Obscured by Clouds: The Impact of Weather-induced Managerial Mood on Corporate Tax Avoidance

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Abstract

Using variation in local sunshine as a mood-priming construct, we examine the impact of managerial mood on corporate tax avoidance. For a large sample of U.S. publicly listed firms, we report strong, robust evidence that negative managerial mood induced by cloudy weather leads firms to undertake more aggressive tax positions. Reinforcing the intuition underlying our main result, we find that negative weather-induced mood is positively associated with managers' subjective perceptions of firms' financial constraints, but not with their actual financial constraints. In cross-sectional analysis, consistent with expectations, we find that the importance of weather-induced mood to tax avoidance subsides when the board has more directors with financial expertise and the threat that the firm will experience an Internal Revenue Service (IRS) audit is greater. We also find that firms are more apt to purchase tax services from their auditor when local weather is cloudy. Collectively, our evidence implies that corporate tax avoidance rises when managerial mood is negative, although external monitoring by directors with financial expertise and the IRS constrains this behavior.

JEL Classification: G02, G30, M40, M41

Keywords: Weather; Managerial mood; Tax avoidance

1. Introduction

Tax avoidance is a socially important issue that remains understudied (Arnold 2009; Hanlon and Heitzman 2010). There has been a recent steep rise in interest in corporate tax avoidance among the academy, policymakers, the media, and the general public stemming from a variety of political, economic, and technological forces (Anesa et al. 2019).[1] Managers make corporate tax planning decisions based on their judgments of the costs and benefits of tax avoidance (Cowell 2004; Crocker and Slemrod 2005; Goerke 2008; Chen et al. 2010). Although human judgements often involve heuristics and subjective assessments (Tversky and Kahneman 1974; Peecher and Piercey 2008; Chen and Tan 2013; Kadous et al. 2013), extant research seldom evaluates the behavioral aspects of tax planning. In particular, evidence on the role of managers' emotional states, including the importance of their mood to corporate tax planning, remains scarce. This constitutes a major gap in tax research given that prior studies in economics, finance, and psychology show that mood affects individuals' judgments (Johnson and Tversky 1983; Schwarz and Clore 1983; Saunders 1993; Goetzmann et al. 2015; Lerner et al. 2015; DeHaan et al. 2017). The complex and uncertain nature of tax planning strategies can magnify the impact of managerial mood because, lacking a clear choice prescription, individuals tend to rely more heavily on affective cues (Forgas 1995; Faraji-Rad and Pham 2017). Against this backdrop, we examine the influence of managerial mood on corporate tax planning decisions.

We expect to observe evidence implying that negative mood induces managers to pursue more aggressive tax avoidance strategies. Extensive prior research in psychology

[1] Dyreng et al. (2008) define corporate tax avoidance as any corporate activity, legal or illegal, designed to reduce the corporate tax burden relative to the statutory tax rate. Similarly, Hanlon and Heitzman (2010) frame corporate tax avoidance along a continuum that spans from perfectly legal low-risk strategies at one end to strategies that approach tax evasion at the other. After extensive prior research, we interpret the tax avoidance construct to reflect a broad description of tax strategies that lower firms' taxes in comparison to their book incomes. Although these strategies may lie in a grey area, undertaking aggressive tax positions does not necessarily suggest that the firm has illegally evaded taxes. For expositional convenience, we use the terms 'tax aggressiveness', 'tax planning' and 'tax avoidance' interchangeably in this paper.

suggests that a negative mood engenders a more pessimistic outlook evident in individuals tending to overestimate (underestimate) the likelihood of negative (positive) events (e.g., Johnson and Tversky 1983; Wright and Bower 1992). It follows that managers in a negative mood are more likely to exhibit a pessimistic outlook concerning the firm's future cash flows from operations and access to external financing; i.e., these managers are more likely to perceive that the firm will suffer financial constraints. Since corporate tax avoidance generates internal funds that alleviate firms' financial constraints (Law and Mills 2015; Edwards et al. 2016), we expect that perceived financial constraints will motivate managers to implement more aggressive tax planning strategies.[2] In contrast, managers in a good mood will perceive the firm as less financially constrained, lowering the incentive to become more tax aggressive in order to generate internal funds. Accordingly, we predict that, on average, firms undertake more aggressive tax positions when managers are in a negative mood.

Despite the potential role that managerial mood plays in corporate tax planning, providing reliable evidence on this research question would involve confronting at least two major challenges. First, mood is hard to measure since it is generally unobservable. Second, corporate tax avoidance is considered socially irresponsible in some circles and participating in socially irresponsible behavior can bring negative mood to decision makers according to prior research (e.g., Rietschlin 1998; Schwartz et al. 2003). Consequently, it is difficult to establish a causal effect of managerial mood on corporate tax avoidance.

We address these two challenges by using variation in the level of sunshine in the area where a firm's headquarters is located as a mood-priming construct. Prior research implies that sunshine has a significant impact on a person's mood in that cloudy weather leads to bad mood whereas sunny weather results in good mood (e.g., Persinger 1975; Cunningham

[2] Reflecting the large magnitude of cash outflows stemming from corporate taxes, Dyreng et al. (2008) estimate that aggregate cash tax payments over a ten-year period amount to one third of aggregate pre-tax book income over this period.

1979; Saunders 1993; De Silva et al. 2012; Bassi et al. 2013). Highlighting that sunshine is one of the key environmental drivers of mood, Howarth and Hoffman (1984) investigate an extensive list of weather variables and show that sunshine is the only variable significantly related to the mood of optimism. Prior research shows that senior managers influence tax planning by setting "the tone from the top" (e.g., Dyreng et al. 2010). Since senior managers typically reside near their firm's headquarters where major business decisions are routinely made (Berrone et al. 2010; Alam et al. 2014), we expect that variation in the level of local sunshine around firm headquarters will shape their mood.[3] Further, prior research asserts that, through social interactions, mood spreads and amplifies within groups, eliciting shared emotions ("emotional contagion") among group members (Barsade and Gibson 1998; Totterdell et al. 1998; Kelly and Barsade 2001, Bartel and Saavedra 2000). As emotional contagion can strengthen the impact of individuals' mood on group decisions (Sanchez-Burks and Huy 2009), it follows that sunshine-induced mood will have a pronounced effect on corporate decisions made by the executive team. Importantly, variation in the level of sunshine is exogenous to corporate tax planning decisions, which is constructive for identifying the casual impact of managerial mood on tax avoidance.

Employing a comprehensive sample of U.S. public firms and building on prior work on the impact of sunshine on mood (Persinger 1975; Bassi et al. 2013), we use the variation in local sunshine to construct our measure of weather-induced mood. We follow extensive research by relying on unexpected sky coverage to gauge weather-induced mood (e.g., Hirshleifer and Shumway 2003; Goetzmann et al. 2015; Chhaochharia et al. 2017a). Specifically, for each firm-year observation, we calculate the unexpected sky coverage as the

[3] Given that the luminosity of sunlight penetrates office windows and car windshields, sunlight can prime mood even amongst people who primarily spend their time indoors (Keller et al. 2005; Bruyneel et al. 2009). Consistent with this notion, prior evidence implies that variation in sunlight primes mood in institutional investors and investment analysts (Goetzmann et al. 2015; DeHaan et al. 2017). Since senior executives tend to occupy 'the corner office' where they are exposed to natural light, it follows that variation in the level of local sunlight will shape executives' mood.

deviation between the level of sky coverage around a firm's headquarters in a given year and the average level of sky coverage around the same geographic location in the preceding five years.[4] As cloudy weather induces negative mood, executives are more likely to experience bad mood during a cloudy year, which, in turn, shapes their tax planning decisions in that year. It is important to stress that our analysis captures average mood during the year under study. We examine yearly variation rather than daily variation in order to ensure consistency between theory and empirical design since firms undertake tax planning throughout the year (Mills et al. 1998). Our approach to measuring weather-induced mood is consistent with the recent stream of research examining its impact on decisions that involve long-term horizons (e.g., Chhaochharia et al. 2017a; Chen et al. 2017; Zolotoy et al. 2018), although we continue to find highly supportive evidence when we narrow the focus to the quarter from the year.[5]

We find that, on average, firms have lower cash effective tax rates when there is higher unexpected sky coverage around their headquarters. This evidence suggests that managers engage in more tax avoidance when they are in a bad mood. The impact of weather-related mood on tax avoidance is also economically significant in that moving from the bottom to the top decile of unexpected local sky coverage translates into a decline of 1.90 percentage

[4] This measure teases out normal level of sky coverage from the raw level in a given geographic location and captures the unexpected level of sky coverage in the location. The average level of sky coverage exhibits substantial variation across geographic locations. However, both firms' propensity to engage in tax avoidance and their geographic location could be correlated with some underlying firm-level attribute (e.g., industry clusters in certain geographic areas), executive-level attribute (e.g., executives' religious beliefs) or local regulatory environment (e.g., different state tax rates). Such correlations could result in a spurious relation between the raw (i.e., location unadjusted) sky coverage in a given location and tax avoidance. Using unexpected (i.e., location-adjusted) sky coverage mitigates this concern. Nonetheless, to further address this issue, we control for firms' geographic location fixed effects in all estimations.

[5] Supporting that weather-related mood can impact behavior spanning relatively long horizons, recent research implies that weather-induced mood affects managers' decisions on hiring and investment, the impact of managers' equity incentives on corporate risk-taking, and inventors' decisions on innovation during the year (Chhaochharia et al. 2017a; Chen et al. 2017; Zolotoy et al. 2018). In a similar vein, analyzing survey data on managerial sentiment, Hribar et al. (2017) document that sentiment of bank managers affects bank accrual estimates, implying that sentiment matters to decisions involving a relatively long horizon. Additionally, Shu et al. (2016) and Bernile et al. (2018) show that negative emotions of professional investors influence their financial decisions for at least one year.

points in firms' cash effective tax rates. For perspective, this equates to cash savings of $4.566 million, which corresponds to 1.61 percent of the average sample firm's operating cash flows. Although fluctuations in local sky coverage are likely to capture only a fraction of the variation in managerial mood, these results suggest that the associated mood changes play an economically material role in corporate tax avoidance.

To evaluate the sensitivity of our core evidence, we conduct a battery of tests. Since local sky coverage could potentially be correlated with the incidence of natural disasters in the area where firms' headquarters are located, we consider the possibility that our results could reflect tax levies granted to firms that are headquartered in areas hit by natural disasters, rather than the impact of weather-induced mood on tax avoidance. To help dispel this competing explanation, we control for the occurrences and the magnitudes of natural disasters in our sample period. We also consider the possibility that our findings stem from the impact of local weather on the economic output of firms in weather sensitive-industries. To examine this issue, we repeat our analysis after excluding firms in weather-sensitive industries from our sample. Additionally, we provide evidence implying that sunshine-induced shirking by executives is not spuriously responsible for our core results. We also verify that our main results persist after including firm and CEO fixed effects to ensure that our results are not an artifact of some unobservable firm or manager characteristics. Moreover, we control for systematic changes in effective tax rates over time (Dyreng et al. 2017) to verify that common trends in corporate tax avoidance and local sky cover are not behind our findings. Another series of sensitivity analyses help dispel any lingering concern that spurious correlations between the unexpected sky coverage and corporate tax avoidance, or peculiarities of the data distributions, explain our evidence. Finally, we continue to find supportive results when we focus on several alternative proxies for corporate tax avoidance.

The critical assumption underlying our prediction is that managers in a bad mood perceive their firms as more financially constrained. This assumption is consistent with individuals in a bad mood possessing a pessimistic outlook concerning economic prospects (e.g., Wright and Bower 1992; Bagozzi et al. 1999; Hirshleifer and Shumway 2003). To help justify the empirical relevance of this assumption, we directly analyze its validity in our setting. Specifically, we follow recent research by measuring managers' perceptions about financial constraints with the language tone of their firms' 10-K filings (Bodnaruk et al. 2015; Law and Mills 2015). We find that managers tend to use more negative words in 10-K filings in years with low levels of local sunshine. Moreover, our mediation analysis confirms that the role that weather-related mood plays in corporate tax avoidance occurs through managers' perceptions of financial constraints. We further examine whether managers' perceptions about financial constraints induced by cloudy weather could reflect rational projections of firms' access to external financing or their operating cash flows, rather than mood-driven behavior. We find no evidence that variation in local sunshine has a perceptible impact on firms' future debt or equity financing costs, or future operating cash flows. Collectively, these results reinforce that our main evidence on the link between local sky coverage and corporate tax avoidance reflects mood-driven tax planning, rather than rational managerial judgment.

We further gauge whether the role that mood plays in corporate tax avoidance varies systematically with monitoring structures that are directly relevant to our research question. Extensive prior research in psychology implies that the impact of mood on decision-making subsides when an individual expects to be held responsible for their decisions (Bodenhausen et al. 1994; Lerner et al. 1998). More specifically, anticipation of accountability motivates individuals to undertake conscious pre-emptive self-monitoring of their judgment processes (Tetlock 1985; Tetlock and Kim 1987; Trotman et al. 2015). We begin our cross-sectional analysis by examining whether the presence of directors with financial expertise, who are known to effectively evaluate the costs and benefits of tax strategies proposed by management (e.g., Armstrong et al. 2015), constrains mood-induced tax avoidance. Consistent with this intuition, we find that the link between managerial mood and corporate tax avoidance subsides when board financial expertise is greater.

Next, we consider whether the importance of managerial mood to firms' tax avoidance hinges on the threat of corporate tax enforcement. Prior evidence suggests that firms undertake less aggressive tax positions when the IRS imposes stricter monitoring (e.g., Hoopes et al. 2012). Grounded in prior research (e.g., Tetlock 1985; Lerner et al. 1998), we expect to observe that tight external monitoring by the IRS constrains the impact of managerial mood on firms' tax avoidance. The results lend support to this prediction. Collectively, the evidence is consistent with stricter external monitoring of firms' tax positions moderating the relation between managerial mood and corporate tax avoidance.

Finally, we examine the impact of managerial mood on a firm's decision to purchase tax services from external audit firms. We examine this issue as previous work implies that tax services provided by audit firms help their clients to reduce corporate tax payments by devising more aggressive tax avoidance strategies (McGuire et al. 2012; Cook and Omer 2013; Hogan and Noga 2015). Consistent with the argument that bad mood leads managers to prefer more aggressive corporate tax planning, we find that bad mood is positively associated with the probability of purchasing tax services from external audit firms.

We primarily contribute to extant research in three ways. First, in responding to calls for more research on the determinants of corporate tax avoidance (e.g., Arnold 2009; Hanlon and Heitzman 2010), we extend evidence on this issue to include weather-induced managerial mood. Prior research implicitly assumes that managers are fully rational in tax planning, thereby ignoring the potential impact of managers' emotional states on corporate tax avoidance. However, this assumption sits uncomfortably with studies showing that individuals' emotional states (particularly mood) affect their decision-making (Johnson and

Tversky 1983; Wright and Bower 1992; Saunders 1993; Hirshleifer and Shumway 2003). We help close this gap by examining whether corporate tax avoidance is sensitive to managerial mood. Recent research establishes links between firms' tax avoidance activities and managerial ability (Koester et al. 2017), narcissism (Olsen and Stekelberg 2016), personal tax aggressiveness (Chyz 2013), military experience (Law and Mills 2017) and managerial task interruption (Long and Basoglu 2016). We extend this line of research by emphasizing the salience of managers' emotional state—mood—in shaping corporate tax positions, enriching our understanding of the behavioral aspects of tax planning.

Second, we advance research on the role that weather-related mood plays in economic outcomes. Prior studies in this area mainly examine whether weather-induced mood influences investors' decisions (e.g., Saunders 1993; Hirshleifer and Shumway 2003; Goetzmann et al. 2015). Moreover, DeHaan et al. (2017) find that unpleasant weather delays analysts' reaction to earnings announcements, undermining price discovery in the stock market. Besides extant evidence implying that the weather-induced mood of investors impacts their information processing and thus shapes their decisions, emerging research analyzes whether managers' mood induced by weather affects their decisions involving long-term horizons (e.g., Chhaochharia et al. 2017a; Zolotoy et al. 2018). We contribute to this strand of research by showing that weather-related mood matters to executives' decisions on corporate tax planning.

Third, we add to recent research analyzing the role that financial constraints play in corporate tax avoidance. Law and Mills (2015) and Edwards et al. (2016) report that firms engage in more aggressive tax avoidance when they are more financially constrained. We extend this research by providing evidence suggesting that managerial mood, which shapes managers' perceptions concerning financial constraints but not actual financial constraints, also affects corporate tax avoidance. Accordingly, our analysis complements prior studies by documenting that managers' subjective perceptions (instead of objective assessments) of firm's financial constraints can also alter corporate tax planning.

The rest of the paper is organized as follows. Section 2 reviews prior theory and evidence in developing the motivation for our study. Section 3 describes the sample and regression variables. Section 4 covers the main findings and Section 5 presents the results of our sensitivity analysis. Section 6 examines the validity of the key assumptions underlying our prediction. Section 7 outlines the results of supplemental analyses and Section 8 concludes.

2. Motivation

2.1. *Sunshine, Mood and Pessimism*

Extensive prior research in psychology implies that sunny weather leads to good mood and cloudy weather results in bad mood. Cunningham (1979) and Schwartz and Clore (1983) find that agents report experiencing a happier mood when they are exposed to more sunshine. Parrott and Sabini (1990) show that exposure to cloudy (clear) skies serves as an effective way to elicit bad (good) moods. Prior work also demonstrates the efficacy of sunshine exposure as a mood stimulus. Sunshine has been shown to improve the mood of clinically depressed individuals, including those suffering from seasonal (Rosenthal et al. 1984) and non-seasonal (Kripke 1998) forms of clinical depression. Light therapy is also effective in treating many types of mood disturbances and depressive disorders (Lam et al. 2006; Prasko 2008; Sanassi 2014).[6] More generally, prior research implies that exposure to sunlight affects mood in both depressed and non-depressed individuals (Keller et al. 2005).

Extant research suggests that individuals in a bad mood rely on negative cues and tend to possess a pessimistic outlook. Tversky and Kahneman (1973) stress that individuals

[6] Studies in neurobiology show the biological mechanism through which sunshine affects human mood. Lambert et al. (2002) and Spindelegger et al. (2012) provide evidence that sunshine exposure triggers the release of serotonin, a neurotransmitter associated with happiness and elevated emotional states. In contrast, when humans are exposed to less sunshine, their brains produce melatonin, which is associated with depression, sleepiness, and fatigue (Lieberman et al. 1984).

in bad (good) mood are more likely to retrieve negative (positive) information from memory. Isen et al. (1978) and Bower (1981) also find that mood increases the availability of mood-congruent thoughts or information. Carlson et al. (1988) demonstrate that bad mood causes people to perceive things in a negative light and that people store information in memory according to its affective tone. Johnson and Tversky (1983) show that individuals in a bad mood tend to overestimate the likelihood of negative outcomes and events and underestimate the likelihood of positive outcomes and events; in contrast, the opposite holds for individuals in a good mood. Schwarz (2000) provides evidence that individuals are more likely to evaluate targets pessimistically when they are in a bad mood.

Emerging research in finance also lends support to the intuition that bad mood stemming from cloudy weather engenders a pessimistic outlook. In particular, several studies report that stock market investors are more pessimistic on cloudy days, translating into lower stock returns (e.g., Hirshleifer and Shumway 2003; Goetzmann et al. 2015). In analyzing the importance of local sunshine to the decisions of lower-level bank financial officers, Cortes et al. (2016) find that they are more likely to approve credit application on sunny days, which the authors attribute to the weather inducing these employees to become more optimistic. Besides research focusing on shorter horizons, recent studies imply that mood stemming from cloud cover matters to decisions involving longer-term horizons (e.g., Chen et al. 2017; Chhaochharia et al. 2017a, 2017b; Zolotoy et al. 2018). For example, Chen et al. (2017) report that inventors exposed to more sunshine during the year generate more patents and patents with higher value. Chhaochharia et al. (2017a) document that weather-related mood influences both capital investment and employee recruitment in small businesses. Zolotoy et al. (2018) find that higher level of abnormal sunshine during the year accentuates executives' responsiveness to equity compensation incentives. We extend recent research by providing initial evidence on the role that weather-induced mood plays in shaping tax avoidance, an important decision made by senior corporate managers (Dyreng et al. 2010).

2.2. ***Financial Constraints and Corporate Tax Avoidance***

In the presence of capital market frictions, financially constrained firms resort to relying more on internal financing given that external financing is costly for them (e.g. Greenwald et al. 1984; Myers and Majluf 1984). Although financially constrained firms could implement cost-saving measures (such as cutting research and development expenditures) to preserve resources, this may undermine operations to their longer-term detriment. Instead, recent evidence implies that firms suffering financial constraints are eager to generate internal funds by reducing their taxes (e.g., Law and Mills 2015; Edwards et al. 2016). In short, undertaking aggressive tax positions can enable firms to avoid or defer (benefitting firms in the form of an interest-free loan from the government) tax payments. Prior evidence suggests that financially constrained firms are more apt to generate internal funds by pursuing aggressive tax planning strategies. As highlighted earlier, research in psychology shows that bad mood engenders a more pessimistic outlook in that individuals tend to overestimate the likelihood of negative events and underestimate the likelihood of positive events (Johnson and Tversky 1983; Wright and Bower 1992). It follows that managers in a bad mood are more likely to experience a pessimistic outlook concerning the firm's future cash flows from operations and access to external financing; i.e., they perceive the firm as more financially constrained. This perception surrounding the firm's financial condition may motivate managers to more aggressively avoid taxes in order to generate more internal cash flows. Accordingly, we expect to observe that weather-induced bad mood leads to managers undertaking more aggressive tax positions.

However, injecting tension into our analysis, prior research implies that corporate tax strategies are difficult to quickly modify (e.g., Dyreng et al. 2008). In the presence of frictions stemming from transaction costs, information asymmetry, and incomplete markets, Kim et al. (2016) estimate that firms converge, on average, toward their optimal tax avoidance level at a rate of 69 percent within a three-year period. In survey evidence supporting that adjustment speeds are slightly faster, Hoopes et al. (2012) report that tax executives perceive that 69 (90) percent of tax positions can be changed within one year (three years). To the extent that frictions constrain managers from modifying the firm's tax positions during the year, it becomes harder for our analysis to reject the null hypothesis that weather-induced mood is irrelevant to corporate tax avoidance. Moreover, some individuals involved in corporate tax planning, including outside consultants, may be located in more distant places.[7] Additionally, managers experiencing a negative mood may form a pessimistic outlook that manifests in overestimating the severity of IRS tax enforcement that their firms will encounter. Relatedly, managers in a negative mood may experience fatigue (DeHaan et al. 2017), undermining their tax planning productivity. However, these potential impacts would run in the opposite direction of our prediction, making it more difficult to detect that negative managerial mood stemming from cloudy weather leads firms to undertake more aggressive tax positions. Accordingly, our empirical tests are likely to provide a conservative estimate of the magnitude of the mood-driven tax planning.

3. Research Design

3.1. *Measuring Tax Avoidance*

Hanlon and Heitzman (2010) stress in their survey of tax research that it is important to select a tax avoidance measure appropriate to the research question under study. The rationale underlying our prediction is that managers in a bad mood engage in more

[7] Besides that this issue makes it more difficult for our analysis to reject the null hypothesis, we examine later in the paper the role that geographic distance plays in our setting. This includes gauging whether our core evidence varies systematically with the extent of the geographic dispersion of firms' operations under the rationale that firms with operations spread over a larger geographic area are more likely to have individuals involved in the tax planning process located farther from corporate headquarters.

aggressive tax avoidance in order to generate more internal funds to finance firms' activities. In other words, we expect that mood influences managers' subjective assessments of the benefits from cash savings generated through tax planning activities. Accordingly, we use cash effective tax rate (*CASH_ETR*) as our primary proxy for tax avoidance since it directly measures a firm's cash tax burden (Edwards et al. 2016). Additionally, relying on *CASH_ETR* that reflects a wide range of corporate tax planning activities suits our focus on broad tax avoidance, instead of strictly very aggressive forms. After specifying *CASH_ETR* as the ratio of cash taxes paid to pretax income, we follow prior research by winsorizing this variable at the 0 and 1 values (e.g., Dyreng et al. 2008; McGuire et al. 2012).[8]

3.2. *Measuring Managerial Mood*

We follow extensive prior research by measuring weather-induced mood with local sky coverage (e.g., Saunders 1993; Cortes et al. 2016; DeHaan et al. 2017). We collect the sky coverage data from the Integrated Surface Database (ISD), which is available from the National Oceanic and Atmospheric Administration (www.ncdx.noaa.gov/pub/data/noaa). The database contains hourly observations from over 20,000 active and inactive weather stations worldwide. As the focus of our study is U.S. firms, we collect the data from all active weather stations located in the U.S. (7,610 weather stations).

The ISD measures sky coverage in oktas (i.e. eighths), where 0 oktas cover is reported as CLR (clear sky), 1-2 oktas cover is reported as FEW (few clouds), 3-4 oktas cover is reported as SCT (scattered clouds), 5-7 oktas cover is reported as BKN (broken clouds), and 8 oktas cover is reported as OVC (overcast or full cloud coverage). We assign to each of these categories an integer value on a scale of one to five, where one indicates clear sky (CLR) and five indicates full cloud coverage (OVC). For each weather station, we compute daily

[8] Although focusing on cash ETRs suits our research question, we concede that this measure does not reflect conforming tax avoidance given the scaling by book income and our inferences do not extend to unprofitable firms since we restrict our analysis to firms with non-negative pre-tax income. We later examine whether our core results persist under alternative tax avoidance measures.

sky coverage by averaging hourly sky coverage between 6am and midnight. The ISD database also provides the location coordinates of each weather station (i.e., latitude and longitude). For each firm in Compustat, we calculate its geographic distance from each weather station based on the harvesine distance formula.[9] The location coordinates of Compustat firms are recorded at the ZIP code level.

Next, we calculate firm-level annual sky coverage by taking the average values of daily sky coverage for all the weather stations within a 50-mile radius of the firm's ZIP code centroid in a given fiscal year. Last, we calculate unexpected sky coverage (SKY_COVER) as the difference between annual sky coverage and its moving average over the previous five years (with the minimum of three prior years of data available). We use unexpected sky coverage in the analysis because unexpected weather can shape human mood while expected weather has limited impact (Guven and Hoxha 2015).[10] Another important advantage of using unexpected sky coverage is that it helps to tease out potential effects of firm's geographic location.[11] A higher value of SKY_COVER indicates relatively heavy sky coverage—and, by inference, a lower amount of sunshine—around firm's headquarters compared to the normal sky coverage in that location. In this setup, a high value of SKY_COVER is associated with negative managerial mood.

3.3. *Control Variables*

[9] The harvesine formula calculates distance between location *1* and *2* as $d_{1,2} = 2 \times R \times \arcsin(\min(1, \sqrt{A})$, where R is the earth's radius (approximately 6,371 kilometres), $A = sin^2\left(\frac{\Delta lat}{2}\right) + \cos(lat_1) + \cos(lat_2) \times sin^2(\frac{\Delta lon}{2})$. In this expression, $\Delta lat = (lat_2 - lat_1)$ and $\Delta lon = (lon_2 - lon_1)$, where *lat* and *lon* refer to latitude and longitude, respectively.

[10] Although people can adapt to their environment such that their sensory systems hardly respond to constant stimulus, they are sensitive to changes in the environment (e.g., Chung et al. 2002; Dougherty et al. 2005).

[11] Raw sky coverage is largely determined by firms' geographic location and firm location influences their tax liabilities because tax rules vary across states (Ljungqvist et al. 2016). Therefore, the link between raw cloudy coverage and the cash effective tax rate could be driven by firm location. Using the measure of unexpected sky coverage mitigates this concern because the effect of firm location on cloud coverage is teased out in the measure. To further control for potential impact of firm's geographic location on the cash effective tax rate, we include location-fixed effects in our analyses.

As discussed earlier, we posit that mood impacts tax avoidance by shaping executives' perceptions of the firm's financial constraints (i.e., managers' subjective perceptions of the firm's ability to obtain funds in the future). Consequently, it is important to ensure that our results are indeed driven by managers' perceptions of the firm's financial constraints associated with bad mood but not actual financial constraints. To that end, we include several measures of actual financial constraints as control variables. Specifically, we include cash holdings (*CASH*) to control for firm financial resources and the firm-level financial constraints index (*HP_INDEX*) proposed by Hadlock and Pierce (2010).[12] Additionally, we follow Edwards et al. (2016) by controlling for the impact of macroeconomic financial constraints on tax avoidance with the net percentage of domestic respondents reporting tightening standards during the year for commercial and industrial loans (*TIGHTEN*) and growth in gross domestic product (*DGDP*).

In addition to firms' financial constraints, we also include a variety of other control variables suggested in prior research (e.g., Chen et al. 2010; Edwards et al. 2016). We include the level of intangible assets (*INTANG*) and property, plant, and equipment (*PPE*) to control for a firm's ability to shield income through depreciation and amortization. Equity income in earnings (*EQINC*) and research and development expenses (*R&D*) are included to control for a firm's investment activities, which might generate additional tax shields. To control for the impact of net operating loss on tax expenses, we include both the change in loss carry-forward (*DNOL*) and an indicator for loss carry-forward (*NOL*) in the model.

We include leverage (*LEV*) to capture the effect of debt tax shields; change in goodwill (*POS_GDWL*) to capture the effect of asset impairment on a firm's tax position; firm size

[12] We use the financial constraints index developed by Hadlock and Pierce (2010) as the firm characteristics, comprising this index, are useful indicators of financial constraints faced by the firms. Another commonly used measure of financial constraints is the financial constraints index developed by Kaplan and Zingales (1997). Hadlock and Pierce (2010) argue that their findings "cast serious doubt on the validity of the KZ index as a measure of financial constraints." Nonetheless, as a (untabulated) robustness test, we repeat our analysis using the Kaplan and Zingales (1997) index and Altman (1968) Z-score instead of the Hadlock and Pierce (2010) index to control for firm-level financial constraints (Edwards et al. 2016) and find nearly identical evidence.

(*SIZE*) to control for the "political costs" of tax avoidance and return on assets (*ROA*) to control for the profitability of a firm's operations. We also include earnings volatility (*STDROA*) to control for the volatility of firm operations; foreign income (*FRGNAT*) to control for income shifting by multinational firms; the market-to-book ratio (*MB*) to control for firm investment opportunities; the use of mezzanine finance (*MEZ_FIN*) to control for the differences in book and tax reporting environments; discretionary accruals (*ABACC*) to control for the influence of upward earnings management on tax avoidance (Guenther et al. 2014), and stock compensation expense (*STOCK_EXP*) to reflect the potential role that compensation structure plays in tax avoidance (Law and Mills 2015). Last, we include industry fixed effects based on the 2-digit SIC codes to control for variation in tax shields and tax subsidies across industries (Barth et al. 1998) and location fixed effects based on the 2-digit ZIP codes to further control for potential variations in the tax regimes across geographic locations. Detailed definitions of the variables are shown in Appendix A.

4. Empirical Analysis

4.1. *Sample and Summary Statistics*

We obtain the data for the construction of the sky coverage measure from ISD and firm financial information from Compustat. We exclude observations for which the data necessary to code any of the regression variables is unavailable. We follow Dyreng et al. (2008) and De Simone et al. (2017) by excluding observations with negative pre-tax income to avoid negative denominators in the *CASH_ETR* measure. Our final sample consists of 38,101 firm-year observations for 6,096 unique U.S. firms over the period 1993-2012.[13]

Table 1 shows the summary statistics for the variables employed in our analyses. We report that the mean (median) *CASH_ETR* is 0.263 (0.245), which closely resembles the statistics observed in prior studies (e.g., Dyreng et al. 2008; Cen et al. 2017). The mean

[13] Although the weather data is available from 1990, we require a minimum of three prior years' weather data to calculate the unexpected annual sky coverage, so our sample period starts at 1993.

(median) *SKY_COVER* is -0.06 (-0.031); its standard deviation is 0.231, suggesting that there is ample variation in unexpected sky coverage.[14] Table 2 reports the sample correlation coefficients for the regression variables. *CASH_ETR* is negatively correlated with *SKY_COVER* (*p*-value<0.01), consistent with firms engaging in more tax avoidance when there is higher unexpected sky coverage. The signs of the other correlation coefficients are largely consistent with prior research (e.g., Dyreng et al. 2010; Edwards et al. 2016). Untabulated results show that the largest variance inflation factor (VIF) is well below a commonly applied threshold of 10, suggesting that there is no multicollinearity in our sample (Kennedy 1992).[15]

[Insert Tables 1 and 2 about here]

4.2. *Univariate Analysis*

We begin to examine our research question by conducting a univariate nonparametric regression analysis of the relation between weather-induced mood and corporate tax avoidance. The advantage of this approach is that a nonparametric regression model imposes minimal assumptions on the functional form of the regression (Pagan and Ullah 1999), allowing the data to inform a researcher about the shape of the relation between the dependent variable and the variable of interest. We estimate a nonparametric kernel regression of *CASH_ETR* on *SKY_COVER* and plot the resulting regression curve along with the 95% confidence intervals. Figure 1 depicts a strong negative relation between *CASH_ETR* and *SKY_COVER*. The univariate analysis provides preliminary evidence that higher unexpected sky coverage (i.e., bad mood) is associated, on average, with more aggressive tax avoidance. Next, we analyze whether these initial results hold in a multivariate framework.

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[14] Nonetheless, given that we are eager to dispel the concern that locations at the extremes of the cloud cover distribution are spuriously behind our evidence, we re-estimate the regressions after excluding values outside the 5th and 95th percentiles and find that all core results hold at the 1% level, reinforcing that our evidence reflects pervasive economic phenomena.

[15] The (untabulated) VIF for the explanatory variable of interest (*SKY_COVER*) is 1.02.

[Insert Figure 1 about here]

4.3. ***Multivariate Regression Analysis***

To examine the role that managerial mood plays in corporate tax avoidance, we estimate the following regression specification:

$$CASH\_ETR_{i,t} = \beta_0 + \beta_1 SKY\_COVER_{i,t} + \sum \beta_k Controls_{i,t} + \sum FE + + \varepsilon_{i,t} \qquad (1)$$

where *i* denotes firm, *t* denotes year, *Controls* denotes the set of control variables, *FE* denotes industry and location fixed effects, and *ε* is the error term. The dependent variable is cash effective tax rate (*CASH_ETR*) and the explanatory variable of interest is unexpected sky coverage (*SKY_COVER*). The regression is conducted using pooled ordinary least squares (OLS), with standard errors adjusted for heteroskedasticity and firm-level clustering.

The results reported in Table 3 show that the coefficient for *SKY_COVER* is negative and statistically significant (*t*-statistic=-3.982, *p*-value < 0.01).[16] This finding suggests that, on average, higher unexpected sky coverage (i.e., bad mood) leads to more aggressive tax avoidance, as reflected in lower values of cash effective tax rate.[17] This evidence corroborates the results of the univariate nonparametric analysis reported in the preceding section.

To evaluate the economic significance of the impact of mood on tax avoidance, we convert our variable of interest (i.e., *SKY_COVER*) into decile ranks values (Edwards et al. 2016). To facilitate interpretation of the decile-ranked *SKY_COVER*, we further transform it into [0,1] range, so that the coefficient for the decile-ranked *SKY_COVER* measures the change in cash effective tax rate when *SKY_COVER* moves from the bottom to the top decile. We then re-estimate our baseline model using decile-ranked *SKY_COVER* as the variable of interest. The (untabulated) results show that the coefficient for decile-ranked *SKY_COVER* is -0.019 (*t*-statistic=-5.360, *p*-value<0.01), suggesting that moving from the bottom to the top decile of *SKY_COVER* is associated with a decline of 1.90 percentage points in *CASH_ETR*.

[16] All reported *p*-values are for the two-tailed tests.

[17] We continue to find that *SKY COVER* loads negatively (*t*-statistic=-3.887, *p*-value<0.01) when we gauge tax avoidance with the 3-year cash effective tax rate (Dyreng et al. 2008).

This equates to cash savings of $4.566 million, which corresponds to 1.61 percent of operating cash flows, reinforcing that weather-related mood exerts an economically meaningful impact on corporate tax avoidance.[18]

As outlined earlier, we specify the cash effective tax rate (*CASH_ETR*) as our main measure of tax avoidance because our research question calls for a proxy that captures cash tax payments; i.e., the cash effective tax rate is the most direct measure of a firm's cash tax burden (Edwards et al. 2016). Moreover, *CASH_ETR* suits our setting since we focus on general tax avoidance, rather than strictly very aggressive forms; i.e., this broad measure reflects a wide range of corporate tax planning activities. However, given that measures of tax avoidance are not without debate (Hanlon and Heitzman 2010), we examine in the rest of Table 3 whether our results are robust to several alternatives: (i) the book-tax difference; (ii) the residual book-tax difference; (iii) the GAAP effective tax rate; (iv) deferred taxes; and (v) cash tax non-conformity (e.g., Desai and Dharmapala 2006, 2009; Dyreng et al. 2010; Cheng et al. 2012; Henry and Sansing 2014; Chen et al. 2018).

The book-tax difference is calculated as the difference between accounting income and taxable income, scaled by total assets. Residual book-tax difference is measured as the residual from regressing the book-tax difference on discretionary accruals and a set of firm fixed-effects dummies. The GAAP effective tax rate is calculated as income taxes scaled by pre-tax income. Deferred taxes are estimated as the value of deferred taxes reported in the balance sheet scaled by total assets.[19] Cash tax non-conformity is estimated as the difference between cash taxes paid and the product of pre-tax income and statutory tax rate scaled by total assets. Since this measure involves scaling by assets, rather than pre-tax book income,

[18] For additional perspective, the estimates of our baseline model suggest that a one-standard deviation increase in *SKY_COVER* equates to cash savings of $1.166 million.

[19] In an untabulated test, we measure deferred taxes as tax expense scaled by pre-tax income with no material impact on our findings.

the resulting analysis benefits from including loss firms (Henry and Sansing 2014).[20] For the book-tax difference, residual book-tax difference, and deferred taxes, higher values indicate more aggressive tax avoidance; in contrast, for the GAAP effective tax rate and cash tax non-conformity, a lower value indicates more aggressive tax avoidance.

The results reported in Table 3 show that the coefficient for *SKY_COVER* is significantly positive for the book-tax difference, residual book-tax difference, and deferred taxes (smallest *t*-statistic=2.626, *p*-value<0.01) and significantly negative for cash tax non-conformity (*t*-statistic=-2.823, *p*-value<0.01) and the GAAP effective tax rate (*t*-statistic=-1.871, *p*-value=0.061), lending further support to our prediction that, on average, managers undertake more aggressive corporate tax positions when they are in a negative weather-induced mood.[21]

[Insert Table 3 about here]

5. Sensitivity Analysis

To help validate our main findings, we conduct various robustness tests. For brevity, we only report the coefficient for *SKY_COVER*, although the control variables are included in all regressions.

5.1. *Executives' Absence from Firm Headquarters*

Our analysis so far implicitly assumes that, over the course of the year, executives typically spend their time close to firm headquarters. However, executives are likely absent from firm headquarters for some intervals (e.g., for work or vacation). It is important to reiterate that the potential absence of executives from their firm's headquarters admits noise into the weather-based measure of mood, which should bias against finding evidence that corporate tax avoidance is sensitive to weather-related mood. Nonetheless, although data

[20] The results are almost identical if we exclude firms with negative pre-tax income from the sample.

[21] It is important to stress that GAAP ETRs may not suit our analysis given that they fail to reflect tax avoidance activities that generate temporary book-tax differences by deferring the payment of taxes to later years (Hanlon and Heitzman 2010). Since corporate tax planning routinely involves deferring taxes (e.g., Dyreng et al. 2008), GAAP ETRs tend to underestimate firms' actual tax avoidance.

constraints prevent us from directly controlling for executives' absence, we conduct three tests to tackle this issue indirectly and report the results in Panel A of Table 4.

First, we re-estimate our baseline model after bisecting the sample according to the level of geographic dispersion of firms' operations. Prior research suggests that travel demands for top management rise with geographic dispersion (e.g., Rajan and Wulf 2006). Consequently, restricting the analysis to firms with minimal geographic dispersion helps mitigate the potential impact of executives' absence from firms' headquarters on the link between weather-induced mood and corporate tax avoidance. This analysis involves re-estimating our baseline model on two sub-samples: (i) firms in the bottom five deciles of the geographic dispersion distribution; and (ii) firms in the top five deciles according to the measure developed by Garcia and Norli (2012). We obtain the measure of firm's geographic dispersion from Professor Diego Garcia's homepage (http://leeds-faculty.colorado.edu/garcia/page3.html).

Despite a drastic reduction in sample size stemming from sample bisection, the results show that the coefficient of *SKY COVER* remains significantly negative in both sub-samples (coefficient=-0.026, *p*-value<0.01 for firms with low geographic dispersion; coefficient=-0.014, *p*-value=0.062 for firms with high geographic dispersion). Notably, the magnitude of the coefficient of *SKY COVER* almost doubles for the firms with low geographic dispersion compared to firms with high geographic dispersion, reflecting that firms with operations spread over a larger geographic area are more apt to have individuals involved in the tax planning process located farther from corporate headquarters. To verify that our findings are not driven by shifts in the distribution of geographic dispersion over time, we repeat the analysis using the year-by-year ranking of firms based on their geographic dispersion. The (untabulated) results remain qualitatively similar: the coefficient of *SKY COVER* is significantly negative in both sub-samples (largest *p*-value=0.03), and its economic magnitude is substantially larger for the firms with low geographic dispersion.

In the remaining two tests, we re-estimate our baseline model using two modified measures of *SKY COVER*. The first measure excludes sunshine observations from July and August—months when executives routinely take annual leave (Yermack 2014). In another approach to identifying days when executives are more likely to be elsewhere, the second measure excludes sunshine observations for weekends and public holidays. Reinforcing our earlier evidence, the coefficient of *SKY COVER* remains significantly negative at the 1% level in both regressions. In each of the two tests, the magnitude of the coefficient estimate on *SKY COVER* is larger than the one in the baseline model (see Table 2).

5.2. *Potential Sunshine-driven Shirking*

Next, we consider sunshine-driven shirking by executives as another potential competing explanation for our main results. Unexpected sunshine (lower sky cover) may engender excessive consumption of leisure by managers, which, in turn, may lead to managers shirking their responsibilities in the form of neglecting corporate tax planning that may be evident in, for example, higher cash ETRs or firms deviating from their optimal tax structure (e.g., Kim et al. 2016). Given that the effort executives exert is naturally difficult to measure, we follow Biggerstaff et al. (2017) by gauging leisure consumption with: (i) whether the CEO plays golf during the year; and (ii) the number of rounds of golf that the CEO plays during the year. More generally, frequently spending time on the golf course may reflect an overall preference for leisure. Further, consistent with golf play capturing the extent of shirking by the executives, Biggerstaff et al. (2017) document that CEOs who golf the most are associated with firms that have lower operating performance and firm values. After controlling for potential weather-induced shirking with (i) alone, and (i) and (ii) together in successive regressions, we report in Panel B that the coefficient for *SKY_COVER* in our model remains negative and statistically significant despite that the poor availability of golfing data almost literally decimates our sample.[22] In untabulated results, we continue to find virtually identical supportive evidence when we also control for the CFO's golfing behavior. This evidence collectively implies that it is unlikely that the documented role that sky cover plays in shaping tax avoidance stems from the impact of sunshine-induced shirking by executives on corporate tax planning.

5.3. *Controlling for Potential SAD Effects*

Next, we evaluate the possibility that our results capture the impact of managers suffering Seasonal Affective Disorder (SAD)—individuals afflicted with this condition experience negative emotions and fatigue in darker seasons (e.g., Rosenthal et al. 1984). Importantly, since we use annual measures of tax avoidance and weather-induced mood, our analysis covers both dark and sunny time periods of the year, implying that our findings are unlikely to reflect SAD-driven seasonality in tax avoidance. Nonetheless, we examine this issue by re-estimating our baseline model using two alternative measures of sky cover: (i) *SKY_COVER_DARK_SEASONS* and (ii) *SKY_COVER_BRIGHT_SEASONS*. The *SKY_COVER_DARK_SEASONS* measure is estimated using sky cover data from the first and fourth calendar quarters, whereas *SKY_COVER_BRIGHT_SEASONS* reflects sky cover data from the second and third calendar quarters. For consistency, we restrict this analysis to firms with December fiscal year-ends (i.e., firms with matching calendar and fiscal quarters). Each of the two measures was adjusted to *both* season and location; i.e., they reflect abnormal amounts of sky cover relative to the typical amount of sky cover in a given season and in a given location. If our results are driven by SAD effects, then, in focusing on *seasonally-adjusted* measures of *SKY_COVER*, we should observe no impact of *SKY_COVER* on tax avoidance. However, the results reported in Panel C of Table 4 show that the coefficient remains highly significantly negative for each of the two sky cover measures (*t*-

[22] Golf is an outdoor activity for which participation rises on sunny days. We thank Professor Lee Biggerstaff for generously facilitating this analysis using his data on the golfing activities of CEOs and CFOs of S&P 1500 firms between 2008 and 2012.

statistic=-3.803 and -3.639 for the *SKY_COVER_DARK_SEASONS* and the *SKY_COVER_BRIGHT_SEASONS*, respectively). Reinforcing this evidence, we re-estimate our baseline model with both measures included simultaneously and obtain qualitatively similar results (untabulated for brevity).

5.4. ***Alternative Fixed Effects Specifications***

Next, we conduct two tests to examine the sensitivity of our results to alternative specifications of fixed effects in our baseline model and report the results in Panel D of Table 4. First, we re-estimate our baseline model (Equation (1)) with firm fixed effects to ensure that our findings are not driven by some persistent firm-specific attribute not accounted for in our baseline model specification. The coefficient for *SKY_COVER* remains significantly negative (t-statistic=-3.678, p-value<0.01), suggesting that including firm fixed effects has no material impact on our findings.

Second, we control for CEO fixed effects since Dyreng et al. (2010) show that CEO fixed effects are a significant determinant of firms' tax avoidance. If our results reflect the impact of weather-induced mood on tax avoidance, then such an effect should manifest not only in the cross-section of firms, but also for the same CEO over time. In other words, we expect that the same CEO will be affected by changes in weather-related mood as sky coverage changes. To analyze this issue, we estimate our model with CEO fixed effects. We identify CEO positions in the firm using the ExecuComp database. Despite a drastic reduction in sample size (n=17,416), the coefficient for *SKY_COVER* remains significantly negative (t-statistic=-1.941, p-value=0.052) in this regression, lending additional support to the prediction that weather-induced mood shapes corporate tax avoidance.[23]

[23] By estimating our baseline model with CEO-fixed effects, we control for time-invariant CEO attributes that could potentially affect corporate tax planning. In another sensitivity test (untabulated), we explore whether our results continue to hold after controlling for time-varying CEO characteristics. To examine this issue, we modify our baseline model to include these additional controls (Law and Mills 2017; Koester et al. 2017): managerial ability, CEO age, CEO tenure, sensitivity of CEO equity compensation to stock price (delta), and sensitivity of CEO equity compensation to stock price

5.5. ***Alternative Sample Specifications and Estimation Methods***

Next, we examine whether our core evidence is materially sensitive to alternative sample specifications and model estimation methods. First, we re-estimate our baseline model after excluding firms in weather-sensitive industries from our sample. The purpose of this test is to provide further assurance that our results are not driven by the influence of weather on the performance of firms in weather-sensitive industries; i.e., firms whose output could depend on weather conditions. We follow Dutton (2002) in identifying weather-sensitive industries.[24]

Second, we estimate our baseline model using censored Tobit regression, which may provide a better fit for the firms with a zero cash effective tax rate compared to least squares regression (Law and Mills 2015). Third, we estimate our baseline model using a dynamic panel regression approach (Arellano and Bond 1991) to control for potential effects of mean reversion in effective tax rates (e.g., Kim et al. 2016; Chen et al. 2017). Fourth, we follow De Simone et al. (2017) by estimating our baseline model with non-winsorized cash ETRs using a robust regression approach (Rousseeuw and Yohai 1984) to address potential outliers and to enhance statistical power.[25]

Finally, we consider whether our core evidence holds for quarterly estimates of corporate tax avoidance and unexpected sky coverage. In our main analyses, we employ yearly unexpected sky coverage to capture the average mood given that managers plan taxes throughout the year (Mills et al. 1998). As daily mood is widely measured as daily

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volatility (vega). Despite the fall in sample size for this analysis stemming from limited availability of data on these additional controls (N=6,083 observations), the impact of *SKY_COVER* remains negative and highly significant (*t*-statistic=-3.113; *p*-value<0.01), reinforcing our earlier evidence.

[24] Specifically, we exclude industries with the following 2-digit Standard Industry Classification (SIC) codes: agriculture, forestry, and fishing (SIC codes 01-09), mining (SIC codes 12-13), construction (SIC codes 15-17), railroad/water transportation (SIC codes 40 and 44), electric, gas, and sanitary services (SIC code 49), insurance/real estate (SIC codes 63-65), hotels (SIC code 70), and amusement and recreation services (SIC code 79).

[25] Similarly, our core evidence continues to hold at the 1% level when we follow prior research by truncating cash ETR observations outside the [0,1] range in order to reduce the impact of outliers (e.g., Chen et al. 2010; Law and Mills 2015).

unexpected sky coverage in prior research, our measure of the annual mood is consistent with the intuition that annual mood is the overall status of the daily mood during the specific year. Although annual window analyses are more consistent with the relatively long-horizon nature of tax planning decisions, a potential concern is that the role that mood plays may subside under longer windows. It is important to stress that this would work against rejecting the null hypothesis on the link between annual mood and corporate tax avoidance. In any event, we rely on quarterly estimates of corporate tax avoidance (Dhaliwal et al. 2004; Gleason and Mills 2008) and unexpected sky coverage, as well as the control variables, to evaluate whether our evidence persists in a shorter window. For this analysis, we calculate unexpected sky coverage as the difference between quarterly sky coverage and its moving average for the same quarter over the previous five years (with a minimum of three prior years of data available).

The results reported in Panel E of Table 4 show that the coefficient for *SKY_COVER* remains negative and statistically significant at the 1% level in each of the five tests, reinforcing our earlier evidence.

[Insert Table 4 about here]

5.6. ***Potential Omitted Variable Problem***

In this section, we confront the threat to reliable inference stemming from omitted correlated variables, which could potentially lead to endogenous effects.[26] Recall that we rely on unexpected sky coverage in the area where a firm is headquartered as a mood-priming construct. This measure could potentially be correlated with the occurrence of natural disasters driven by extreme weather conditions near the firm's headquarters. Accordingly, in our first test, we consider the possibility that our results reflect tax levies granted to the firms that are headquartered in areas hit by natural disasters or disruptions in

[26] Endogenous effects could be driven either by reverse causality from the dependent variable to the explanatory variable of interest or by potential omitted correlated variables (Larcker and Rusticus 2010). The exogenous nature of *SKY_COVER* rules out the reverse causality scenario.

economic conditions caused by such disasters. To tackle this issue, we collect data on extreme weather conditions from the National Centre for Environmental Information (NCEI). We use this data to construct two variables: (i) a natural disaster dummy variable which takes the value 1 if the area where a firm's headquarters are located experienced extreme weather conditions in that year, and 0 otherwise; and (ii) the (log-transformed) estimate of monetary damage caused by these extreme weather conditions. We then modify our baseline model (Equation (1)) by adding these two control variables.[27]

In the second test, we control for systematic changes in effective tax rates in our sample. Specifically, we examine the possibility that our findings are an artifact of a common time trend in ETRs and the level of local sky cover. To examine this issue, we modify our baseline model to include a time trend as an additional control variable (Dyreng et al. 2017).

In the third test, we control for potential effects of economic ties among local firms. Such ties may induce commonalities in local firms' economic activities (so-called "spatial autocorrelations"). Failing to control for such commonalities may result in biased estimates of regression coefficients and/or standard errors (Anselin 2006). To address this issue, we modify our baseline model to include measures of local firms' economic activities as additional controls. Specifically, we include the following four variables, each measured at the 2-digit ZIP level: (i) average R&D intensity, (ii) average capital expenditure intensity, (iii) average sales growth, and (iv) average return on assets.

In the fourth test, we control for the impact of additional macroeconomic and financial market conditions on tax avoidance. Since we use localized sky coverage as a mood-priming construct, this measure is unlikely to be correlated with changes in the macroeconomic or market-wide conditions. Further, our baseline model includes macroeconomic controls identified by Edwards et al. (2016). Nonetheless, for completeness, we address this potential

[27] As an additional robustness test, we re-estimate our baseline model after excluding firm-year observations with natural disasters. The (untabulated) results show that the coefficient on *SKY_COVER* remains negative and statistically significant (*t*-statistic=-4.030, *p*-value<0.01).

concern by supplementing our baseline model with these additional control variables: number of IPOs, unemployment index, and Chicago Fed National Financial Conditions index (Lowry 2003; Zolotoy et al. 2017).

In results not reported in tables, we find that for each of the four tests the coefficient for *SKY_COVER* remains significantly negative at the 1% level. Similarly, our core evidence persists when we include all the additional controls in the regression. Taken together, the analysis in this section helps dispel the concern that potential omitted correlated variables are spuriously responsible for our results.

5.7. *Additional Analysis*

In our final set of sensitivity analyses, we address the potential concern that our core evidence is an artifact of spurious correlations between the unexpected sky coverage and cash effective tax rates, or peculiarities of the data distributions. We begin by considering the possibility that our findings are driven by shifts in the distribution of *SKY_COVER* across time stemming from country-wide (or global) changes in climate (e.g., global warming). To examine this issue, we re-estimate our baseline model (Equation (1)) using decile-ranked measure of *SKY_COVER* similar to the analysis conducted in Section 4.3, although this time we decile-rank *SKY_COVER* by year to control for potential shifts in the distribution across years in our sample. In untabulated results, we find that the coefficient for the year-by-year decile-ranked *SKY_COVER* remains negative and significant (coefficient=-0.011, *t*-statistic=-3.054, *p*-value<0.01), suggesting that our earlier evidence does not spuriously reflect shifts in distribution of our weather-related mood measure.

To reinforce our confidence that that our results are not driven by artifacts of the underlying data, we follow DeHaan et al. (2017) by running a series of falsification tests. For each firm-year observation in our sample, we match a "false" measure of *SKY_COVER* for the same year and for a randomly selected U.S. zip code located at least 500 miles away from the focal firm. We then re-estimate our baseline model using "false" *SKY_COVER* data, repeat the process 100 times, and compare our actual coefficient estimate to the distribution of "false" coefficient estimates. To facilitate this comparison, both actual and "false" coefficients were estimated using year-by-year decile-ranked measures of actual and "false" *SKY_COVER*, respectively. The (untabulated) results indicate that our actual coefficient estimate of -0.011 (see above) is in the very extreme tail of the distribution of "false" coefficients, implying that our findings are unlikely to stem from spurious correlations.[28]

6. Weather-Induced Mood and Financial Constraints

Our results suggest that managers in a negative mood, on average, undertake more aggressive corporate tax positions. This evidence reconciles with the argument that these managers perceive the firm to be more financially constrained, and, in turn, perceive greater benefits from generating cash savings by lowering taxes. In other words, we interpret our findings as stemming from mood-driven tax planning, which cannot be attributed to rational projections of firms' economic conditions. If this interpretation is valid, then we should observe these two effects in our sample: (i) a positive association between unexpected local sky coverage and managers' perceptions of financial constraints; and (ii) no association between unexpected local sky coverage and actual financial constraints. In this section, we examine these two issues.

6.1. *Weather-Induced Mood and Managers' Perception of Financial Constraints*

We start by analyzing the impact of weather-induced mood on managers' perceptions of their firms' financial constraints. Management perceptions are evident in their language, which enables external observers to "see the world from the eyes of the managers" (Li 2010a; Li 2010b; Davis et al. 2015). We follow Bodnaruk et al. (2015) and Law and Mills (2015) in adopting a linguistic approach to construct a measure of management perceptions of financial constraints. Specifically, for each firm-year observation, we calculate the fraction of

[28] For perspective, the (untabulated) results indicate that 99% of the "false" coefficient estimates lie in the range between -0.007 and 0.009.

negative words used by managers in the firm's annual 10-K filing (*N_WORDS*). We rely on this proxy to reflect managers' perceptions concerning their firms' financial constraints. We download the data for constructing this measure from Professor Bill McDonald's website (http://www3.nd.edu/~mcdonald/).

We estimate the following regression model to examine the impact of weather-induced mood on managers' perceptions of their firms' financial constraints:

$$N\_WORDS_{i,t}=\beta_0+\beta_1 SKY\_COVER_{i,t}+\sum\beta_k Controls_{i,t}+\sum FE+\varepsilon_{i,t} \quad (2)$$

Control variables and fixed effects specifications are the same as in our baseline model (Equation (1)). In Panel A of Table 5, we report in Column (1) that the coefficient for *SKY_COVER* is significantly positive (t-statistic=3.616, p-value<0.01), supporting the argument that managers experiencing a negative mood perceive the firm to be more financially constrained.

For robustness purposes, we repeat our analysis using a composite measure of financial constraints (*PF_WORDS*), constructed using a firm's annual 10-K filing as the common component of the three linguistic measures of financial constraints suggested in prior research (Bodnaruk et al. 2015; Law and Mills 2015): (i) the fraction of negative words, (ii) the fraction of constraining words, and (iii) the fraction of uncertain words. We estimate the common component using an Iterated Principal Factor approach (Hair et al. 1998), which yields a single factor with an eigen value greater than 1 that explains more than 80% of variation in the three individual linguistic measures. The estimated factor loadings are positive for all three individual linguistic measures, suggesting that the higher value of the factor is associated with greater managerial perception of financial constraints. The results reported in Column (2) show that using this alternative measure of perceived financial constraints has no material impact on our evidence in that the coefficient for *SKY_COVER* remains significantly positive (t-statistic=4.631, p-value<0.01).

Our results imply that managers in a bad mood perceive the firm to be more financially constrained. Importantly, we further examine whether managers' perceptions of financial constraints is the mechanism responsible for our earlier evidence that weather-induced mood leads managers to undertake more aggressive tax positions. This involves analyzing whether managers' perceptions of financial constraints serve as a mediator of the unexpected local sky cover-tax avoidance link. To test for such an effect, we utilize a widely used statistical mediation test developed by Sobel (1982). This test allows us to examine whether the impact of weather-related mood on corporate tax avoidance occurs through managers' perceptions of financial constraints (as captured by the *N_WORDS* and *PF_WORDS* measures). We report the corresponding *p*-value of the mediation tests in Panel A of Table 5. For each of these two measures, we find strong evidence of a mediation effect (both p-values<0.01). These results are consistent with our argument that weather-induced mood shapes corporate tax avoidance through its impact on managers' perceptions of their firm's financial constraints.

6.2. *Weather-Induced Mood and Actual Future Financial Constraints*

An alternative mechanism conceivably responsible for our findings is that managers' perceptions of firm financial constraints stemming from a negative mood might reflect their rational expectations concerning the financial constraints that the firm will shortly encounter. In other words, a competing explanation for our results is that unexpected sky coverage predicts worsening economic and/or financial conditions, which, in turn, has an adverse impact on a firm's ability to obtain funds. More specifically, lenders and shareholders may be pessimistic during cloudy weather and thus less willing to provide financing in the near future, resulting in a higher cost of capital for the firm as well as tighter loan covenants. Similarly, cloudy weather may engender a negative mood in customers, with the ensuing pessimism leading to reduced purchasing that undermines firms' operating cash flows in the near future.

It is important to stress, however, that our measure of mood captures unexpected *local* sky coverage near firms' headquarters. To the extent that firms' investor base and customer base are both geographically dispersed, the impact of sky coverage around firms' headquarters on the mood of firms' investors and customers should be limited at best. Nonetheless, to help dispel this competing explanation, we conduct several tests and report the results in Panel B of Table 5.

In the first test, we examine the link between weather-induced mood and firms' future equity financing costs measured using the implied cost of equity approach. Specifically, we estimate the firm's cost of equity as the discount rate that is implied by stock market prices of a firm's stock and analysts' earnings forecasts using four different models developed by Gebhardt et al. (2001), Claus and Thomas (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005), respectively.[29] Since there is little consensus in the literature on which model performs best, we use the average of the estimates from the four models (Hail and Leuz 2006, 2009; Chen et al. 2011). Next, we estimate the implied risk premium (*IMPLIED_RP*) as the difference between the estimate of the implied cost of equity and the yield on the 10-year Treasury bond. We then regress the implied risk premium estimate in year t+1 on *SKY_COVER* in year t and a set of control variables suggested in prior research (Gebhardt et al. 2001; Chen et al. 2011). The data required for constructing the implied risk premium estimates were obtained from IBES, CRSP, and Compustat. The results reported in Column (1) show that *SKY_COVER* has no perceptible impact on firms' equity financing costs (t-statistic=-1.231, p-value=0.218).

[29] An alternative to using analysts' earnings forecasts as a proxy for expected earnings—the approach used in previous studies (e.g., Claus and Thomas 2001; Gebhardt et al. 2001)—is to rely on earnings forecasts from cross-sectional regression analysis (Hou et al. 2012). However, Li and Mohanram (2014) report that the forecasts from the model of Hou et al. (2012) perform worse than those of a naïve random walk model. Further, they find that the implied cost of capital measures estimated using Hou et al.'s (2012) approach shows anomalous correlations with known risk factors. Given, Li and Mohanram's (2014) findings, we use analysts' forecasts in estimating the implied cost of equity measures.

In the second test, we examine the role that local unexpected sky coverage plays in predicting firms' borrowing costs. Analogous to the previous test, we first estimate the spread on the firm's bonds (*CREDIT_SPREAD*) defined as the difference between the offering yield on the firm's bonds in year *t*+1 and the yield on the 10-year Treasury bond. We then regress *CREDIT_SPREAD* in year *t*+1 on *SKY_COVER* in year *t* and a set of control variables after prior research (Fama and French 1993, Güntay and Hackbarth 2010). We obtain the yield data from Mergent Fixed Income Securities Database (FISD). The results reported in Column (2) include that the coefficient for *SKY_COVER* is not significant (*t*-statistic=0.216, *p*-value=0.829), implying that local unexpected sky coverage is irrelevant to firms' borrowing costs.

In the third test, we consider the possibility that unexpected local sky coverage predicts changes in the intensity of covenants attached to firms' loans. To examine this issue, we regress the covenant intensity (*COVENANTS*) in year *t*+1 on *SKY_COVER* in year *t* and control variables. We obtain the covenant data from Dealscan. To account for the integer nature of the dependent variable as well as a substantial number of firm-years with zero covenant intensity, we estimate the model using a zero-inflated Poisson regression approach (Lambert 1992; Hall 2000). The results reported in Column (3) show that the coefficient for *SKY_COVER* is not statistically significant (*t*-statistic=1.355, *p*-value=0.175), lending no support to the argument that unexpected local sky coverage predicts changes in the firm's loan covenant intensity.[30]

Finally, we consider the possibility that changes in local sky coverage influence the mood of local customers, which in turn could affect the firm's operating cash flows in the

[30] In untabulated results, we repeat the analysis in column (3) of Table 5 using the estimated probability of covenant violation as an alternative measure of loan covenant intensity (Demerjian and Owens 2016). We find no significant association between unexpected local sky coverage and probability of covenant violation, reinforcing that the documented impact of unexpected local sky coverage on corporate tax avoidance is unlikely to reflect executives' rational expectations of tightening loan covenants.

near future. To analyze this issue, we regress the ratio of the firm's pretax operating cash flows to total assets in year *t*+1 (*OPERATING_CF*) on *SKY_COVER* in year *t* and a set of control variables suggested in prior research (e.g., Coles et al. 2006). The results reported in Column (4) show that the coefficient for *SKY_COVER* is not significant (*t*-statistic=0.823, *p*-value=0.410). Altogether, the results reported in Table 5 are consistent with the narrative that weather-induced mood influences managers' perceptions of financial constraints, although it is not associated with actual future financial constraints. These findings are consistent with the documented local sky cover-tax avoidance relation reflecting mood-driven tax planning.

[Insert Table 5 about here]

7. Supplemental Analyses

7.1. *The Role of Board Financial Expertise*

In this section, we examine the role that board financial expertise plays in shaping the relation between managerial mood and corporate tax avoidance. Prior research in psychology suggests that the impact of mood on decision-making diminishes when individuals expect to be held responsible for their decisions (Bodenhausen et al. 1994; Lerner et al. 1998). Specifically, anticipation of accountability can induce individuals to engage in conscious preemptive self-monitoring of their judgment processes (Tetlock 1985; Tetlock and Kim 1987; Trotman et al. 2015). As conscious self-monitoring of judgment processes increases, decision-making is thought to become less prone to the influence of incidental affect (Han et al. 2007). Accordingly, we expect that the importance of mood to corporate tax planning will subside in the presence of board members with financial expertise, who are known to closely evaluate tax strategies developed by managers and hold managers more accountable for their tax decisions (Armstrong et al. 2015).[31]

[31] Since board members often reside far from firm headquarters (Alam et al. 2014), they are less likely to be influenced by weather conditions around firm headquarters.

To analyze this issue, we define board financial expertise (*BOARD_FINEXP*) as the proportion of board members with financial expertise. We obtain the data for constructing board financial expertise from BoardEx. We modify our baseline model (Equation (1)) to include *BOARD_FINEXP* and its interaction with *SKY_COVER*. In Column (1) of Table 6, we report that the interaction term between *SKY_COVER* and *BOARD_FINEXP* loads positively (t-statistic=2.113, p-value=0.035), suggesting that the impact of managerial mood on tax avoidance is mitigated in firms with more financial experts on the board.[32]

7.2. *The Role of IRS Corporate Tax Enforcement*

In this section, we examine whether the importance of managerial mood to firms' tax avoidance varies systematically with the threat of IRS tax enforcement. Prior research implies that IRS monitoring deters firms from undertaking aggressive tax positions (e.g., Mills and Sansing 2000; Hoopes et al. 2012). As close external monitoring weakens the mood effect (Tetlock 1985; Tetlock and Kim 1987; Bodenhausen et al. 1994; Lerner et al. 1998), we expect to observe that the impact of mood on corporate tax avoidance subsides when the IRS imposes tougher corporate tax enforcement.

To examine this issue, we modify our baseline model to include the *ex ante* threat of an IRS audit (*PROB_IRS_AUDIT*) and its interaction with *SKY COVER*. Our specification of *PROB_IRS_AUDIT* follows prior research on IRS monitoring (e.g., Guedhami and Pittman 2008; Hoopes et al. 2012). We obtain the data required for constructing *PROB_IRS_AUDIT* from the IRS (https://www.irs.gov) and Transactional Records Access Clearinghouse (http://trac.syr.edu/tracirs/) websites. To ensure that information on IRS enforcement is known to managers, we lag *PROB_IRS_AUDIT* one year, although our evidence in this section is materially insensitive to using contemporaneous measures of corporate tax enforcement on the grounds that managers form rational expectations according to publicly

[32] Alternatively, we re-estimate the model using the (log-transformed) number of board members with financial expertise as our measure of financial expertise. Our core results are materially insensitive to using this alternative measure.

available information on IRS enforcement activities (e.g., Hoopes et al. 2012). The results reported in Column (2) of Table 6 include that the coefficient for the interaction term between *SKY_COVER* and *PROB_IRS_AUDIT* is positive and significant (*t*-statistic=2.410, *p*-value=0.016), implying that the impact of managerial mood on tax avoidance is mitigated in firms that are more likely to experience an IRS audit.

Collectively, the evidence in Table 6 implies that external monitoring by directors with financial expertise and the IRS constrains the impact of weather-related mood on tax avoidance. Although this analysis is interesting in its own right, it is also constructive for improving identification since supportive cross-sectional results help alleviate concerns surrounding alternative explanations for our core findings (Rajan and Zingales 1998); i.e., it would be hard to attribute this pattern of evidence to an explanation other than the role that weather-induced mood plays in tax avoidance.

7.3. *Weather-induced Mood and External Audit Firm Tax Services*

External experts may participate in the tax planning process, although sunshine levels near corporate headquarters would be irrelevant to these individuals when they are geographically distant. However, even if local sunshine does not shape the mood of the external experts, it may influence the senior managers' desire to purchase tax services from them, which would affect the level of corporate tax avoidance. Specifically, if managers in a bad mood perceive a need to undertake more aggressive tax positions in order to generate cash savings (as our results suggest), then these managers are more likely to purchase tax services from external experts. To provide evidence on this conjecture, we examine the impact of mood on the firms' decision to purchase tax services from their external auditors. Prior research implies that tax services provided by their auditors enable firms to devise more aggressive tax avoidance strategies (McGuire et al. 2012; Cook and Omer 2013; Hogan and Noga 2015).

We estimate the following regression model to examine this issue:

$$DUM\_TAXFEES_{i,t} = \beta_0 + \beta_1 SKY\_COVER_{i,t} + \sum \beta_k Controls_{i,t} + \sum FE + \varepsilon_{i,t} \quad (3)$$

where *DUM_TAXFEES* is a dummy variable which takes the value one if a firm purchases tax services from an audit firm, and zero otherwise. Control variables are the same as in the baseline model (Equation (1)). We estimate the model using logit method. The results reported in Column (3) of Table 6 show that the coefficient for *SKY_COVER* is positive and significant (t-statistic=7.606, p-value<0.01), suggesting that managers experiencing a negative mood have higher propensity to purchase tax services from their auditor. This evidence reinforces our earlier results supporting the prediction that managers in a bad mood, on average, engage in more aggressive tax avoidance.

[Insert Table 6 about here]

8. Conclusions

Extensive prior research examines the determinants of corporate tax avoidance. An implicit assumption typically underlying this research is that managers are fully rational, thereby leaving little room for managers' emotional states to shape corporate tax planning decisions. We help close this gap by analyzing whether managerial mood influences firms' tax avoidance. Grounded in prior research in psychology, we expect that managers experiencing a negative mood will undertake more aggressive tax positions. The intuition behind this prediction is straightforward. Managers in a bad mood form a more pessimistic outlook concerning the firm's ability to access external financing such that they become more eager to generate cash savings by implementing more aggressive tax strategies.

In examining this prediction, we follow prior research by relying on variation in local sunshine around firms' headquarters as exogenous shocks to managerial mood. Our evidence implies that negative mood stemming from low sunshine exposure induces managers to pursue more aggressive tax avoidance. Corroborating that the impact of weather-induced mood on corporate tax avoidance is driven by managers' subjective perceptions of the firm's ability to access external funds, we document that a negative mood induced by cloudy weather is associated with managers perceiving that firm financial constraints are worse. Importantly, we find no evidence that bad mood predicts actual financial constraints faced by the firm.

Additional analysis reveals that the role that weather-related mood plays in corporate tax avoidance subsides when the board has more directors with financial expertise and corporate tax enforcement is stricter. We also find that weather-induced bad mood is positively associated with the probability that the firm will purchase tax services from its external auditor. Collectively, our findings are consistent with mood-driven corporate tax planning, reflecting managers' subjective perceptions of their firm's financial condition.

Our analysis contributes to prior research in several ways. First, evidence on the importance of managers' emotional states to corporate tax planning remains scarce. Using the variation in local sunshine as a mood-priming construct, we provide strong, robust evidence that managers in a bad mood undertake more aggressive tax positions. We also extend recent research on the impact of financial constraints on corporate tax avoidance by demonstrating that managers' unwarranted perceptions of their firm's financial constraints can influence corporate tax planning activities. Finally, we advance research on the economic impact of weather-induced mood, which primarily focuses on investor behavior, by examining its role in managers' tax planning decisions.

References

Alam, Z. S., M.A. Chen, C. S. Ciccotello, and H. E. Ryan. 2014. Does the location of directors matter? Information acquisition and board decisions. *Journal of Financial and Quantitative Analysis* 49 (1): 131-164.

Altman, E. I. 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance* 23 (4): 589–609

Anesa, M., N. Gillespie, A. P. Spee, and K. Sadiq. 2019. The legitimation of corporate tax minimization. *Accounting, Organizations and Society* 75: 17-39.

Anselin, L. 2006. Spatial econometrics. In T. C. Mills and K. Patterson (Eds.) *Handbook of Econometrics*: 901–941. Basingstoke, U.K.: Palgrave Macmillan.

Armstrong, C.S., J.L. Blouin, A.D. Jagolinzer, and D.F. Larcker. 2015. Corporate governance, incentives, and tax avoidance. *Journal of Accounting and Economics* 60 (1): 1-17.

Arellano, M., and S. Bond. 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies* 58 (2): 277-297.

Arnold, P. J. 2009. Global financial crisis: The challenge to accounting research. *Accounting, Organizations and Society* 34 (6-7): 803-809.

Bagozzi, R. P., M. Gopinath, and P.U. Nyer. 1999. The role of emotions in marketing. *Journal of the Academy of Marketing Science* 27 (2): 184-206.

Barsade, S. G. and Gibson, D. E. 1998. Group emotion: a view from top and bottom. In D. H. Gruenfeld (Ed.), Research on Managing Groups and Teams: 81–102. Stamford, CT: JAI.

Bartel, C. and Saavedra, R. 2000. The collective construction of work group moods. *Administrative Science Quarterly* 45 (2): 197.

Barth, M. E., W. H. Beaver, and W. R. Landsman. 1998. Relative valuation roles of equity book value and net income as a function of financial health. *Journal of Accounting and Economics* 25 (1): 1-34.

Bassi, A., R. Colacito, and P. Fulghieri. 2013. 'O sole mio: An experimental analysis of weather and risk attitudes in financial decisions. *Review of Financial Studies* 26 (7): 1824-1852.

Bernile, G., V. Bhagwat, A. Kecskes, and P.-A. Nguyen. 2018. Are the risk attitudes of professional investors affected by personal catastrophic experiences? Available at SSRN: https://ssrn.com/abstract= 3024983.

Berrone, P., C. Cruz, L. R. Gomez-Mejia, and M. Larraza-Kintana. 2010. Socioemotional wealth and corporate responses to institutional pressures: do family-controlled firms pollute less? *Administrative Science Quarterly* 55 (1): 82-113.

Biggerstaff, L., D. C. Cicero, and A. Puckett. 2017. FORE! An analysis of CEO shirking. *Management Science* 63(7): 2302-2322.

Bodenhausen, G. V., G. P. Kramer, and K. Suesser. 1994. Happiness and stereotypic thinking in social judgment. *Journal of Personality and Social Psychology* 66 (4): 621–632.

Bodnaruk, A., T. Loughran, and B. McDonald. 2015. Using 10-K text to gauge financial constraints. *Journal of Financial and Quantitative Analysis* 50 (4): 623-646.

Bower, G.H. 1981. Mood and memory. *American Psychologist* 36 (2): 129-148.

Bruyneel, S., S. Dewitte, P.H. Franses, and M. G. Dekimpe. 2009. I feel low and my purse feels light: Depleting mood regulation attempts affect risk decision making. *Journal of Behavioral Decision Making* 22: 153-170.

Carlson M., V. Charlin, and N. Miller. 1988. Positive mood and helping behavior: A test of six hypotheses. *Journal of Personality and Social Psychology* 55 (2): 211–29.

Cen, L., E. L. Maydew, L. Zhang, and L. Zuo. 2017. Customer-supplier relationships and corporate tax avoidance. *Journal of Financial Economics* 123 (2): 377-394.

Chen, S., X. Chen, Q. Cheng, and T. Shevlin. 2010. Are family firms more tax aggressive than non-family firms? *Journal of Financial Economics* 95 (1):41-61.
Chen, K. C. W., Z. Chen, and K. C. J. Wei. 2011. Agency costs of free cash flows and the effect of shareholder rights on the implied cost of capital. *Journal of Financial and Quantitative Analysis* 46 (1): 171-207.
Chen, Y., R. Ge, H. Louis, and L. Zolotoy. 2018. Stock liquidity and corporate tax avoidance. *Review of Accounting Studies,* forthcoming.
Chen, Y., P.-H. Hsu, E. Podolski, and M. Veeraraghavan. 2017. Sunshine, inventor performance, and firm value. Available at SSRN: https://ssrn.com/abstract=2782918
Chen, W., and H.-T. Tan. 2013. Judgment effects of familiarity with an analyst's name. *Accounting, Organizations and Society* 38 (3): 214-227.
Cheng, C. S. A., H. H. Huang, Y. Li., and J. Stanfield. 2012. The effect of hedge fund activism on corporate tax avoidance. *The Accounting Review* 87 (5): 1493-1526.
Chhaochharia, V., D. Kim, G. M. Korniotis, and A. Kumar. 2017a. Mood, firm behavior, and aggregate economic outcomes. *Journal of Financial Economics,* In Press.
Chhaochharia, V., G. Korniotis, and A. Kumar. 2017b. Prozac for depressed states? Effect of mood on local economic recessions. Available at SSRN: https://ssrn.com/abstract=2584491
Chung, S., X. Li, and S. B. Nelson. 2002. Short-term depression at thalamocortical synapses contributes to rapid adaptation of cortical sensory responses in vivo. *Neuron* 34 (3): 437-446.
Chyz, J. A. 2013. Personally tax aggressive executives and corporate tax sheltering. *Journal of Accounting and Economics* 56 (2–3): 311-328.
Claus, J., and J. Thomas. 2001. Equity premia as low as three percent? Evidence from analysts' earnings forecasts for domestic and international stock markets. *Journal of Finance* 56 (5): 1629–1666.
Coles, J., N. Daniel, and L. Naveen. 2006. Managerial incentives and risk- taking. *Journal of Financial Economics* 79 (2): 431-468.
Cook, K. A., and T. C. Omer. 2013. The cost of independence: Evidence from firms' decisions to dismiss auditors as tax-service providers. Working Paper, University of Arizona and Texas A&M University.
Cowell, F. 2004. Carrots and Sticks in Enforcement. *The Crisis in Tax Administration*. Edited by Aaron, H., and J. Slemrod, Washington, D.C.: Brookings Institution Press.
Cortés, K., R. Duchin, and D. Sosyura. 2016. Clouded judgment: The role of sentiment in credit origination. *Journal of Financial Economics* 121 (2): 392-413.
Crocker, K. J., and J. Slemrod. 2005. Corporate tax evasion with agency costs. *Journal of Public Economics* 89 (9): 1593-1610.
Cunningham, M. R. 1979. Weather, mood, and helping behavior: Quasi experiments with the sunshine Samaritan. *Journal of Personality and social Psychology* 37 (11): 1947-1956.
Davis, A. K., W. Ge, D. Matsumoto, and J. L. Zhang. 2015. The effect of manager-specific optimism on the tone of earnings conference calls. *Review of Accounting Studies* 20 (2): 639-673.
De Silva, G. Dakshina, R. A. J. Pownall, and L. Wolk. 2012. Does the sun 'shine' on art prices? *Journal of Economic Behavior and Organization* 82 (1): 166-178.
De Simone, L., J. Nickerson, J. K., Seidman, and B. Stomberg. 2017. How reliably do financial statement proxies identify tax avoidance? Working paper. Available at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2534058
Demerjian, P.R., and E. L. Owens. 2016. Measuring the probability of financial covenant violation in private debt contracts. *Journal of Accounting and Economics* 61 (2): 433-447.
Desai, M. A., and D. Dharmapala. 2006. Corporate tax avoidance and high-powered

incentives. *Journal of Financial Economics* 79 (1): 145-179.
Desai, M. A., and D. Dharmapala. 2009. Corporate tax avoidance and firm value. *The Review of Economics and Statistics* 91 (3): 537-546.
DeHaan, E., J. Madsen, and J. D. Piotroski. 2017. Do weather-induced moods affect the processing of earnings news? *Journal of Accounting Research* 55(3): 509-550.
Dhaliwal, D. S., C. A. Gleason, and L. F. Mills. 2004. Last-chance earnings management: using the tax expense to meet analysts' forecasts. *Contemporary Accounting Research* 21 (2): 431-459.
Dougherty, D. P., G. A. Wright, and A. C. Yew. 2005. Computational model of the cAMP-mediated sensory response and calcium-dependent adaptation in vertebrate olfactory receptor neurons. *Proceedings of the National Academy of Sciences of the United States of America* 102 (30): 10415-10420.
Dyreng, S. D., M. Hanlon, and E. L. Maydew. 2008. Long-run corporate tax avoidance. *The Accounting Review* 83 (1): 61-82.
Dyreng, S. D., M. Hanlon, and E. L. Maydew. 2010. The effect of executives on corporate tax avoidance. *The Accounting Review* 85 (4): 1163-1189.
Dyreng, S. D,, M. Hanlon, E. L. Maydew, and J. Thornock. 2017. Changes in corporate effective tax rates over the past 25 years. *Journal of Financial Economics* 124 (3): 441-463.
Dutton, J. A. 2002. Opportunities and priorities in a new era for weather and climate services. *Bulletin of the American Meteorological Society* 83 (9): 1303-1311.
Easton, P.D. 2004. PE ratios, PEG ratios, and estimating the implied expected rate of return on equity capital. *The Accounting Review* 79 (1): 73-96.
Edwards, A., C. Schwab, and T. Shevlin. 2016. Financial constraints and cash tax savings. *The Accounting Review* 91 (3): 859-881.
Fama, E. F., and K. R. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33 (1): 3-56.
Faraji-Rad, A. and M. T. Pham. 2017. Uncertainty increases the reliance on affect in decisions. *Journal of Consumer Research* 44 (1): 1-21.
Forgas, J. P. 1995. Mood and judgment: the Affect Infusion Model (AIM). *Psychological Bulletin* 117: 39-66.
Garcia, D., and Ø. Norli. 2012. Geographic dispersion and stock returns. *Journal of Financial Economics* 106 (3): 547-565.
Gebhardt, W. R., C. Lee, and B. Swaminathan. 2001. Toward an implied cost of capital. *Journal of Accounting Research* 39 (1): 135-176.
Gleason, C. A., and L. F. Mills. 2008. Evidence of differing market responses to beating analysts' targets through tax expense decreases. *Review of Accounting Studies* 13 (2-3): 295-318.
Goerke, L. 2008. Tax overpayments, tax evasion, and book-tax differences. *Journal of Public Economic Theory* 10 (4): 643-671.
Goetzmann, W. N., D. Kim, A. Kumar, and Q. Wang. 2015. Weather-induced mood, institutional investors, and stock returns. *Review of Financial Studies* 28 (1): 73-111.
Greenwald, B. C., J. E. Stiglitz, and A. Weiss. 1984. Informational imperfections in the capital market and macro-economic fluctuations. *American Economic Review* 74 (2): 194-199.
Guedhami, O., and J. Pittman. 2008. The importance of IRS monitoring to debt pricing in private firms. *Journal of Financial Economics* 90 (1): 38-58.
Guenther, D. A., L. K. Krull, and B. M. Williams. 2014. Are 'tax aggressive' firms just inflating earnings? Available at SSRN: https://ssrn.com/abstract=2409688.
Guven, C., and I. Hoxha. 2015. Rain or shine: Happiness and risk-taking. *The Quarterly Review of Economics and Finance* 57 (C): 1-10.
Güntay, L., and D. Hackbarth. 2010. Corporate bond credit spreads and forecast dispersion. *Journal of Banking and Finance* 34 (10): 2328-2345.

Hadlock, C. J., and J. R. Pierce. 2010. New evidence on measuring financial constraints: Moving beyond the KZ index. *Review of Financial Studies* 23 (5): 1909-1940.
Hail, L., and C. Leuz. 2006. International differences in the cost of equity capital: Do legal institutions and securities regulation matter? *Journal of Accounting Research* 44 (3): 485-531.
Hail, L., and C. Leuz. 2009. Cost of equity effects and changes in growth expectations around U.S. cross-listings. *Journal of Financial Economics* 93 (3): 428-454.
Hall, Daniel B. 2000. Zero-inflated Poisson and binomial regression with random effects: A case study. *Biometrics* 56 (4): 1030-1039.
Han, S., J.S. Lerner, and D. Keltner, 2007. Feelings and consumer decision making: The appraisal-tendency framework. *Journal of Consumer Psychology* 17 (3): 158–168.
Hanlon, M., and S. Heitzman. 2010. A review of tax research. *Journal of Accounting and Economics* 50 (2): 127-178.
Hair, J.F. Jr., R.E. Anderson, R.L. Tatham, and W.C. Black, 1998. Multivariate Data Analysis, (5th Edition). Upper Saddle River, NJ: Prentice Hall.
Hasan, I., C.K. Hoi, Q. Wu and H. Zhang. 2017. Does social capital matter in corporate decisions? Evidence from corporate tax avoidance. *Journal of Accounting Research* 55(3): 629-668.
Henry, E., and R. Sansing. 2014. Data truncation bias and the mismeasurement of corporate tax avoidance. American Taxation Association Midyear Meeting. Available at SSRN: https://ssrn.com/abstract=2329694
Hirshleifer, D., and T. Shumway. 2003. Good day sunshine: Stock returns and the weather. *Journal of Finance* 58 (3): 1009-1032.
Hogan, B. and T. Noga. 2015. Auditor-provided tax services and long-term tax avoidance. *Review of Accounting and Finance* 14(3): 285-305.
Hoopes, J. L., D. Mescall, and J. A. Pittman. 2012. Do IRS audits deter corporate tax avoidance? *The Accounting Review* 87(5): 1603-1639.
Hou, K., M.A. Van Dijk, and Y. Zhang. 2012. The implied cost of equity: A new approach. *Journal of Accounting and Economics* 53 (3): 504-526.
Howarth, E., and M. S. Hoffman. 1984. A multidimensional approach to the relationship between mood and weather. *British Journal of Psychology* 75 (1): 15-23.
Hribar, P., S. J. Melessa, R. C. Small, and J. H. Wilde. 2017. Does managerial sentiment affect accrual estimates? Evidence from the banking industry. *Journal of Accounting and Economics* 63 (1): 26-50.
Isen, A. M., T. E. Shalker, M. Clark, and L. Karp. 1978. Affect, accessibility of material in memory, and behavior: A cognitive loop? *Journal of Personality and Social Psychology* 36 (1): 1-12.
Johnson, E. J., and A. Tversky. 1983. Affect, generalization, and the perception of risk. *Journal of Personality and Social Psychology* 45 (1): 20-31.
Kadous, K., J. Leiby, and M. E. Peecher. 2013. How do auditors weight informal contrary advice? The joint influence of advisor social bond and advice justifiability. *The Accounting Review* 88 (6): 2061-2087.
Kaplan, S. N., and L. Zingales. 1997. Do investment-cash flow sensitivities provide useful measures of financing constraints? *The Quarterly Journal of Economics* 112 (1): 169-215.
Keller, M. C., B. L. Frederickson, O. Ybarra, S. Côté, K. Johnson, J. Mikels, A. Conway, and T. Wager. 2005. A warm heart and a clear head: The contingent effects of weather on mood and cognition. *Psychology Science* 16 (1): 724-731.
Kelly, J. & Barsade, S. 2001. Mood and emotions in small groups and work teams. *Organizational Behavior and Human Decision Processes* 86 (1): 99-130.
Kennedy, P. 1992. *A Guide to Econometrics*. Oxford: Blackwell.
Kim, J., S. McGuire, S. Savoy, and R. Wilson. 2016. How quickly do firms adjust to target

levels of tax avoidance? Working paper.
Koester, A., T. Shevlin, and D. Wangerin. 2017. The role of managerial ability in corporate tax avoidance. *Management Science* 63(10): 3285-3310.
Kripke, D. F. 1998. Light treatment for non-seasonal depression: Speed, efficacy, and combined treatment. *Journal of Affective Disorders* 49 (2): 109-117.
Larcker, D. F., and T. O. Rusticus, 2010. On the use of instrumental variables in accounting research. *Journal of Accounting and Economics* 49 (3): 186-205.
Lam, R. W., A. J. Levitt, R. D. Levitan, M. W. Enns, R. Morehouse, E. E. Michalak, and E. M. Tam. 2006. The Can-SAD study: A randomized controlled trial of the effectiveness of light therapy and fluoxetine in patients with winter seasonal affective disorder. *American Journal of Psychiatry* 163 (5): 805-812.
Lambert, D. 1992. Zero-inflated Poisson regression, with an application to defects in manufacturing. *Technometrics* 34 (1): 1-14.
Lambert, G.W., C. Reid, D. Kaye, G.L. Jennings, and M.D. Esler. 2002. Effect of sunlight and season on serotonin turnover in the brain. *The Lancet* 360 (9348): 1840-1842.
Law, K. K., and L. F. Mills. 2015. Taxes and financial constraints: Evidence from linguistic cues. *Journal of Accounting Research* 53 (4): 777-819.
Law, K. K., and L. F. Mills. 2017. Military experience and corporate tax avoidance. *Review of Accounting Studies* 22 (1): 141-184.
Lerner, J. S., J.H. Goldberg, and P.E Tetlock. 1998. Sober second thought: The effects of accountability, anger and authoritarianism on attributions of responsibility. *Personality and Social Psychology Bulletin* 24 (6): 563–574.
Lerner, J. S., Y. Li, P. Valdesolo, and K. S. Kassam. 2015. Emotion and decision making. *Annual Review of Psychology* 66: 799-823
Li, F. 2010a. Textual analysis of corporate disclosures: A survey of the literature. *Journal of Accounting Literature* 29 (1): 143-165
Li, F. 2010b. Managers' self-serving attribution bias and corporate financial policies. Unpublished working paper. Available at SSRN: https://ssrn.com/abstract=1639005
Li, K. K., and P. Mohanram. 2014. Evaluating cross-sectional forecasting models for implied cost of capital. *Review of Accounting Studies* 19 (3): 1152-1185.
Lieberman, H. R., F. Waldhauser, G. Garfield, H. J. Lynch, and R. J. Wurtman, 1984. Effects of melatonin on human mood and performance. *Brain Research* 323 (2): 201-207.
Ljungqvist, A., L. Zhang, and L. Zuo. 2016. Sharing risk with the government: How taxes affect corporate risk-taking. *Journal of Accounting Research* 55 (3): 669-707.
Long, J. H., and K. A. Basoglu. 2016. The impact of task interruption on tax accountants' professional judgment. *Accounting, Organizations and Society* 55: 96-113.
Lowry, M. 2003. Why does IPO volume fluctuate so much? *Journal of Financial Economics* 67 (1): 3-40.
McGuire, S. T., T. C. Omer, and D. Wang. 2012. Tax avoidance: Do industry experts make a difference? *The Accounting Review* 87 (3): 975-1003.
Mills, L. F., E. Maydew, and M. Erickson. 1998. Investments in tax planning. *Journal of the American Taxation Association* 20: 1-20.
Mills, L. F. and R. C. Sansing. 2000. Strategic tax and financial reporting decisions: Theory and evidence. *Contemporary Accounting Research* 17 (1): 85-106.
Modigliani, F. and M. H. Miller. 1958. The cost of capital, corporation finance and the theory of investment. *The American Economic Review* 48 (3): 261-297.
Myers, S. C. and N. S. Majluf. 1984. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics* 13 (2): 187-221.
Ohlson, J. A., and B. E. Juettner-Nauroth. 2005. Expected EPS and EPS growth as determinants of value. *Review of Accounting Studies* 10 (2): 349-365.

Olsen, K.J. and J. Stekelberg. 2016. CEO narcissism and corporate tax sheltering. *The Journal of the American Taxation Association* 38 (1): 1-22.

Pagan, A., and A. Ullah. 1999. Nonparametric Econometrics, Cambridge University Press.

Parrott, W. G., and J. Sabini. 1990. Mood and memory under natural conditions: Evidence for mood incongruent recall. *Journal of Personality and social Psychology* 59 (2): 321-336.

Peecher, M. E., and M. D. Piercey. 2008. Judging audit quality in light of adverse outcomes: Evidence of outcome bias and reverse outcome bias. *Contemporary Accounting Research* 25 (1): 243-274.

Persinger, M. 1975. Lag responses in mood reports to changes in the weather matrix. *International Journal of Biometeorology* 19 (2): 108-114.

Prasko, J. 2008. Bright light therapy. *Neuro endocrinology letters* 29: 33-64.

Rajan, R. G., and L. Zingales. 1998. Financial dependence and growth. *American Economic Review* 88 (3): 559–586

Rajan, R. G., and J. Wulf. 2006. Are perks purely managerial excess? *Journal of Financial Economics* 79 (1): 1-33.

Rietschlin, J. 1998. Voluntary association membership and psychological distress. *Journal of Health and Social Behavior* 39 (4): 348-355.

Rosenthal, N.E., D.A. Sack, J.C. Gillin, A.J. Lewy, F.K. Goodwin, Y. Davenport, P.S. Mueller, D.A. Newsome, and T.A. Wehr. 1984. Seasonal affective disorder: A description of the syndrome and preliminary findings with light therapy. *Archives of General Psychiatry* 41 (1): 72-80.

Rousseeuw, P., and V. Yohai. 1984. Robust regression by means of S-estimators. Pp. 256-272 in: Jürgen Franke, Wolfgang Hardle, and Douglas Martin (eds.). Robust and Nonlinear Time Series Analysis. Lecture Notes in Statistics Vol. 26. Berlin: Springer.

Sanassi, L. A. 2014. Seasonal affective disorder: Is there light at the end of the tunnel? *Journal of the American Academy of Physician Assistants* 27 (2): 18-22.

Sanchez-Burks, J. and Q. Huy. 2009. Emotional aperture and strategic change: The accurate recognition of collective emotions. *Organization Science* 20 (1): 22-34.

Saunders, E. M. 1993. Stock prices and Wall Street weather. *The American Economic Review* 83 (5): 1337-1345.

Schwarz, N. 2000. Agenda 2000: Attitudes and Social Judgment – Warmer, more social and less conscious. *European Journal of Social Psychology* 30: 149-176.

Schwarz, N., and G. L. Clore. 1983. Mood, misattribution, and judgments of well-being: Informative and directive functions of affective states. *Journal of Personality and social Psychology* 45 (3): 513-523.

Schwartz, C., J. B. Meisenhelder, Y. Ma, and G. Reed. 2003. Altruistic social interest behaviors are associated with better mental health. *Psychosomatic Medicine* 65 (5): 778-785.

Shu, T., J. Sulaeman, and P. E. Yeung. 2016. Does Sadness Influence Investor Behavior? Evidence from Bereaved Fund Managers. Working Paper. Available at: http://www.cicfconf.org/sites/default/files/paper_801.pdf

Sobel, M. E. 1982. Asymptotic confidence intervals for indirect effects in structural equation models. *Sociological Methodology*. 13: 290–312.

Spindelegger, C., P. Stein, W. Wadsak, M. Fink, M. Mitterhauser, U. Moser, M. Savli, L.K. Mien, E. Akimova, A. Hahn, and M. Willeit. 2012. Light-dependent alteration of serotonin-1A receptor binding in cortical and subcortical limbic regions in the human brain. *The World Journal of Biological Psychiatry* 13 (6): 413-422.

Tetlock, P. E. 1985. Accountability: A social check on the fundamental attribution error. *Social Psychology Quarterly* 48 (3): 227–236.

Tetlock, P. E, and J.I. Kim. 1987. Accountability and judgment processes in a personality prediction task. *Journal of Personality and Social Psychology* 52 (4): 700–709.

Totterdell, P., Kellett, S., Teuchmann, K., & Briner, R. 1998. Evidence of mood linkage in work groups. *Journal of Personality & Social Psychology* 74 (6): 1504-1515.

Trotman, K. T., T. D. Bauer, and K. A. Humphreys. 2015. Group judgment and decision making in auditing: Past and future research. *Accounting, Organizations and Society* 47: 56-72.

Tversky, A., and D. Kahneman. 1973. Availability: A heuristic for judging frequency and probability. *Cognitive Psychology* 5 (2): 207-232.

Tversky, A., and D. Kahneman. 1974. Judgment under uncertainty: Heuristics and biases. *Science* 185 (4157): 1124-1131.

Wright, W. F., and G. H. Bower. 1992. Mood effects on subjective probability assessment. *Organizational Behavior and Human Decision Processes* 52 (2): 276-291.

Yermack, D. 2014. Tailspotting: Identifying and profiting from CEO vacation trips. *Journal of Financial Economics* 113 (2): 252-269.

Zolotoy, L., J.R. Frederickson, and J. D. Lyon. 2017. Aggregate earnings and stock market returns: The good, the bad, and the state-dependent. *Journal of Banking and Finance* 77: 157-175.

Zolotoy, L., D. O'Sullivan, G.P. Martin, and M. Veeraraghavan. 2018. The role of affect in shaping the behavioral consequences of CEO option incentives. *Journal of Management*, forthcoming

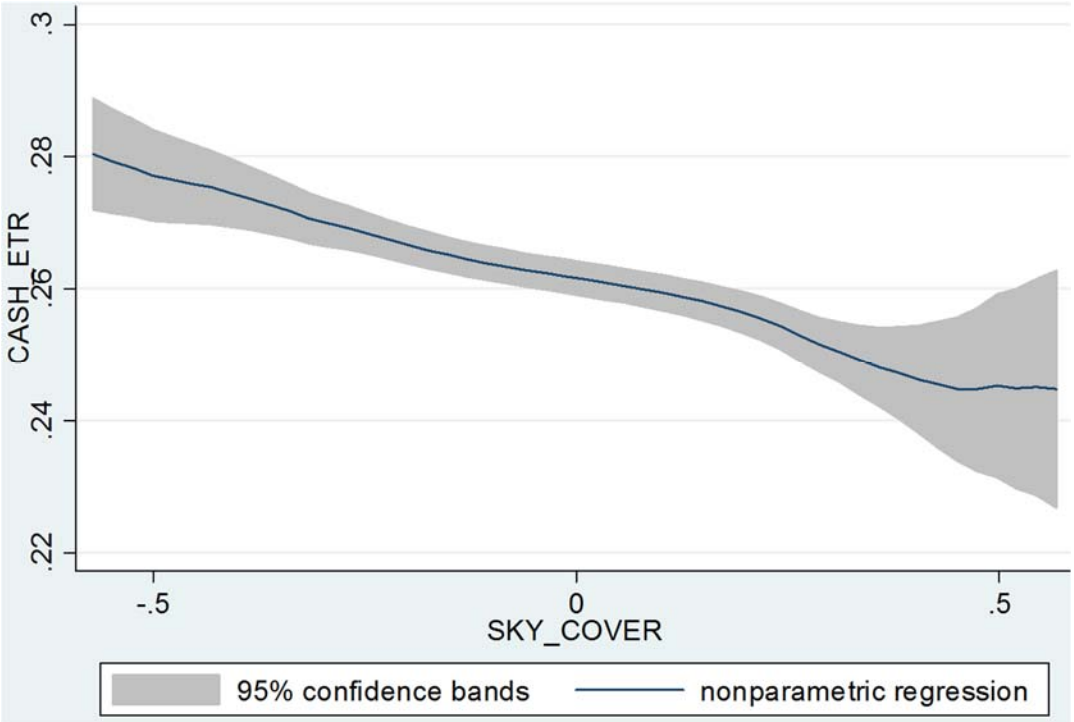
Appendix A
Variables and Definitions

Abnormal accruals (*ABACC*)	Absolute value of abnormal accruals estimated following Kothari et al. (2005)
Auditor tax services (*DUM_TAXFEES*)	Dummy variable which takes value of 1, if a firm purchases tax services from an audit firm and 0 otherwise.
Board financial expertise (*BOARD_FINEXP*)	Proportion of board members with financial expertise.
Bond maturity (*LN_MATURITY*)	Natural logarithm of bond issue maturity.
Bond with call option (*CALL*)	An indicator variable which takes value of 1, if the bond has call option, and zero otherwise.
Bond with put option (*PUT*)	An indicator variable which takes value of 1, if the bond has put option, and zero otherwise.
Cash effective tax rate (*CASH_ETR*)	Taxes paid (TXPD) scaled by pre-tax income (PI).
Cash holdings (*CASH*)	Cash and cash equivalents (CHE) scaled by lagged total assets (AT).
Change in goodwill (*POS_GDWL*)	Change in goodwill (GDWL) scaled by lagged total assets (AT). If the value is negative, then it is set to zero.
Change in loss carry-forward (*DNOL*)	Change in net operating loss carry-forward (TLCF) over year t scaled by lagged total assets (AT).
Common component of linguistic financial constraints measures (*PF_WORDS*)	The common factor of the fraction of negative words (Law and Mills 2015), the fraction of constraining words (Bodnaruk et al. 2015), and the faction of uncertainty words (Bodnaruk et al. 2015) in a firm's annual 10-K filing.
Covenant intensity on loans (*COVENANTS*)	The number of covenants on a firm's loans.
Credit spread (*CREDIT_SPREAD*)	Difference between the offering yield on a corporate bond and the yield on the 10-year Treasury bond
Equity income in earnings (*EQINC*)	Equity income in earnings (ESUB) scaled by lagged total assets (AT).
Face value (*LN_FVALUE*)	Natural logarithm of bond issue face value.
Financial constraints (*HP_INDEX*)	Hadlock and Pierce (2010) financial constraint index, decile ranked by year.
Firm size (*SIZE*)	Natural logarithm of total assets (AT)
Foreign income (*FRGNAT*)	Foreign income, estimated following Edwards et al. (2016).
Fraction of negative words (*N_WORDS*)	The fraction of negative words in a firm's annual 10-K filing.
Global bond issue (*GLOBAL*)	An indicator variable that takes value of 1 if the bond issue is global and zero otherwise.
Growth in GDP (*DGDP*)	Annual growth in gross domestic product
Implied risk premium (*IMPLIED_RP*)	The difference between the implied cost of equity and the yield on the 10-year Treasury bond. Implied cost of equity is estimated as the discount rate that is implied by market prices and analysts' earnings forecasts.
Intangible assets (*INTANG*)	Intangible assets (INTAN) scaled by lagged total assets (AT).
Leverage (*LEV*)	Long term debt (DLTT) scaled by total assets (AT).

Loss carry-forward dummy (*NOL*)	An indicator variable that equals one if net operating loss carry-forward (TLCF) is positive for year t-1.
Market-to-book ratio (*MB*)	The ratio of market value of common equity to book value of common equity.
Mezzanine finance (*MEZ_FIN*)	Convertible debt and preferred stock (DCPSTK) divided by total assets (AT).
PPE assets (*PPE*)	Net property, plant, and equipment (PPENT) scaled by lagged total assets (AT).
Pretax operating cash flows (*OPERATING_CF*)	Pretax operating cash flows scaled by total assets.
Probability of IRS audit (*PROB_IRS_AUDIT*)	Probability of firm being audited by the Internal Revenue Services (IRS) estimated following Hoopes et al. (2012).
Research and development expenses (*R&D*)	Research and development expenses (XRD) scaled by total assets (AT)
Return on assets (*ROA*)	Income before extraordinary items (IB) divided by lagged total assets (AT).
ROA volatility (*STDROA*)	Standard deviation of ROA over the past five years.
Stock compensation expenses (*STOCK_EXP*)	An indicator variable which takes value of 1 if stock compensation expense (STKCO) is non-zero, and zero otherwise.
Stock turnover (*TURNOVER*)	Average monthly share turnover over the fiscal year.
Stock returns (*CUMRET*)	Cumulative stock returns over the fiscal year.
Stock return volatility (*STDRET*)	Volatility of monthly stock returns over the fiscal year.
Tightening loan standards (*TIGHTEN*)	Net percentage of domestic respondents reporting tightening standards during the year for commercial and industrial loans.
Top five management team equity risk taking incentives (*TMT_VEGA*)	Natural logarithm of dollar change of top five management's option holdings in response to 0.01 unit change in stock return volatility.
Top five management team pay-for-performance sensitivity (*TMT_DELTA*)	Natural logarithm of dollar change of top five management's option holdings in response to 1 percent change in stock price.
Unexpected sky coverage (*SKY_COVER*)	The difference between annual sky coverage and its moving average over previous five years.

The characters in the parentheses in the right column of the table refer to the item names in the Compustat database.

FIGURE 1
Weather-induced Mood and Tax Avoidance: Nonparametric Analysis



This figure presents the results for nonparametric analysis on the relation between weather-induced mood and tax avoidance.

TABLE 1
Descriptive Statistics

	Mean	**S.D.**	**25%**	**Median**	**75%**
CASH_ETR	0.263	0.226	0.079	0.245	0.366
SKY_COVER	-0.060	0.231	-0.144	-0.031	0.056
SIZE	5.904	1.989	4.487	5.834	7.219
MB	2.687	3.213	1.257	1.947	3.148
LEV	0.169	0.175	0.004	0.127	0.279
ROA	0.118	0.098	0.047	0.091	0.159
STDROA	0.083	0.102	0.027	0.052	0.099
POS_GDWL	0.023	0.072	0.000	0.000	0.004
PPE	0.313	0.279	0.097	0.228	0.454
ABACC	0.082	0.092	0.024	0.055	0.107
STOCK_EXP	0.374	0.484	0.000	0.000	1.000
CASH	0.180	0.233	0.023	0.086	0.251
NOL	0.301	0.458	0.000	0.000	1.000
DNOL	-0.001	0.103	0.000	0.000	0.000
EQINC	0.001	0.005	0.000	0.000	0.001
FRGNAT	0.014	0.040	0.000	0.000	0.010
INTANG	0.145	0.207	0.000	0.055	0.218
HP_INDEX	-2.769	0.445	-3.133	-2.911	-2.543
R&D	0.029	0.066	0.000	0.000	0.030
MEZ_FIN	0.018	0.068	0.000	0.000	0.000
TIGHTEN (%)	5.255	20.937	-10.625	-1.230	8.600
DGDP (%)	2.784	1.702	1.800	2.800	4.000
Obs.			38,101		

This table presents the descriptive statistics of the variables in the analysis. Detailed variable definitions are shown in Appendix A.

TABLE 2
Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
(1)*CASH_ETR*	1.00																					
(2)*SKY_COVER*	-0.03	1.00																				
(3)*SIZE*	0.03	0.02	1.00																			
(4)*MB*	-0.06	0.00	0.05	1.00																		
(5)*LEV*	-0.06	-0.02	0.28	-0.05	1.00																	
(6)*ROA*	-0.07	0.00	-0.12	0.36	-0.27	1.00																
(7)*STDROA*	-0.11	0.00	-0.26	0.12	-0.14	0.20	1.00															
(8)*POS_GDWL*	0.01	0.01	0.06	0.02	0.08	0.08	0.05	1.00														
(9)*PPE*	-0.07	-0.03	0.14	-0.03	0.34	-0.04	-0.13	-0.02	1.00													
(10)*ABACC*	-0.07	-0.00	-0.16	0.13	-0.09	0.29	0.21	0.07	-0.05	1.00												
(11)*STOCK_EXP*	-0.05	0.09	0.27	0.03	-0.02	-0.02	0.01	0.05	-0.10	-0.01	1.00											
(12)*CASH*	-0.07	0.04	-0.18	0.21	-0.36	0.37	0.31	0.00	-0.28	0.23	0.09	1.00										
(13)*NOL*	-0.10	0.04	0.07	0.02	0.03	-0.08	0.10	0.06	-0.10	0.03	0.24	0.05	1.00									
(14)*DNOL*	0.03	-0.01	0.04	0.01	0.03	-0.06	-0.02	0.04	0.01	-0.03	0.01	-0.01	0.07	1.00								
(15)*EQINC*	-0.03	0.01	0.10	0.00	0.04	0.03	-0.04	-0.01	0.04	-0.01	0.00	-0.06	-0.02	0.00	1.00							
(16)*FRGNAT*	-0.01	0.02	0.18	0.12	-0.06	0.19	0.01	0.04	-0.04	0.06	0.13	0.12	0.11	0.02	0.03	1.00						
(17)*INTANG*	0.03	0.02	0.20	0.01	0.17	-0.00	0.01	0.57	-0.21	0.00	0.23	-0.09	0.16	0.04	-0.02	0.06	1.00					
(18)*HP_INDEX*	-0.06	-0.01	-0.89	-0.03	-0.29	0.10	0.26	-0.07	-0.15	0.16	-0.23	0.16	-0.06	-0.05	-0.07	-0.16	-0.20	1.00				
(19)*R&D*	-0.07	0.02	-0.15	0.18	-0.24	0.16	0.27	0.02	-0.21	0.17	0.03	0.43	0.10	-0.01	-0.05	0.12	-0.03	0.15	1.00			
(20)*MEZ_FIN*	-0.04	0.01	0.04	0.03	0.24	-0.03	0.09	0.04	-0.04	0.03	0.03	0.09	0.07	0.01	-0.02	0.01	0.07	-0.07	0.05	1.00		
(21)*TIGHTEN*	-0.04	-0.04	0.05	-0.03	0.01	-0.05	0.02	0.02	-0.03	0.01	0.09	0.02	0.04	0.01	0.00	0.01	0.04	-0.05	-0.01	-0.01	1.00	
(22)*DGDP*	0.06	-0.09	-0.16	0.02	0.02	0.05	0.00	-0.01	0.06	0.03	-0.51	-0.05	-0.15	-0.01	-0.01	-0.08	-0.11	0.12	0.01	0.00	-0.58	1.00

This table presents the correlation matrix of the variables in the analysis. Detailed variable definitions are shown in Appendix A.

TABLE 3
Weather-induced Mood and Tax Avoidance: Baseline Analysis

Dependent variable	CASH_ETR		Book-tax difference		Residual book-tax difference		GAAP_ETR		Deferred taxes		Cash tax non-conformity	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
SKY_COVER	**-0.021*****	**(-3.982)**	**0.005*****	**(2.626)**	**0.006*****	**(2.642)**	**-0.007***	**(-1.871)**	**0.004*****	**(3.100)**	**-0.005*****	**(-2.823)**
SIZE	-0.007***	(-3.109)	0.002	(1.465)	-0.000	(-0.279)	-0.008***	(-4.354)	0.007***	(7.705)	0.000	(-0.117)
MB	-0.001**	(-2.569)	0.001	(0.732)	-0.000	(-1.238)	-0.001	(-1.580)	-0.001***	(-3.554)	0.000	(-0.031)
LEV	-0.118***	(-9.520)	0.009	(1.404)	0.004	(1.013)	-0.041***	(-3.594)	-0.013***	(-3.678)	-0.027***	(-4.208)
ROA	-0.181***	(-8.531)	0.195***	(-8.531)	0.111***	(9.941)	0.077***	(4.888)	0.024***	(3.664)	-0.321***	(-16.470)
STDROA	-0.132***	(-7.131)	0.047**	(2.099)	-0.023	(-1.569)	-0.093***	(-6.047)	0.000	(0.042)	-0.015	(-1.224)
POS_GDWL	0.028	(1.277)	-0.017	(-1.391)	0.014	(1.108)	-0.046***	(-2.734)	0.012	(1.145)	-0.004	(-0.276)
PPE	-0.051***	(-5.369)	0.022***	(4.167)	0.014	(1.048)	0.001	(0.106)	0.068***	(14.43)	0.018*	(1.848)
ABACC	-0.025*	(-1.670)	0.024	(1.563)	-0.047***	(-4.063)	-0.011	(-0.860)	0.021***	(2.786)	0.044***	(2.995)
STOCK_EXP	-0.010***	(-2.783)	-0.002	(-1.327)	-0.000	(-0.252)	-0.009***	(-3.077)	-0.003***	(-2.794)	0.001	(0.267)
CASH	-0.033***	(-4.050)	0.001	(0.102)	-0.003	(-0.571)	-0.044***	(-6.215)	0.008*	(1.833)	-0.006	(-0.808)
NOL	-0.049***	(-13.22)	0.019***	(11.01)	0.005***	(3.390)	-0.022***	(-7.369)	-0.003***	(-3.497)	-0.012***	(-8.302)
DNOL	0.071***	(6.222)	-1.154***	(-40.23)	-0.766***	(-19.84)	0.045***	(3.739)	0.002	(0.243)	0.021**	(2.449)
EQINC	-1.113***	(-3.559)	0.517***	(3.269)	0.300***	(2.907)	-1.145***	(-4.231)	0.238*	(1.873)	0.006	(0.047)
FRGNAT	0.066	(1.129)	-0.017	(-0.356)	0.049*	(1.787)	-0.162***	(-3.008)	-0.001	(-0.026)	0.032	(0.787)
INTANG	0.011	(1.001)	0.001	(0.151)	-0.004	(-0.719)	0.056***	(6.125)	0.051***	(10.79)	0.024***	(3.575)
HP_INDEX	-0.071***	(-7.466)	0.018**	(2.406)	-0.008**	(-2.008)	-0.079***	(-10.19)	0.011***	(3.638)	-0.004	(-0.816)
R&D	-0.123***	(-3.506)	-0.068**	(-2.259)	-0.094***	(-3.936)	-0.128***	(-4.299)	-0.025***	(-3.098)	0.238***	(3.494)
MEZ_FIN	-0.037	(-1.635)	0.007	(0.741)	-0.000	(-0.007)	-0.008	(-0.387)	-0.009*	(-1.697)	0.003	(0.450)
TIGHTEN	-0.019***	(-2.583)	0.006**	(2.061)	0.011***	(3.337)	0.027***	(4.784)	-0.007***	(-4.646)	-0.003	(-0.521)
DGDP	0.538***	(5.246)	-0.205***	(-3.477)	0.006	(0.124)	0.646***	(8.070)	-0.049**	(-2.107)	0.051	(0.804)
Predicted sign for *SKY_COVER* coeff.	(−)		(+)		(+)		(−)		(+)		(−)	
Obs.	38,101		21,506		21,506		38,101		36,378		53,692	
Adjusted R^2	0.085		0.766		0.525		0.111		0.321		0.241	

This table presents the regression results on weather-induced mood and tax avoidance. The regression is performed by OLS, with the *t*-statistics (in parentheses) computed using standard errors robust to both clustering at the firm level and heteroskedasticity. Industry and location fixed effects are included but not tabulated for brevity. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Detailed variable definitions are shown in Appendix A.

TABLE 4
Weather-induced Mood and Tax Avoidance: Robustness Tests

	Dependent variable = CASH_ETR			
	Coeff. of *SKY_COVER*	***t-stat.***	***p*-value**	**No. Obs.**
Panel A: Executives' absence from headquarters				
(1a) Firms in the bottom five deciles of geographic dispersion	-0.026***	(-3.149)	<0.01	14,264
(1b) Firms in the top five deciles of geographic dispersion	-0.014*	(-1.868)	0.062	12,802
(2) *SKY COVER*, July and August observations excluded	-0.025***	(-3.536)	<0.01	38,101
(3) *SKY COVER*, weekend and public holiday observations excluded	-0.028***	(-3.840)	<0.01	38,101
Panel B: Controlling for potential sunshine-driven shirking				
(1) Control for CEO golfer indicator	-0.041**	(-2.018)	0.044	4,770
(2) Control for CEO golfer indicator and the number of golf rounds	-0.042**	(-2.042)	0.041	4,770
Panel C: Controlling for potential SAD effects				
(1) Using *SKY COVER_DARK_SEASONS* in baseline regression	-0.015***	(-3.803)	<0.01	17,158
(2) Using *SKY COVER_BRIGHT_SEASONS* in baseline regression	-0.014***	(-3.639)	<0.01	17,158
Panel D: Alternative fixed effect specifications				
(1) Firm fixed effects	-0.021***	(-3.678)	<0.01	38,101
(2) CEO fixed effects	-0.018*	(-1.941)	0.052	17,416
Panel E: Alternative sample specifications and estimation methods				
(1) Excluding weather-sensitive industries	-0.023***	(-4.281)	<0.01	32,177
(2) Dynamic panel estimation	-0.069***	(-3.642)	<0.01	21,408
(3) Censored Tobit estimation	-0.023***	(-3.973)	<0.01	38,101
(4) Robust regression estimation with non-winsorized cash ETRs	-0.019***	(-4.150)	<0.01	38,101
(5) Using quarterly estimates of the variables	-0.047***	(-5.241)	<0.01	61,089

This table presents the results of robustness checks. The results are reported in five panels. Panel A presents the results for executives' absence from headquarters. Panel B presents the results for controlling for executives' shirking. Panel C presents the results for controlling for SAD effects. Panel D presents the results for alternative fixed-effect specifications, and Panel E presents the results for alternative sample specifications and estimation methods. The *t*-statistics (in parentheses) are computed using standard errors robust to both clustering at the firm level and heteroskedasticity. Control variables are included in all regressions but not tabulated for brevity. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

TABLE 5
Weather-induced Mood and Firm Financial Constraints

Panel A: Weather-induced Mood and Managers' Perception of Firm Future Financial Constraints

Dependent variable	**N_WORDS**		**PF_WORDS**	
Column	**(1)**		**(2)**	
	Coeff.	***t*-stat.**	**Coeff.**	***t*-stat.**
SKY_COVER	**0.040********	**(3.616)**	**0.089********	**(4.631)**
SIZE	0.013**	(2.213)	-0.001	(-0.123)
MB	-0.002*	(-1.803)	-0.005***	(-2.828)
LEV	0.000	(0.002)	0.152***	(3.218)
ROA	-0.553***	(-12.336)	-1.023***	(-12.878)
STDROA	0.598***	(12.891)	0.948***	(11.877)
POS_GDWL	-0.043	(-0.954)	-0.217***	(-2.763)
PPE	-0.247***	(-10.721)	-0.351***	(-8.663)
ABACC	0.301***	(8.804)	0.542***	(9.219)
STOCK_EXP	0.179***	(21.573)	0.463***	(31.915)
CASH	0.162***	(7.208)	-0.292***	(-7.561)
NOL	0.056***	(6.631)	0.104***	(7.110)
DNOL	0.011	(0.492)	0.007	(0.180)
EQINC	-0.139	(-0.180)	-0.714	(-0.566)
FRGNAT	-0.144	(-1.499)	-0.312*	(-1.826)
INTANG	-0.009	(-0.366)	0.142***	(3.104)
HP_INDEX	-0.121***	(-4.294)	-0.300***	(-6.212)
R&D	0.048	(0.661)	-0.009	(-0.086)
MEZ_FIN	-0.019	(-0.381)	-0.119	(-1.396)
TIGHTEN	-0.042***	(-2.710)	-0.001***	(-5.001)
DGDP	-0.305***	(-13.646)	-0.081***	(-20.824)
Test of mediation of mood-tax avoidance relationship (Null hypothesis: no mediation effect)	*p*-value<0.01		*p*-value<0.01	
Obs.	27,040		27,040	
Adjusted R^2	0.296		0.361	

Panel B: Weather-induced Mood and Actual Future Financial Constraints

Dependent variable	IMPLIED_RP		CREDIT_SPREAD		COVENANTS		OPERATING_CF	
Column	(1)		(2)		(3)		(4)	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
SKY_COVER	**-0.002**	**(-1.231)**	**0.001**	**(0.216)**	**0.029**	**(1.355)**	**0.003**	**(0.823)**
SIZE	0.004***	(5.154)	-0.003***	(-4.097)	-0.194***	(-10.272)	-0.005***	(-3.255)
MB	-0.001***	(-6.389)	-0.001***	(-2.541)	-0.002	(-0.978)	0.003***	(6.413)
LEV	0.032***	(6.912)	0.003	(0.687)	0.731***	(13.958)	-0.018*	(-1.772)
ROA	-0.037***	(-6.373)	-0.024***	(-3.073)	-0.644***	(-5.890)	0.674***	(30.095)
STDROA	0.035***	(4.841)	-0.004	(-0.383)	0.438***	(5.406)	-0.014	(-0.804)
ABACC	0.020***	(3.754)	-0.001	(-0.089)	0.275***	(4.354)	0.075***	(3.411)
HP_INDEX	0.039***	(8.312)	-0.002	(-0.242)	-0.842***	(-10.245)	0.019	(1.305)
CASH					0.075	(1.335)	-0.057***	(-6.663)
INTANG					0.483***	(12.423)	-0.018***	(-2.608)
PPE					-0.095**	(-2.171)	0.042***	(5.097)
R&D					-1.086***	(-4.291)	0.070	(1.454)
MEZANINE					-0.046	(-0.457)	0.046	(0.838)
TMT_DELTA							0.003***	(3.574)
TMT_VEGA							0.001**	(1.996)
CUMRET	-0.006***	(-8.624)						
STDRET	0.146***	(16.058)						
TURNOVER	0.019***	(3.889)						
GLOBAL			0.001	(0.755)				
PUT			-0.042***	(-23.485)				
CALL			0.011***	(6.767)				
LN_FVALUE			0.004***	(3.850)				
LN_MATURITY			0.009***	(8.817)				
TIGHTEN	-0.009***	(-4.602)	0.000	(0.048)	0.047	(1.408)	0.000	(0.071)
DGDP	-0.419***	(-15.926)	-0.001**	(-2.265)	-0.544	(-1.035)	0.003***	(5.750)
Obs.	21,262		3,083		16,766		16,007	
Adjusted R^2	0.160		0.215		-		0.450	
Log-likelihood	-		-		-30988.80		-	

This table presents the results on tests of the association between weather-induced mood and firm financial constraints. Panel A presents the results for managers' perception of firm future financial constraints and Panel B presents the results for actual future financial constraints. The regression is performed by OLS, with the *t*-statistics (in parentheses) computed using standard errors robust to both clustering at the firm level and heteroskedasticity. Industry and location fixed effects are included but not tabulated for brevity. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Detailed variable definitions are shown in Appendix A.

TABLE 6

Supplemental Analyses: The Roles of Board Financial Expertise, IRS Monitoring and External Audit Firm Tax Services

Dependent variable	CASH_ETR		CASH_ETR		DUM_TAXFEES	
Column	(1)		(2)		(3)	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
SKY COVER	-0.046***	(-3.054)	-0.048***	(-3.569)	**0.706*****	**(7.606)**
SKY COVER×BOARD_FINEXP	**0.087****	**(2.113)**				
SKY COVER×PROB_IRS_AUDIT			**0.095****	**(2.410)**		
SIZE	-0.003	(-0.837)	-0.007***	(-3.336)	0.369***	(9.733)
MB	-0.000	(-0.553)	-0.0017***	(-3.402)	0.009	(1.301)
LEV	-0.093***	(-5.257)	-0.112***	(-8.966)	-0.170	(-0.951)
ROA	-0.174***	(-5.647)	-0.201***	(-9.438)	-0.336	(-1.197)
STDROA	-0.118***	(-4.471)	-0.132***	(-7.143)	-0.081	(-0.349)
POS_GDWL	0.025	(0.884)	0.0243	(1.133)	0.632**	(2.169)
PPE	-0.072***	(-4.992)	-0.0543***	(-5.674)	-0.093	(-0.597)
ABACC	-0.003	(-0.133)	-0.0174	(-1.142)	-0.133	(-0.617)
STOCK_EXP	0.019***	(4.151)	0.000	(0.010)	0.113**	(2.165)
CASH	-0.061***	(-4.871)	-0.0342***	(-4.135)	0.104	(0.784)
NOL	-0.031***	(-6.492)	-0.048***	(-12.881)	0.102*	(1.928)
DNOL	0.074***	(4.499)	0.071***	(6.175)	0.199	(1.352)
EQINC	-0.787*	(-1.751)	-1.095***	(-3.491)	-4.134	(-0.854)
FRGNAT	0.121	(1.600)	0.079	(1.350)	2.774***	(3.764)
INTANG	0.002	(0.142)	0.013	(1.200)	-0.086	(-0.498)
HP_INDEX	-0.029**	(-1.991)	-0.051***	(-5.067)	0.615***	(3.703)
R&D	-0.168**	(-2.511)	-0.132***	(-3.632)	-0.513	(-1.224)
MEZ_FIN	-0.002	(-0.094)	-0.045***	(-1.985)	0.479	(1.226)
TIGHTEN	0.011	(1.174)	-0.000	(-0.020)	-1.169***	(-15.300)
DGDP	0.497***	(3.782)	0.006***	(5.570)	-22.950***	(-15.856)
BOARD_FINEXP	-0.045***	(-3.341)				
PROB_IRS_AUDIT			0.112***	(7.267)		
Obs.	18,167		38,101		21,362	
Adjusted R^2/Pseudo-R^2	0.087		0.087		0.107	

This table presents the results of supplemental analyses. The results are presented in three columns. Column (1) reports the results for board financial expertise, column (2) reports the results for IRS monitoring and column (3) reports the results for external audit firm tax services. The regression is performed by OLS, with the *t*-statistics (in parentheses) computed using standard errors robust to both clustering at the firm level and heteroskedasticity. Industry and location fixed effects are included but not tabulated for brevity. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Detailed variable definitions are shown in Appendix A.