster, and zero otherwise; *CLIMATE_DAMAGE* measures the magnitude of the climate disaster in a given county–month. *TVALUE / TVOL*, *TVOLUME / TVOL*, and *#TRADE / TVOL* are three alternative measures of insider trading, where *TVALUE* is the logarithm of one plus the insider trading value, *TVOLUME* is the logarithm of one plus the insider trading volume, *#TRADE* is the logarithm of one plus the number of insider trades, and *TVOL* is the logarithm of total trading volume. We control for all models for industry, county, and year–month fixed effects. The *t*-statistics, computed using standard errors robust to heteroscedasticity and clustered simultaneously on firm and year dimensions (Petersen, 2009), are reported in parentheses. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

Appendix A6
Alternative Distraction Measure from EDGAR.

Panel A: Climate Disaster

	#TRADE		*TVALUE*		*TVOLUME*	
	High Distraction	Low Distraction	High Distraction	Low Distraction	High Distraction	Low Distraction
	(1)	(2)	(3)	(4)	(5)	(6)
CLIMATE_DUMMY	0.0417***	−0.0130	0.3917***	−0.2387	0.3079***	−0.1625
	(2.64)	(−0.87)	(2.83)	(−1.53)	(2.90)	(−1.33)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	219,007	217,619	219,007	217,619	219,007	217,619
Observations	0.0547	0.0587	0.0599	0.0584	0.0560	0.0559
SUR & Wald test for differences in coefficients:						
χ^2 test	4.91**		7.44***		6.84***	
p-Value	(0.03)		(0.01)		(0.01)	

Panel B: Climate Damage

	#TRADE		*TVALUE*		*TVOLUME*	
	High Distraction	Low Distraction	High Distraction	Low Distraction	High Distraction	Low Distraction
	(1)	(2)	(3)	(4)	(5)	(6)
CLIMATE_DUMMY	0.0022***	−0.0006	0.0201***	−0.0115	0.0158***	−0.0077
	(2.70)	(−0.74)	(2.83)	(−1.42)	(2.92)	(−1.21)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year–month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
S.E. clustered by firm and year	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	219,007	217,619	219,007	217,619	219,007	217,619
Observations	0.0547	0.0587	0.0599	0.0584	0.0560	0.0559
SUR & Wald test for differences in coefficients:						
χ^2 test	4.44**		6.73***		6.16**	
p-Value	(0.04)		(0.01)		(0.01)	

This table presents the results of the effect of investor distraction, measured by EDGAR searches, on the climate disaster–insider trading link. We define high and low distraction based on the sample median of the firm-level EDGAR searches. The variable *CLIMATE_DUMMY* is a dummy that equals one in the county–months in which there is a climate disaster, and zero otherwise. The variable *CLIMATE_DAMAGE* measures the magnitude of the climate disaster, and *TVALUE*, *TVOLUME*, and *#TRADE* are three measures of insider trading, where *TVALUE* is the logarithm of one plus the insider trading value, *TVOLUME* is the logarithm of one plus the insider trading volume, and *#TRADE* is the logarithm of one plus the number of insider trades. We control all models for industry, county, and year–month fixed effects. The *t*-statistics, computed using standard errors robust to heteroscedasticity and clustered simultaneously on firm and year dimensions (Petersen, 2009), are reported in parentheses. We employ seemingly unrelated estimation and Wald tests for the coefficient differences across these two subgroups. *** and ** indicate the significance levels of 1% and 5% respectively.

Appendix A7
Climate *SVI* Values during Disaster versus Non-Disaster Periods.

	Disaster	Non-Disaster	Difference (A - B)	
	(A)	(B)	Mean	p-Value
Climate *SVI*	3.0623	2.6514	0.4109***	(0.00)
Climate *ASVI*	0.3176	−0.0798	0.3974***	(0.00)

This table presents the means of climate *SVI* values over climate disaster and non-disaster periods. We obtain state-level climate SVI data using climate keywords based on climate keywords, including *climate disaster*, *hurricane*, *storm*, *tornado*, *flooding*, *drought*, *winter*, *weather*, and *wildfire*. The climate SVI data are monthly for the period 2004–2016. Climate ASVI calculated as the logarithm of one plus the climate SVI value during the current month, minus the logarithm of one plus the average value of the climate SVI value during the previous six months. In the final two columns, we examine the statistical significance of mean differences using a *t*-test. *** indicates the significance level of 1%.

Appendix A8
Climate Disaster and Return Volatility.

	RETVOL	*RETVOL*
	(1)	(2)
CLIMATE_DUMMY	0.0584*	
	(1.70)	
CLIMATE_DAMAGE		0.0033*
		(1.82)
Industry fixed effects	Yes	Yes
Year–month fixed effects	Yes	Yes
County fixed effects	Yes	Yes
S.E. clustered by firm and year	Yes	Yes
Adjusted R-squared	0.1939	0.1939
Observations	1,099,898	1,099,898

The table presents the impact of climate disasters on stock return volatility in the month following disasters. Return volatility is measured as the standard deviation of all daily returns in a given month. We control all models for industry, county, and year–month fixed effects. The *t*-statistics, computed using standard errors robust to heteroscedasticity and clustered simultaneously on firm and year dimensions (Petersen, 2009), are reported in parentheses. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

References

Aboody, D., & Lev, B. (2000). Information asymmetry, R&D, and insider gains. *Journal of Finance, 55*, 2747–2766.
Ali, U., & Hirshleifer, D. (2017). Opportunism as a firm and managerial trait: Predicting insider trading profits and misconduct. *Journal of Financial Economics, 126*, 490–515.
Alldredge, D., & Cicero, D. (2015). Attentive insider trading. *Journal of Financial Economics, 115*, 84–101.
Alok, S., Kumar, N., & Wermers, R. (2020). Do fund managers misestimate climatic disaster risk? *Review of Financial Studies, 33*, 1146–1183.
Amiram, D., Bozanic, Z., Cox, J. D., Dupont, Q., Karpoff, J. M., & Sloan, R. (2018). Financial reporting fraud and other forms of misconduct: A multidisciplinary review of the literature. *Review of Accounting Studies, 23*, 732–783.
Armstrong, C. S., Core, J. E., Taylor, D. J., & Verrecchia, R. E. (2011). When does information asymmetry affect the cost of capital? *Journal of Accounting Research, 49*(1), 1–40.
Baker, S. R., Bloom, N., & Terry, S. J. (2020). *Using disasters to estimate the impact of uncertainty. National Bureau of Economic Research (Working Paper No. w27167)*.
Bao, D., Kim, Y., Mian, G. M., & Su, L. (2019). Do managers disclose or withhold bad news? Evidence from short interest. *The Accounting Review, 94*(3), 1–26.
Barrot, J.-N., & Sauvagnat, J. (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics, 131*(3), 1543–1592.
Ben-Rephael, A., Da, Z., & Israelsen, R. D. (2017). It depends on where you search: Institutional investor attention and underreaction to news. *The Review of Financial Studies, 30*(9), 3009–3047.
Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics, 119*(1), 249–275.
Bertrand, M., & Mullainathan, S. (2003). Enjoying the quiet life? Corporate governance and managerial preferences. *Journal of Political Economy, 111*(5), 1043–1075.
Billings, M. B., & Cedergren, M. C. (2015). Strategic silence, insider selling and litigation risk. *Journal of Accounting and Economics, 59*(2–3), 119–142.
Bourveau, T., Lou, Y., & Wang, R. (2018). Shareholder litigation and corporate disclosure: Evidence from derivative lawsuits. *Journal of Accounting Research, 56*(3), 797–842.
Bowen, R., Dutta, S., Tang, S., & Zhu, P. (2018). Inside the "black box" of private in-house meetings. *Review of Asset Pricing Studies, 23*, 487–527.
Brochet, F. (2010). Information content of insider trades before and after the Sarbanes–Oxley Act. *The Accounting Review, 85*, 419–446.
Carhart, M. (1997). On persistence in mutual fund performance. *Journal of Finance, 52*, 57–82.
Cheng, Q., & Lo, K. (2006). Insider trading and voluntary disclosures. *Journal of Accounting Research, 44*, 815–848.
Clayton, S. (2020). Climate anxiety: Psychological responses to climate change. *Journal of Anxiety Disorders, 74*, Article 102263.
Cohen, L., & Frazzini, A. (2008). Economic links and predictable returns. *Journal of Finance, 63*, 1977–2011.
Cohen, L., Malloy, C., & Pomorski, L. (2012). Decoding inside information. *Journal of Finance, 67*, 1009–1043.
Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *Journal of Finance, 66*, 1461–1499.
Dai, L., Fu, R., Kang, J.-K., & Lee, I. (2016). Corporate governance and profitability of insider trading. *Journal of Corporate Finance, 40*, 235–253.
Dai, L., Parwada, J., & Zhang, B. (2015). The governance effect of the media's news dissemination role: Evidence from insider trading. *Journal of Accounting Research, 53*, 331–366.
Davidson, R. H., & Pirinsky, C. (2022). The deterrent effect of insider trading enforcement actions. *The Accounting Review, 97*(3), 227–247.
DeHaan, E., Shevlin, T., & Thornock, J. (2015). Market (in) attention and the strategic scheduling and timing of earnings announcements. *Journal of Accounting and Economics, 60*(1), 36–55.
Denis, D. J., & Xu, J. (2013). Insider trading restrictions and top executive compensation. *Journal of Accounting and Economics, 56*(1), 91–112.
Dessaint, O., & Matray, A. (2017). Do managers overreact to salient risks? Evidence from hurricane strikes. *Journal of Financial Economics, 126*, 97–121.
Duellman, S., Guo, J., Zhang, Y., & Zhou, N. (2018). Expertise rents from insider trading for financial experts on audit committees. *Contemporary Accounting Review, 35*(2), 930–955.
Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging climate change news. *Review of Financial Studies, 33*(3), 1184–1216.
Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy, 81*(3), 607–636.
Fama, E., & French, K. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*, 3–56.
Fidrmuc, J. P., Goergen, M., & Renneboog, L. (2006). Insider trading, news releases, and ownership concentration. *Journal of Finance, 61*, 2931–2973.
Frankel, R., & Li, X. (2004). Characteristics of a firm's information environment and the information asymmetry between insiders and outsiders. *Journal of Accounting and Economics, 37*(2), 229–259.
Gao, F., Lisic, L. L., & Zhang, I. X. (2014). Commitment to social good and insider trading. *Journal of Accounting and Economics, 57*(2–3), 149–175.

Giglio, S., Kelly, B., & Stroebel, J. (2021). Climate finance. *Annual Review of Financial Economics, 13*(1), 15–36.

Gow, I., Ormazabal, G., & Taylor, D. (2010). Correcting for cross-sectional and time-series dependence in accounting research. *The Accounting Review, 85*(2), 483–512.

Hong, H., Karolyi, G., & Andrew, and Scheinkman, Jose A.. (2020). Climate finance. *Review of Financial Studies, 33*, 1010–1023.

Hsu, P.-H., Lee, H.-H., Peng, S.-C., & Yi, L. (2018). Natural disasters, technology diversity, and operating performance. *Review of Economics and Statistics, 100*(4), 619–630.

Huddart, S. J., & Ke, B. (2007). Information asymmetry and cross-sectional variation in insider trading. *Contemporary Accounting Research, 24*(1), 195–232.

Huddart, S., Ke, B., & Shi, C. (2007). Jeopardy, non-public information, and insider trading around SEC 10-K and 10-Q filings. *Journal of Accounting and Economics, 43*, 3–36.

Huynh, T. D., & Xia, Y. (2021). Climate change news risk and corporate bond returns. *Journal of Financial and Quantitative Analysis, 56*(6), 1985–2009.

Jagolinzer, A. D., Larcker, D. F., Ormazabal, G., & Taylor, D. J. (2020). Political connections and the informativeness of insider trades. *Journal of Finance, 75*(4), 1833–1876.

Jagolinzer, A. D., Larcker, D. F., & Taylor, D. J. (2011). Corporate governance and the information content of insider trades. *Journal of Accounting Research, 49*, 1249–1274.

Kahneman, D. (1973). *Attention and effort* (Vol. 1063). Englewood Cliffs, NJ: Prentice-Hall.

Kim, I., & Skinner, D. (2012). Measuring securities litigation risk. *Journal of Accounting and Economics, 53*, 290–310.

Krueger, P., Sautner, Z., & Starks, L. (2020). The importance of climate risks for institutional investors. *Review of Financial Studies, 33*, 1067–1111.

Lakonishok, J., & Lee, I. (2001). Are insider trades informative? *Review of Financial Studies, 14*, 79–111.

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. *Journal of Finance, 49*, 1541–1578.

Lins, K. V., Servaes, H., & Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *Journal of Finance, 72*(4), 1785–1824.

Llorente, G., Michaely, R., Saar, G., & Wang, J. (2002). Dynamic volume-return relation of individual stocks. *Review of Financial Studies, 15*, 1005–1047.

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica, 55*(3), 703–708.

Nordhaus, W. (2019). Climate change: The ultimate challenge for economics. *American Economic Review, 109*(6), 1991–2014.

Pástor, Ľ., Stambaugh, R. F., & Taylor, L. A. (2022). Dissecting green returns. *Journal of Financial Economics, 146*(2), 403–424.

Peress, J., & Schmidt, D. (2020). Glued to the T.V.: Distracted noise traders and stock market liquidity. *Journal of Finance, 75*(2), 1083–1133.

Petersen, M. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies, 22*, 435–480.

Ravina, E., & Sapienza, P. (2010). What do independent directors know? Evidence from their trading. *The Review of Financial Studies, 23*, 962–1003.

Rehse, D., Riordan, R., Rottke, N., & Zietz, J. (2019). The effects of uncertainty on market liquidity: Evidence from hurricane Sandy. *Journal of Financial Economics, 134*(2), 318–332.

Rogers, J., Skinner, D., & Zechman, S. (2016). The role of the media in disseminating insider-trading news. *Review of Accounting Studies, 21*, 711–739.

Rozeff, M. S., & Zaman, M. A. (1998). Overreaction and insider trading: Evidence from growth and value portfolios. *Journal of Finance, 53*, 701–716.

Ryan, S., Tucker, J., & Zhou, Y. (2016). Securitization and insider trading. *The Accounting Review, 91*, 649–675.

Schüwer, U., Lambert, C., & Noth, F. (2020). How do banks react to catastrophic events? Evidence from Hurricane Katrina. *Review of Finance, 23*(1), 75–116.

Servaes, H., & Tamayo, A. (2013). The impact of corporate social responsibility on firm value: The role of customer awareness. *Management Science, 59*(5), 1045–1061.

Seyhun, N. H. (1986). Insiders' profits, costs of trading, and market efficiency. *Journal of Financial Economics, 16*, 189–212.

Skaife, H. A., Veenman, D., & Wangerin, D. (2013). Internal control over financial reporting and managerial rent extraction: Evidence from the profitability of insider trading. *Journal of Accounting and Economics, 55*(1), 91–110.

Thompson, S. B. (2011). Simple formulas for standard errors that cluster by both firm and time. *Journal of Financial Economics, 99*(1), 1–10.

Wang, K., Wang, R., Wei, J. K. C., Zhang, B., & Zhou, Y. (2022). Insider sales under the threat of short sellers: New hypothesis and new tests. *The Accounting Review, 97*(2), 427–451.

Zhang, I. X., & Zhang, Y. (2018). Insider trading restrictions and insiders' supply of information: Evidence from earnings smoothing. *Contemporary Accounting Research, 35*(2), 898–929.