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Too gloomy to invest: Weather-induced mood and crowdfunding

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A R T I C L E I N F O

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A B S T R A C T

Do investors' moods influence their contributions to risky investments in equity crowdfunding? Yes. We use cloud cover as a proxy for mood because besides serving as powerful mood stimulus, changes in weather are plausibly exogenous and orthogonal to attributes of crowdfunding campaigns, yielding an advantageous identification strategy. Our results, based on data from Companisto – one of the largest European equity crowdfunding platforms, indicate that change in sky cloud cover from zero to full reduces each investor's contribution amount by about 10–15% (across different specifications). Our paper highlights the broader role of financiers' moods and emotions in providing valuable financial resources to entrepreneurs.

1. Introduction

Financial resources afford entrepreneurial ventures an opportunity to survive and grow (Bertoni et al., 2011). Although venture capital (VC) historically constitutes a considerable source of financing for entrepreneurs, this source is inappropriate for or inaccessible to many; besides seeking to fund ventures with certain attributes such as large addressable markets, VCs favor entrepreneurs that are educationally, socially, professionally, and geographically proximate to themselves (Hegde and Tumlinson, 2014; Rider, 2012; Sorenson and Stuart, 2001). With the potential to help overcome these constraints and the promise to democratize access to finance (Cumming et al., 2018), entrepreneurs have turned to crowdfunding (Walthoff-Borm et al., 2018). In the UK, for example, crowdfunding platforms' share of all early-stage equity funding grew from less than 1% in 2012 to 17% in 2016 (Zhang et al., 2018). The benefits of crowdfunding to entrepreneurs range from ability to experiment, seeking market validation, to assessing market demand (by engaging a community of early adopters, and facilitating the promotions of product and services through the word of mouth). It is however less clear what influences individuals' contributions to crowdfunding campaigns?

A crowdfunding campaign's success, and indeed the success of crowdfunding as an alternative source of funding institution, hinges upon answering what factors influence crowdfunding contributions.[1] In exploring the success of equity crowdfunding, while scholars have focused on *demand-driven* factors including (i) the characteristics of the campaigns such as target goal and the share of equity offered, (ii) the attributes of the product and market potential, and (iii) the quality of management team (Ahlers et al., 2015; Kleinert et al., 2018; Vismara, 2016a; Shafi, 2019), they have less scrutinized *investor-driven* factors, with the exception of studies that

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[1] While the answer likely depends on the type of crowdfunding model (i.e. reward-based, peer-to-peer lending, donation-based, and equity crowdfunding). This research's focus is only on equity crowdfunding, defined as as a form of financing in which entrepreneurs make an open call to sell a specified amount of equity in a venture on the Internet, hoping to attract a large group of investors (Ahlers et al., 2015). Initial evidence seems to indicate that investors on equity-based crowdfunding primarily participate for financial gains (Cholakova and Clarysse, 2015).

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document herding behavior among crowdfunders (Hornuf and Schwienbacher, 2018; Block et al., 2018; Vismara, 2016b). Understanding funders' motivations and behavior deserves scholarly attention because asking crowds money involves leveraging those factors that encourage investors' giving. Our study fills this gap by focusing on emotions and moods, one of the central constructs in psychology (Clore et al., 1994).

This paper explores whether weather-induced moods can explain crowdfunders' contributions. To follow this line of reasoning, we highlight two sets of observations. First, people feel better on sunny days. The premise that sunshine has a large and monotonic effect on mood is established in a variety of research settings in psychology, neurobiology (Lambert et al., 2002; Praschak-Rieder et al., 2008; Spindelegger et al., 2012), medicine (Lam et al., 2006), and experimental economics. Schwarz and Clore (1983) report that individuals report happier moods and greater life satisfaction when questioned on sunny days relative to overcast days – other psychologists have replicated these observations in other settings and have found similar results (Parrott and Sabini, 1990; Howarth and Hoffman, 1984; Rind, 1996). There might be neuro-foundations explaining the link between sunlight and mood as light therapy is effective as anti-depressants (Rosenthal et al., 1984; Kripke, 1998; Benedetti et al., 2003; Prasko, 2008; Sanassi, 2014). Second, people in good moods are more likely to make riskier choices (Yuen and Lee, 2003; Chou et al., 2007; Kuhnen and Knutson, 2011) (for a review, see Grable and Roszkowski (2008)). For example, Bassi et al. (2013) provide experimental evidence that bad weather increases risk aversion, whereas good weather promote risk-taking behavior. They also establish weather affects risk aversion through its impact on mood. Given the effect of weather-induced changes of mood on risk aversion, we specifically hypothesize that crowd-investors make larger investment amounts in equity crowdfunding campaigns on sunny days relative to overcast days.

There are several useful properties as an empirical identification strategy to use weather as a mood proxy, which has inspired its use in experimental settings (Bassi et al., 2013) and real financial markets including contexts such as stock returns, trading behavior (Hirshleifer and Shumway, 2003; Goetzmann et al., 2014; Saunders, 1993; Goetzmann and Zhu, 2005; Bushee and Friedman, 2015), equity analyst forecasts (Dehaan et al., 2017), and mortgage originations (Cortés et al., 2016). First, weather (e.g., cloud cover) serves as powerful mood stimulus. Second, changes in weather are plausibly orthogonal to economic fundamental or other attributes of campaigns. Third, by exploiting daily variation in sunshine, our empirical design holds constant other drivers of funding decisions, shown relevant in other studies, that are invariant in the short term, such as campaign characteristics, financials, and management quality. Finally, in contrast to measures of sentiment that assume market-wide homogeneity (or nation-wide homogeneity) such as entrepreneurial orientation or the impact of national culture on risk-taking, our proxy provides rich cross-sectional variation across geographic regions on any given day.

To perform quantitative analyses, we use data from Companisto, one of the largest equity crowdfunding platforms in Europe. Our sample consists of 102 campaigns, receiving 67,982 pledges. We proxy for investors' mood using sky cloud cover measured at investor's city on the day of their investment. This measure has been used by previous scholars (Goetzmann and Zhu, 2005; Chhaochharia et al., 2019; Cortés et al., 2016; Bassi et al., 2013). Consistent with our hypothesis, we find that sky changing in cloud cover from zero to full reduces investors' contribution amounts by about 10–15% (across different specifications). We also find that negative effect of cloud cover on contribution amounts weakens as the experience of investors increases. Moreover, the negative effect of cloud cover on contribution amounts is weaker for less risky campaigns: ventures in growth stage (compared with seed and early stage) and campaigns using venture loan instead of equity. We attribute these findings to how mood-inducing cues related to weather affect risk preferences in financial decisions of individuals. Overall, our paper provides evidence on the role of weather-induced mood in the day-to-day decisions of crowd investors.

We contribute to two strands of literature. First, we add to the literature that investigates the funding behavior of investors in crowdfunding (Colombo et al., 2015). Scholars have highlighted the role of social information causing information cascades (Vismara, 2016b), auction-based allocation mechanisms (Hornuf and Schwienbacher, 2018), and certain types of updates by entrepreneurs (Block et al., 2018). Additionally, given that crowd investors are primarily motivated by financial returns in equity crowdfunding (Cholakova and Clarysse, 2015), risk calculations are of significant relevance for financial payoffs in equity crowdfunding. For example, Mohammadi and Shafi (2018) show how female investors are risk-averse in selecting equity crowdfunding campaigns. To this stream of literature, our study adds the role of mood fluctuations, induced by weather, in influencing the amount of contributions to equity crowdfunding campaigns, possibly mediated by risk preferences. We hope our study inspires additional mood-based and emotion-based explanations to interpret investors' behavior in crowdfunding markets.

Second, we contribute to the literature on how moods driven by various sources influence financial market outcomes, investors' behaviors, and financial decision makings given increasing scholarly interest on the role of affect and mood in economic choices (Loewenstein et al., 2001; Rick and Loewenstein, 2008).[2] We complement the extant evidence on the link between weather as a mood stimulus and outcomes in various financial markets (Chhaochharia et al., 2019) by focusing on equity crowdfunding context, which is remarkably different from other well-established financial markets previously studied. Equity crowdfunding is nascent, but growing in relevance in providing entrepreneurial finance, and it presents investors with adverse selection risks associated with information asymmetry, and principal-agency issues associated with the dispersed nature of investors and separation of ownership from control (Cumming et al., 2019). Thus, by exploring investors' decision-making in equity crowdfunding, our paper extends the contextual scope of evidence on the relationship between mood and financial market outcomes.

[2] Additional exogenous mood-priming devices include changes in daylight saving time (Kamstra et al., 2000), lunar cycles (Dichev and Janes, 2003; Lucey, 2010), sporting events' outcomes (Edmans et al., 2007; Drake et al., 2016; Kaplanski and Levy, 2010), cultural holidays (Bergsma and Jiang, 2016), and extreme negative events such as mass shootings, terrorist attacks (Wang and Young, 2019), and aviation disasters (Kaplanski and Levy, 2010).

2. Related literature

2.1. Equity-based crowdfunding

Crowdfunding has different flavors, including, but not limited to, reward-based, equity-based, donation-based, lending-based, and initial coin offering. Equity-based crowdfunding is distinguished from other models by allowing entrepreneurs to sell a specified amount of equity in a venture to multitude of investors, generating accessibility to early-stage venture investing for a broad segment of individuals. Equity crowdfunding is a financial technology innovation that disintermediates the traditional sources of financing from venture capitalists, although it remains an open question to what extent funding from equity crowdfunding competes or complements that of VC. While the market for equity crowdfunding is nascent, in some countries with favorable regulations such as the UK, crowdfunding platforms' share of all early-stage equity funding is growing (Zhang et al., 2018). Walthoff-Borm et al. (2018) find that ventures resort to equity crowdfunding only when they lack internal funds and additional debt capacity.

Research on equity crowdfunding extensively explores the host of factors that make campaigns more successful. These factors include the quality of human capital on the board (Ahlers et al., 2015), entrepreneurs' business education and their experience (Piva and Rossi-Lamastra, 2018), receipt of prior external funding (Ralcheva and Roosenboom, 2018; Lukkarinen et al., 2016; Kleinert et al., 2018), retained equity by entrepreneurs (Vismara, 2016a). Shafi (2019) reports that while crowd investors pay attention to the aspects of product, business, and management, they don't incorporate financial information into their decision making. Overall, these findings broadly appear to be consistent with factors that professional investors consider in venture investing.

Scholars are also interested in unravelling the processes that influence crowds' decisions and behaviors and the underlying dynamics during fund raising. Most of the research in this stream has focused on herding, describing a process according to which early contributions of backers encourage more backing from prospective backers (Vismara, 2016b; Vulkan et al., 2016; Hornuf and Schwienbacher, 2018), which is prevalent in other types of crowdfunding markets (Colombo et al., 2015). Such herding processes can be subject to other factors. For example, Vismara (2016b) reports that investors with a public profile make the offer more appealing to early investors, who in turn attract subsequent investors. Additionally, campaign organizers can regularly update prospective backers about certain events such as new business developments to increase the chances of funding success (Block et al., 2018). Finally, scholars are challenging the assumption that the crowds are a homogeneous community of individuals. For example, Mohammadi and Shafi (2018) suggest that female investors compared with male ones choose to invest in less risky offerings. The current literature can benefit from zooming in on investors' characteristics or other attributes such as personality traits or psychological states, which can influence contributions to crowdfunding campaigns.

2.2. Risk in equity crowdfunding

Risks associated with investing in equity crowdfunding are similar to those faced by professional investors such as business angels and venture capitalists. Adverse selection risks and moral hazard problems loom large in venture investing. Adverse selection stems from hidden information or information asymmetries between investors and entrepreneurs and describes a situation that investors select a low-quality project that they would have believed to be a high-quality project (Amit et al., 1998). This selection risk reflects the fact that entrepreneurs have typically more information about the quality of their ventures compared with prospective investors. Entrepreneurs might lack credible means of communicating that information such as limited track record or historical operational performance, restricting reliable information on the progress of the venture; Or, entrepreneurs have incentives, are optimistic, or overconfident to exaggerate their prospects or withdraw negative information (Cooper et al., 1988; Busenitz and Barney, 1997). Even if information scarcity or the noise-to-signal ratio of such information were not major concerns, because assessing new ventures in early-stages is often tied to growth expectations or entrepreneurial vision rather than historical performance, erroneous valuation of investment opportunities is typically unavoidable.

Prospective investors also face moral hazard problems, which is an instance of information asymmetry on the intentions of entrepreneurs where entrepreneurs can engage in opportunistic behavior with the funding from investors. For example, entrepreneurs might shirk their fiduciary responsibilities, engage in excessive risk-taking, enjoy perks or other conspicuous consumption to maximize their private benefits. The hidden action/intention problem is exacerbated in the context of entrepreneurship because of pursuit of experimentation and exploration in opportunity identification and exploitation, that might overstep the bounds of pre-specified contractual use for financial resources. Additionally, the uncertainties involved in introducing new offerings into market increase the causal ambiguity surrounding entrepreneurs' intentions and actions (Harris et al., 2009). While prospective investors face adverse selection risks and moral hazard problems in venture investing, they appear more severe for small investors representative of equity crowdfunding investors (Ahlers et al., 2015).

Unlike professional investors, small investors representative of crowdfunders are disadvantaged both in their financial expertise, and their resources and time to evaluate investment opportunities. In addition to potentially possessing limited financial expertise or personal knowledge and experience relevant for venture investing, crowds tend to invest relatively small amounts of money and this won't justify expending great amounts of resources and time for performing due diligence, which might not have at their disposal. The limitations in capabilities, resources, and incentives associated with crowd investors highlight the accentuated risks involved in equity investing for crowds relative to professional investors.

2.3. Weather and participating in financial markets

The first set of evidence suggests how weather is correlated with stock market returns, despite lack of direct evidence on daily weather fluctuations affecting fundamentals. Saunders (1993) documents that aggregate U.S. stock returns are lower on days with higher cloud cover in New York City. Testing this relationship out of sample in eighteen out of the twenty-six cities of a country's leading stock exchange, Hirshleifer and Shumway (2003) find that such negative relationship holds true between cloud cover and aggregate stock returns. Collectively, these findings document that mood fluctuations induced by the weather influence stock returns (Saunders, 1993; Hirshleifer and Shumway, 2003; Goetzmann and Zhu, 2005; Bushee and Friedman, 2015).

Relatedly, a second set of evidence focuses on the behaviors of market participants. Goetzmann and Zhu (2005) report that the liquidity of NYSE stocks changes with weather. For example, bid-ask spreads increase on cloudy days and decrease with sunny days. They interpret such evidence as NYSE market makers become more risk-averse on cloudy days, which subsequently influences markets. Goetzmann et al. (2014) use survey data and suggest that weather-induced negative moods (e.g., local cloudiness) increases institutional investors' perceived overpricing in both individual stocks and the index of Dow Jones Industrial Average. Focusing on sell-side equity analysts, Dehaan et al. (2017) show that unpleasant local weather generates analyst pessimism and decreases muted or delayed responses to earnings announcements.

A third set of evidence highlights the role of weather on managers' financial decision-making. Using sky cloud cover as a proxy for mood, Chhaochharia et al. (2019) show that mood affects the economic expectations of small business managers and managerial expectations (instrumented by cloud cover) influence the hiring and capital investment plans of small business managers. They also show that, at the aggregate level, mood affects U.S. state-level job creation and new business starts. Cortés et al. (2016) find that the approval rate for credit applications increases by 52 basis points (or 0.80%) on perfectly sunny days and drops by 113 basis points (or 1.41%) on overcast days. While the variation in weather captures only a fraction of the daily variation in loan officers' moods, these results show that correlated mood changes produce significant real consequences.[3]

3. Hypothesis development: weather and crowdfunding

To draw the link between weather and crowdfunding contributions, we establish that happy moods promote risk-taking, and that good weather conditions are associated with better moods. The idea that people have better moods on sunny days is established in a variety of research settings in psychology, neurobiology, medicine, and experimental economics. For example, sunlight helps with the release of serotonin, a neurotransmitter in connection with feelings of well-being and happiness (Lambert et al., 2002; Praschak-Rieder et al., 2008; Spindelegger et al., 2012) – drugs that regulate brain serotonin levels are in use for treating depression. Additionally, sunlight prohibits the secretion of melatonin (Crowley et al., 2003; Claustrat and Leston, 2015), a hormone that regulates fatigue and sleepiness – melatonin is one of the most popular over-the-counter sleep remedy in the US.

Moods affect risk-taking behavior, which is a key aspect of financial decision-making (Rick and Loewenstein, 2008). Experimental studies find that people in a good mood are more likely to make riskier choices (Yuen and Lee, 2003; Chou et al., 2007; Kuhnen and Knutson, 2011) (for a review, see Grable and Roszkowski (2008)). Loewenstein et al. (2001) proposed the hypothesis of risk-as-feelings that emphasizes the impact of emotions (experienced during the decision making progress) for risk-taking behavior. Recent studies find support for this hypothesis in experimental settings. Bassi et al. (2013) document that people are reporting more positive mood states on sunny days, and exhibit higher risk tolerance in a lottery choice task when the experiment is conducted on a sunny day. Sunshine promotes risk-taking behavior, while overcast conditions enhance risk-aversion. Cortés et al. (2016) exploit variation in local sunshine as a driver of loan officers' mood and show evidence that loan officers in a good mood show higher risk tolerance and approve a greater fraction of risky loans.

We hypothesize that crowdinvestors make larger investment amounts in equity crowdfunding campaigns on sunny days relative to cloudy days. It is likely that positive mood induced by good weather promotes risk-taking as the underlying nature of investing in equity crowdfunding characterizes risk capital. Additionally, small investors typically have limited incentives or capabilities (as discussed above) that makes them more prone to affective judgments as research indicates that mood infusion into judgments are more likely when individuals perceive that they have low expertise (Ottati and Isbell, 1996; Sedikides, 1995) or low processing capacity (Greifeneder and Bless, 2007; Siemer and Reisenzein, 1998). Unlike professional investors who are expert and have developed routines and mental processes to asses complex and multi-faceted information about new ventures' prospects, crowd investors may resort to simple heuristics, increasing the chances that affective states shape crowdfunders' judgments. We focus on investment amount as a proxy for risk-taking, which is consistent with experimental studies that consider an individual investor with a given budget as taking more risk when they choose to invest their money in assets with probabilistic returns (e.g., financial assets) rather than to keep their money as cash or equivalent guaranteed payments (Charness and Gneezy, 2012; Kramer and Weber, 2012). Therefore, we hypothesize the following:

Hypothesis 1. Higher sky cloud cover decreases the amount of investors' contributions to crowdfunding campaigns.

Now we turn our attention to the characteristics of crowdfunders and how these individual differences moderate the relationship

[3] Researchers have linked weather to many other outcomes including life satisfaction (Schwarz and Clore, 1983), helping others and tipping (Rind, 1996), purchase behavior (Conlin et al., 2007; Busse et al., 2015), response to advertising (Li et al., 2017), patent examination process (Kovács, 2017), and even one of life's most thought-about decisions: college enrollment (Simonsohn, 2009).

between sky cloud cover and contributions to crowdfunding campaigns. One distinguishing feature influencing investment decisions is gender preferences towards risk (for a review, see Croson and Gneezy (2009)). More specifically, female investors tend to be more risk averse than their male counterparts (Powell and Ansic, 1997), which is a robust finding documented across different contexts including experimental settings (Eckel and Grossman, 2008; Byrnes et al., 1999), portfolio selection (Sunden and Surette, 1998), and CEO's financial decisions (Faccio et al., 2016). More recently, Mohammadi and Shafi (2018) investigate gender differences in risk preferences of investors in firms seeking equity funding and report that female investors are less likely to invest in the equity of firms that are younger and high tech, and have a higher percentage of equity offerings. Hervé et al. (2019) find that female investors in crowdfunding invest less in the riskiest (equity) investments but more in safer ones (bonds). Given that women tend to be risk averse and choose conservative options, we expect that they are less sensitive to changes in weather-induced moods for their financial risk-taking. Thus, we propose:

Hypothesis 2. The negative relationship between sky cloud cover and the amount of contributions to crowdfunding campaigns is weaker for female investors compared with male investors.

Another relevant dimension of individual differences in investment decisions relates to investors' experience in equity crowdfunding. We expect that investors with more experience on equity crowdfunding are less sensitive to changes in weather-induced moods for how much they decide to invest in a campaign. Experience generally influences the quality of investors' decision making by improving investors' efficiency in information processing and forming mental models and patterns. For example, with doing more investments, investors can develop expertise in assessing opportunities by getting more familiarity and feedback from their investments, and even devise strategies to overcome adverse selection risks in venture investing (by portfolio diversification). Following increased familiarity and knowledge about equity investing from learning by doing, we argue that such experience will decrease the influence of affective states associated with weather on contributions to campaigns. To do so, we draw on the link between cognition and affect.

Wyer Jr et al. (1999) view affect as information and note that affect can be the basis of bias in individuals' judgments. Additionally, their work suggests that motivation and ability are two corrective forces in adjusting for affect-induced bias in judgments. To highlight some evidence underlying the effects of motivation and ability on correcting for mood-induced bias, Isbell and Wyer Jr (1999) and Ottati and Isbell (1996) ask participants in an experiment to report their evaluation of political candidates. Those participants with little knowledge about politics or those with little motivation to engage in information processing reported more favorable evaluations when they were happy. However, these evaluations were less favorable for participants with more political expertise or for those motivated to be accurate when these participants were happy rather than when they were not. Accordingly, individuals with more experience are more likely to engage in cognitive processing necessary for correcting the influence of judgment-relevant affect in decisions. This is so because correction is an additional cognitive step and individuals with experience are likely to have sufficient amount of cognitive capacity to process and evaluate information in an efficient manner before fully exhausting their cognitive resources. Thus, the infusion of mood into judgments are less likely when individuals perceive that they have more expertise (Ottati and Isbell, 1996; Sedikides, 1995) or more processing capacity (Greifeneder and Bless, 2007; Siemer and Reisenzein, 1998). Thus, we suggest that the role of affect (here, weather-induced) as an input in investment decisions will be weaker (it is corrected) when crowdfunders have gained more investment experience.

Hypothesis 3. The negative relationship between sky cloud cover and the amount of contributions to crowdfunding campaigns is weaker for investors with more investment experience in equity crowdfunding.

Now we turn our attention to the risk-related characteristics of projects and further hypothesize that crowdinvestors make investments in more risky equity crowdfunding campaigns on sunny days relative to cloudy days. As we have previously argued that risk associated with information asymmetry and moral hazard makes the task of venture financing challenging. Thus, to bolster our confidence in change in risk attitudes as a mechanism for the link between weather-induced moods and investment decisions, we investigate whether the effect of cloud cover on contributions is stronger when uncertainty and risk is lower. We focus on two factors that that affect risk: (i) the development stage of the venture; (ii) whether the requested funding is loan offering or equity offering.

Crowdfunders perceive offerings from ventures that require funding for growth (proven products with sales) as less risky than offerings that seek seed funding to develop a prototype or a product. Some of the underlying reasons seed-stage and early-stage ventures tend to be riskier than growth-stage or late-stage ventures include greater uncertainties on technological feasibility and demand for the innovative product, greater uncertainties on access to quality resources such as talent, raw materials, distribution channels, and suppliers, and finally greater uncertainties on management in areas such as execution abilities and their fit with product and market. Newly founded ventures are prone to failure since they face a constellation of issues, including liability of innovation (Schoonhoven et al., 1990) whereby innovation requires resolving technical feasibility, differentiating the product from competitors, and eventually finding early-adopter customers in the marketplace. All these challenges may be time consuming, which delays covering expenses by revenues. Thus, the progress of a venture reduces uncertainty by making available necessary information on track record of performance that helps with informed judgments by prospective investors (Stuart et al., 1999; Shafi et al., 2020). Thus, if the underlying mechanism activated by positive mood is risk-taking, then we expect that crowdfunders experiencing cloudy days select ventures that are in growth stage relative to seed and early-stage.

Another dimension of risk related to the campaign for venture investors is whether the entrepreneur is seeking funding using debt versus equity. Equity financing is riskier than debt financing. Stock owners are not guaranteed capital gains and at the extreme in case of bankruptcy, stock owners have a lower claim on venture assets. Accordingly, equity investors demand higher returns (equity risk premium) than bond investors to compensate them for such additional risk taking. Thus, if changes in risk attitudes underlie the link

Table 1
Descriptive statistics.

Variable	Mean	S.D.	Min	Max
Panel A: Campaign level				
Goal	537,000	518,000	50,000	2,500,000
Share Offered	0.126	0.071	0.024	0.375
Growth stage	0.049	0.217	0	1
Venture loan	0.059	0.236	0	1
Berlin	0.471	0.502	0	1
Panel B: Investment level				
Amount (log)	5.132	1.69	1.609	11.513
Cloud coverage	0.61	0.219	0	1
Clear day	0.052	0.222	0	1
Investor's total prior investments (log)	4.616	3.432	0	12.324
First investment	0.307	0.461	0	1
Distance (log)	5.39	1.71	0	9.833
Previous day's total investment (log)	7.415	3.159	0	12.352
Percentage funded	0.046	0.089	0	0.999
Panel C: Moderators at investor level				
Female	0.106	0.308	0	1
Investment experience	6.364	9.131	1	92

Panel A presents descriptive statistics of all campaign-level variables. The number of observations (N) for all variables is 102, except for the variable *Share offered* with $N = 96$ (only equity-based campaigns). Panel B presents descriptive statistics of variables at investment-level ($N = 67{,}982$). Panel C presents descriptive statistics of moderating variables at investment-level (for *Female* $N = 65{,}880$ while for *Investment experience* $N = 67{,}982$).

between weather-induced moods and investment decisions, we expect that crowdfunders experiencing cloudy days select campaigns with loan offerings instead of equity offerings.

Hypothesis 4. The negative relationship between sky cloud cover and the amount of contributions to crowdfunding campaigns is stronger for campaigns organized by seed-stage and early-stage ventures compared with those organized by growth-stage ventures.

Hypothesis 5. The negative relationship between sky cloud cover and the amount of contributions to crowdfunding campaigns is stronger for campaigns that are equity offerings compared with venture loan offerings.

4. Data

4.1. Crowdfunding data

Crowdfunding data come from Companisto, accessible at https://www.companisto.com/ and one of the largest crowdfunding platforms in Germany (Hornuf and Schwienbacher, 2018). There are two types of investment opportunities we consider in this study: equity-based and venture loan (%6 of all campaigns). While Companisto started by facilitating equity-based crowdfunding, the platform ventured into venture loans for high-growth companies with annual revenues of at least €500,000 (https://www.companisto.com/en/your-startup-on-companisto). By the end of March, 2019 (at the time of data collection), campaigns on Companisto received over €22 Million from over 40,000 investors. Only ventures located in Germany, Austria, and Switzerland can list and raise money through Companisto. However, registered users across the world (except USA) can invest in campaigns and view information on the campaigns such as the management team, description of the campaign and offerings, and percentage of offered equity. If the campaign is successful, ventures pay 15% of the total money raised as commission fee. Ventures request funding ranging from €50,000 to €2,500,000, also known as target goal. Ventures raising funding on Companisto are from diverse industries such as e-commerce, software, electronics, food and beverage, and cosmetics. All campaigns are based on "all-or-nothing" model (Hornuf and Schwienbacher, 2018), meaning that ventures receive the pledged contributions only if they reach or exceed a predefined target goal. During the campaign, registered users can observe information associated with the time, amount, and identity of prior investors.

Our final sample includes 67,982 investments in 102 campaigns, which include all equity-based and venture-loan campaigns posted on Companisto from 2012 to the end of March 2019. After scraping the website, we extracted the following set of information: the location (city) of investors, the timestamp of investment from the activity log of campaigns, a host of information on campaigns such as the location of the venture and target goal. Table 1 provides descriptive statistics at the campaign level (Panel A, $N = 102$) and at the investment level (Panel B, $N = 67{,}982$). At the campaign level, the average target goal is €537,000 with equity offered at about 12%. 4.9 (5.9) percent of campaigns are in growth stage (venture loan). 47% of ventures are located in Berlin, Germany. At the investment level, average (median) investment of amount invested by each individual in our sample is equal to €636.9 (€200). We log-transform this variable to reduce skewness concerns to arrive at this study's dependent variable: *Amount (log)*.

4.2. Weather data

We obtain weather data from Dark Sky API documented at https://darksky.net/dev/docs. Dark Sky provides meteorological global conditions and weather data based on the geographic coordinates and a historical timestamp. To retrieve investors' geographic coordinates based on their location, we first used Google Geocoding API at https://developers.google.com/maps/documentation/geocoding/intro to retrieve the coordinates of investors. In the few cases that Dark Sky failed to provide weather data for that specific geographic coordinate, we retried to retrieve weather data based on the coordinates for the closest airport to the investor's coordinates (i.e., latitude, longitude) using Lufthansa Open API, accessible at https://developer.lufthansa.com/docs/read/api_details/reference_data/Nearest_Airport.

Consistent with prior studies on weather and the financial markets (Saunders, 1993; Loughran and Schultz, 2004; Hirshleifer and Shumway, 2003), we use sky *Cloud cover* as the main proxy for mood fluctuations. *Cloud cover* is defined as the percentage of sky occluded by clouds, and range between zero and one, inclusive. As an additional proxy for weather, we define *Clear day* and is equal to one when Dark Sky API reports the text summary of this data point as clear day, otherwise it is set at zero (the text summary is for example rain, snow, cloudy, partly-cloudy, and fog.). Table A1 provides summery statistics of weather variables (*Cloud cover* and *Clear day*) across different months (Panel A) and years (Panel B).

5. Methods

The ordinary least squared (OLS) specifications are employed to estimate the parameter of interest β in the following specification:

$$Log\left(B_{ij}\right) = \alpha + \beta w_{kt} + \Lambda C_{ijt} + \upsilon_j + \omega_k + \varepsilon_t \tag{1}$$

B_{ij} refers to investor i's investment amount (Euro) in campaign j. w_{kt} represents two related independent variables of the *Cloud cover* and *Clear day* on day t. To control for (unobservable) heterogeneity in the quality of team and offering that might influence campaign outcomes, we include campaign specific fixed-effects (υ_j). We also include investor's city specific fixed-effect to control for general socio-demographic, economic, cultural, and entrepreneurial orientation of residents in a city that could potentially affect their investment behaviors (ω_k)(Florida, 2005). ε_t denotes the error term. Note that in all OLS models, the robust standard errors are clustered around campaigns. We alternatively clustered standard errors around investors and investors' city, and results are similar (and available upon request from authors). In unreported analyses, we also clustered standard errors around year or quarter and obtain similar results to the main analyses. Finally, C_{ijt} is a vector of control variables, which we will explain below.

Table 1 provides summery statistics of all control variables and Table A2 provides the definition of variables used in this study. The first set of control variables relates to observable characteristics of investors. We consider each investor's crowdfunding experience by calculating the total sum of their previous contributions. We log-transform this variable after increasing by one to generate *Investor's total prior investments (log)*. The average (median) of investor's total prior investments in our sample is equal to 2242.28 (€260). Similarly, we control for *First investment*, defined as a dummy variable equal to one when it is the first time the focal investor is investing (e.g. new investor to the platform), and zero otherwise. 30.7% of all observations are investments by new investors. The second set of control variables relates to investor-venture dyad. To control for home bias observed in crowdfunding settings (Hornuf and Schmitt, 2016; Guenther et al., 2018), we include *Distance* between the investor and location of the venture running the campaign (this variable is log-transformed after increasing by one). The distance is calculated using great-circle distances ("Geodist" command in STATA). The average (median) distance between investors and ventures is 439 (385) kilometers. The third set of control variables relates to the dynamics of campaigns over time. To control alternative explanations related to herding (Vismara, 2016b), we control for the total contributions made on the previous day (day $t-1$) by all investors (*Previous day's total investment (log)*) and total amount of funding received over the target goal of the campaign (*Percentage funded*). On average (median) the *Previous day's total investment (log)* and *Percentage funded* are equal to €13,716.5 (€3825) and 4.6 (1.5) percent. Finally, we control for neutral time trends by including day-of-week, day-of-month, month specific fixed-effects in all specifications.

To test Hypotheses 2 and 3, we include interaction terms between w_{kt} and two investor characteristics: *Female* and *Investment experience*. *Female* is a dummy variable equal to 1 when investor is female, and otherwise 0. We algorithmically classify the gender of investors based on their name by using the API of genderize.io. We use localization, meaning the algorithm classifies genders in the scope of a specific country. This method is used by other researchers (e.g. Mohammadi and Shafi (2018)). We were able to identify gender of investors for 97% of investments (65,880); the rest of investors use company names or pseudonyms. *Investment experience* counts the total number of prior investments that an investor made on the platform Companisto.

While Eq. (1) is at the level of investment, we use an alternative analyses at the level of campaign-city-day level, which is specified in the following Eq. (2). We chose this level of analyses to test Hypotheses 4 and 5. This level of analyses has an advantage in which we can explore whether the effect of *Cloud cover* on reducing investment size is driven by investment size or by change in number of investors investing from the same city on the campaign. This is important since if investment size reduces (as we showed in Table 3) but the number of investors increases, the total effect for funding raised for a campaign might be negligible.

$$Log\left(A_{jkt}\right) = \alpha + \beta w_{kt} + \Lambda M_{jt} + \upsilon_j + \omega_k + \varepsilon_t \tag{2}$$

A_{jkt} is the total sum of investments (in Euro) in campaign j originated from investors located in city k on a given day t; for instance, the dependent variable *City_day_amount (log)* is defined as the natural logarithm of the total sum of contributions invested in a campaign and originated from a given city on a day. w_{kt} is defined similar to the previous Eq. (1) and represents two related independent variables of the *Cloud cover* and *Clear day* on day t. We also include campaign specific fixed-effects (υ_j) and city specific fixed-effects (ω_k). Finally, M_{jt} includes a host of control variables: *Distance*, *Previous day's total investment (*log*)*, and *Percentage funded*. In all models, the robust standard errors are clustered around campaigns. To test Hypotheses 4 and 5, we include interaction between w_{kt} (i.e., *Cloud cover* and *Clear day*) and two risk-related project characteristics: *Growth stage* and *Venture loan*. *Growth stage* is equal to one if

Table 2
Effect of weather on investment size.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: Amount (log)						
Cloud cover	−0.188***	−0.150***	−0.106***			
	(0.030)	(0.027)	(0.028)			
Clear day				0.140***	0.097***	0.060**
				(0.029)	(0.023)	(0.025)
Investor's total prior investments (log)		0.506***	0.453***		0.506***	0.453***
		(0.010)	(0.010)		(0.010)	(0.010)
First investment		3.596***	3.139***		3.597***	3.139***
		(0.084)	(0.081)		(0.084)	(0.081)
Distance (log)		0.003	−0.025***		0.003	−0.025***
		(0.005)	(0.006)		(0.005)	(0.006)
Previous day's total investment (log)		0.028***	0.025***		0.029***	0.025***
		(0.003)	(0.003)		(0.003)	(0.003)
Percentage funded		1.503***	1.667***		1.498***	1.663***
		(0.177)	(0.174)		(0.177)	(0.174)
Campaign FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	No	No	Yes	No	No	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of month FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	67,982	67,982	67,982	67,982	67,982	67,982
Number of campaigns	102	102	102	102	102	102
R^2	0.159	0.360	0.469	0.158	0.359	0.469
Adj. R^2	0.157	0.358	0.427	0.157	0.358	0.427

The dependent variable in all models is *Amount (log)*, defined as the natural logarithm of investment size in Euro invested by individuals. The specification is OLS with robust standard errors clustered on campaigns. For the definition of all variables see Table A2. *, **, and *** indicate statistical significance at levels of 10%, 5%, and 1%, respectively.

the venture development stage is growth phase; otherwise, it is set to zero for seed-stage or early-stage ventures. The venture development stage is explicitly specified on the campaign webpage on the platform. *Venture loan* indicates whether investment is in the form of loan or equity (the loan maturity is 4 years with fixed annual interest rate of 8%).

6. Results

Table 2 presents the estimates of fitted specifications based on Eq. 1 that test Hypothesis 1. The dependent variable in all models is the natural logarithm of individual investors' investment amount (in Euro) contributed to a campaign. Models 1–3 report estimates using the main independent variable: *Cloud cover*. Model 2 adds all control variables and Model 3 complements the previous model by including the investor's city fixed-effects. The coefficients of *Cloud cover* are negative and statistically significant in Models 1–3 (Model 1:-0.188, $p<0.01$; Model 2: −0.150, $p<0.01$; Model 3: −0.106, $p<0.01$). For example, in terms of economic magnitude, changes from zero *Cloud cover* to full *Cloud cover* reduces contribution amounts by 15 (10.6) percent based on Model 2 (3); this change is equivalent to €95.53 (€63.7) on average.[4] These results support Hypothesis 1.

Models 4–6 in Table 2 use *Clear day* as an alternative independent variable. Model 4 adds all control variables and Model 5 stacks investor's city fixed effects to the previous model. The results show positive and statistically significant coefficients in all models, which is well-aligned with our main findings. In terms of economic magnitude, investments on days with good weather conditions (*Clear day*) are 9.7 (6) percent larger on average than investments on other days based on the coefficient in Model 5 (6).

We present the estimates related to the test of Hypothesis 2 in Table 3. We first repeat the previous analyses of Table 2 for the sample that we could identify the gender of investors (Model 1–3) and proceed to include the interaction between *Cloud cover* and *Female* in subsequent Models 4–6. While the effect of *Cloud cover* is similar to the previous analyses, the coefficients of interaction terms are negative but not statistically different from zero. These results do not support Hypothesis 2. Results are also non-significant for interaction term between *Clear day* and *Female*.

Table 4 presents the estimates related to the test of Hypothesis 3. In this analyses we introduce an interaction term between *Cloud cover* and *Investment experience*. In Models 1 and 2 we include all investors (models labeled "All"). In Models 3 and 4 we include serial investors, defined as investors with investment experience greater than one (models labeled "Serial"). This latter grouping allows us to show that the results are not driven by investors that have made only one investment - these could be family and friends. In all models, the coefficient of interaction between *Cloud cover* and *Investment experience* are positive and statistically significant at 10% level. The coefficients in Model 2 of Table 4 implies that for an investor at average levels of investment experience (i.e., about 6 investments) the

[4] A project receives on average (median) 903 (792) investments. For a given project with all investors in no cloud coverage compared with all investors in complete cloud coverage, the total amount of investment is higher by Euro 57,521 (50450).

Table 3
Moderating factors associated with gender of investors.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: Amount (log)					
Cloud cover	−0.188***	−0.146***	−0.100***	−0.186***	−0.143***	−0.090***
	(0.029)	(0.025)	(0.028)	(0.030)	(0.027)	(0.030)
Female				−0.097	−0.025	−0.018
				(0.063)	(0.062)	(0.065)
Cloud cover × Female				−0.013	−0.023	−0.096
				(0.096)	(0.094)	(0.102)
Investor's total prior investments (log)		0.503***	0.448***		0.502***	0.447***
		(0.010)	(0.010)		(0.010)	(0.010)
First investment		3.549***	3.087***		3.550***	3.087***
		(0.084)	(0.081)		(0.084)	(0.081)
Distance (log)		0.004	−0.026***		0.003	−0.026***
		(0.005)	(0.006)		(0.005)	(0.006)
Previous day's total investment (log)		0.029***	0.025***		0.029***	0.025***
		(0.003)	(0.003)		(0.003)	(0.003)
Percentage funded		1.734***	1.784***		1.736***	1.786***
		(0.194)	(0.187)		(0.194)	(0.186)
Campaign FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	No	No	Yes	No	No	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of month FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	65,880	65,880	65,880	65,880	65,880	65,880
Number of campaigns	102	102	102	102	102	102
R^2	0.162	0.361	0.469	0.162	0.361	0.470
Adj. R^2	0.160	0.359	0.427	0.160	0.359	0.428

The dependent variable in all columns is *Amount (log)*, defined as the natural logarithm of investment amount in Euro. Models 1–3 repeat Models 1–3 from Table 2 on sample with non-missing gender of investors. The specification is OLS with robust standard errors clustered around campaigns. Table A2 provides the definitions of all variables. *, **, and *** indicate statistical significance at levels of 10%, 5%, and 1%, respectively.

Table 4
Moderating effect of experience.

	(1)	(2)	(3)	(4)
	Dependent variable: Amount (log)			
	All	All	Serial	Serial
Cloud cover	−0.144***	−0.129***	−0.138***	−0.108**
	(0.038)	(0.040)	(0.042)	(0.043)
Investment experience	−0.082***	−0.078***	−0.082***	−0.076***
	(0.004)	(0.004)	(0.004)	(0.004)
Cloud cover × investment experience	0.009*	0.008*	0.009*	0.008*
	(0.004)	(0.004)	(0.005)	(0.004)
Investor's total prior investments (log)	0.676***	0.606***	0.687***	0.612***
	(0.011)	(0.011)	(0.010)	(0.010)
First investment	0.001	−0.022***	0.002	−0.014**
	(0.005)	(0.005)	(0.004)	(0.005)
Distance (log)	4.164***	3.707***	4.277***	3.774***
	(0.082)	(0.081)	(0.076)	(0.076)
Previous day's total investment (log)	0.021***	0.020***	0.018***	0.017***
	(0.003)	(0.003)	(0.003)	(0.003)
Percentage funded	1.850***	1.851***	1.657***	1.686***
	(0.166)	(0.168)	(0.161)	(0.156)
Campaign FE	Yes	Yes	Yes	Yes
City FE	No	Yes	No	Yes
Day of Week FE	Yes	Yes	Yes	Yes
Day of month FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
N	67,982	67,982	57,256	57,256
Number of campaigns	102	102	102	102
R^2	0.479	0.553	0.554	0.608
Adj. R^2	0.478	0.518	0.552	0.585

The dependent variable in all columns is *Amount* (log), defined as the natural logarithm of investment amount in Euro. The subsample in Models 1 and 2 include all investors. The subsample in Models 3 and 4 include only serial investors, defined as investors with more than one investment. The specification is OLS with robust standard errors clustered around campaigns. Table A2 provides the definitions of all variables. *, **, and *** indicate statistical significance at levels of 10%, 5%, and 1%, respectively.

Table 5
Effect of weather on investment size and count.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	City_day_amount (log)				City_day_count (log)			
Cloud cover	−0.186***	−0.103***			0.001	0.002		
	(0.030)	(0.035)			(0.009)	(0.010)		
Clear day			0.129***	0.062*			−0.003	0.003
			(0.036)	(0.037)			(0.008)	(0.008)
Distance (log)	−0.067***	−0.059***	−0.066***	−0.059***	−0.049***	−0.016***	−0.049***	−0.016***
	(0.009)	(0.011)	(0.009)	(0.011)	(0.004)	(0.004)	(0.004)	(0.004)
Previous day's total investment (log)	0.046***	0.038***	0.046***	0.038***	0.006***	0.006***	0.006***	0.006***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)
Percentage funded	4.442***	5.164***	4.434***	5.160***	1.397***	1.769***	1.397***	1.770***
	(0.367)	(0.360)	(0.365)	(0.359)	(0.101)	(0.113)	(0.101)	(0.113)
Campaign FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	No	Yes	No	Yes	No	Yes	No	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	55,881	55,881	55,881	55,881	55,881	55,881	55,881	55,881
Number of campaigns	102	102	102	102	102	102	102	102
R^2	0.160	0.381	0.159	0.381	0.097	0.230	0.097	0.230
Adj. R^2	0.157	0.321	0.157	0.321	0.094	0.156	0.094	0.156

The dependent variable in Models 1–4 is *City_day_amount (*log*)*, defined as the natural logarithm of total sum of investments (in Euro) in a campaign originated from investors located in a city on a given day. The dependent variable in Models 5–8 is *City_day_count (*log*)*, defined as the natural logarithm of total count of all investments in a campaign originated from investors located in a city on a given day. The specification is OLS at campaign-city-day level with robust standard errors clustered around campaigns. For the definitions of all variables, see Table A2. *, **, and *** indicate statistical significance at levels of 10%, 5%, and 1%, respectively.

effect of full cloud coverage is 35% smaller than for investors with no prior investment experience.[5]

Before proceeding to test Hypotheses 4 and 5 that investigate the risk-related characteristics of investment opportunities presented in the campaigns, we make several observations. First, we assess whether the main results hold using Eq. (2); this specification is at the campaign-city-day level (all investments originating from a city on any given day in one campaign will collapse into one observation in this type of analysis). We chose this level of analyses to explore whether the effect of *Cloud cover* on reducing investment size is driven by investment size or by changes in number of investors investing from the same city in the campaign. If investment size reduces (as we showed in Table 3) but the number of investors increases, the total effect on contributions for a campaign might be negligible.

We present the estimates of Eq. (2) in Table 5 at the campaign-city-day level. In Models 1–4, the dependent variable, *City_day_amount (log)*, is defined as the natural logarithm of the total sum of contributions invested in a campaign and originated from a given city on a day. The estimates suggest that the total sum of contributions to a campaign from investors located in a given city decreases for investors experiencing more *Cloud cover* on that day. In subsequent models (Models 5–8), the dependent variable is *City_day_counts (log)*, and is defined as the total number of investors from a given city on a day invested in a campaign. These estimates don't indicate that total number of investors increases during overcast days in a given city. Overall, these results are supporting our claims about the negative relationship between weather-induced mood and contributions to equity crowdfunding campaigns.

Table 6 report the estimates testing Hypotheses 4 and 5. We include interaction terms between our weather variables (*Cloud cover* and *Clear day*) and risk-related project characteristics: *Growth stage* and *Venture loan*. Note that after including campaign fixed-effects, the direct effect of *Growth stage* and *Venture loan* drops as these variables do not vary within a campaign. The dependent variable in all models is *City_day_amount (log)*, which is defined as the natural logarithm of the total sum of contributions invested in a campaign and originated from a given city on a day. In Models 1 and 3 (2 and 4) the coefficients of interaction terms between *Cloud cover* (*Clear day*) and project characteristics of *Growth stage* and *Venture loan* are positive (negative) (Model 1:0.060, n.s; Model 2: −0.194, $p<0.01$; Model 3: 0.260, $p<0.1$; Model 4: −0.367, $p<0.01$). These estimates provide partial support for Hypothesis 4 and full support for Hypothesis 5. To highlight the economic size for Model 2 that includes the interaction term between *Clear day* and *Growth stage*, on clear days ventures in seed and early stage receive 8.7% more investment amounts relative to unclear days; however, on clear days ventures in growth stage receive 10.7% less investment amounts relative to unclear days. For Model 4 that includes the interaction term between *Clear day* and *Venture loan*, on clear days projects with equity offerings receive 8.1% more investment amounts relative to unclear days; however, on clear days projects with venture loan receive 28.6% less investment amounts relative to unclear days.

[5] In Table 14 we added *Female* and *Investment experience* as additional control variables. Results are robust to this inclusion.

Table 6
Moderating factors denoting risk of campaigns.

	(1)	(2)	(3)	(4)
	City_day_amount (log)			
Cloud cover	−0.101***		−0.122***	
	(0.037)		(0.035)	
Cloud cover × Growth stage	0.060			
	(0.112)			
Clear day		0.087**		0.081**
		(0.038)		(0.038)
Clear day × Growth stage		−0.194***		
		(0.046)		
Cloud cover × Venture Loan			0.260*	
			(0.142)	
Clear day × Venture Loan				−0.367***
				(0.107)
Distance (log)	−0.059***	−0.059***	−0.059***	−0.059***
	(0.011)	(0.011)	(0.011)	(0.011)
Previous day's total investment (log)	0.037***	0.037***	0.037***	0.037***
	(0.004)	(0.004)	(0.004)	(0.004)
Percentage funded	5.015***	5.019***	5.017***	5.014***
	(0.330)	(0.329)	(0.329)	(0.328)
Campaign FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes
Day of month FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
N	55,881	55,881	55,881	55,881
Number of campaigns	102	102	102	102
R^2	0.381	0.381	0.381	0.381
Adj. R^2	0.321	0.321	0.321	0.321

The dependent variable in all models is *City_day_amount (*log*)*, defined as the natural logarithm of total sum of investments (in Euro) in a campaign originated from investors located in a city on a given day. The specification is OLS at campaign-city-day level with robust standard errors clustered around campaigns. For the definitions of all variables, see Table A2. *, **, and *** indicate statistical significance at levels of 10%, 5%, and 1%, respectively.

7. Additional analyses

7.1. Does unexpected increase in cloud coverage reduce investment contributions?

This subsection explores whether deviations from expected cloud coverage (unexpected part of the daily cloud coverage) influence contributions to campaigns. To obtain *Cloud cover deviation daily*, we first compute the expected cloud coverage as the last five-day (t_{day-5}, …, t_{day-1}) equal-weighted average of cloud coverage and then calculate the difference between *Cloud cover* (t_{day}, previously labeled as t) and the expected cloud coverage. We follow the same procedure to obtain *Cloud cover deviation yearly* by using the values of cloud coverage on the last five years (t_{year-5}, …, t_{year-1}) at the same exact time of the year preceding the investment t_{year}.

Table 7 presents the estimates related to unexpected cloud coverage. Models 1–3 report estimates using the *Cloud cover deviation yearly* as independent variable. Model 2 adds all control variables and Model 3 complements the previous model by including the investor's city fixed-effects. The coefficients of *Cloud cover deviation yearly* are negative and statistically significant in Models 1–3. Models 4–6 repeat the analyses in previous models using the *Cloud cover deviation daily* as independent variable. The coefficients of *Cloud cover deviation daily* are negative and statistically significant in all models. Thus, our results suggest that increases in *Cloud cover* more than expected based on historical data is associated with lower investment amounts.

For further robustness checks, we also use the last five years (days) unequal weighted average of cloud coverage where dates closer to the investment date are given a higher weight. Results reported in Table A4 show similar results. Additionally, we use changes in cloud coverage only from the previous day and report results in Table A5. We again obtain similar results.

7.2. Does the effect of cloud coverage on investment contributions vary across seasons?

This subsection investigates whether there are seasonal variations for the effect of cloud coverage on investment contributions. Kamstra et al. (2003) find evidence consistent with lower (higher) demand for risky stock in the fall (spring) after controlling for stock return regularities. Kamstra et al. (2017) find that investors prefer safer (riskier) investments in autumn (spring). We expect based on the mood hypothesis that cloud coverage should have stronger negative effects on the link between cloud cover and contributions to crowdfunding in spring and summer. This is so since individuals have higher expectations for cloud coverage in autumn and winter compared with spring and summer. Table A6 shows the average size of investments across seasons. Additionally, we run the main analyses on sub-samples based on the season in which investment happens. Table 8 presents the estimates for all seasons: spring

Table 7
Effect of deviation from expected cloud coverage on investment.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: Amount (log)						
Cloud cover deviation yearly	−0.082**	−0.062**	−0.078**			
	(0.037)	(0.031)	(0.034)			
Cloud cover deviation daily				−0.084**	−0.077**	−0.083**
				(0.038)	(0.033)	(0.033)
Investor's total prior investments (log)		0.512***	0.448***		0.506***	0.442***
		(0.010)	(0.011)		(0.011)	(0.011)
First investment		3.613***	3.080***		3.590***	3.058***
		(0.082)	(0.080)		(0.087)	(0.084)
Distance (log)		0.001	−0.037***		−0.003	−0.034***
		(0.007)	(0.008)		(0.006)	(0.007)
Previous day's total investment (log)		0.034***	0.028***		0.029***	0.022***
		(0.004)	(0.004)		(0.004)	(0.004)
Percentage funded		1.527***	1.615***		1.477***	1.588***
		(0.208)	(0.202)		(0.209)	(0.200)
Campaign FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	No	No	Yes	No	No	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of month FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	44,949	44,949	44,949	45,703	45,703	45,703
Number of campaigns	102	102	102	102	102	102
R2	0.156	0.360	0.489	0.169	0.368	0.499
Adj. R2	0.153	0.358	0.436	0.166	0.366	0.446

The dependent variable in all columns is *Amount (*log*)*, defined as the natural logarithm of investment amount in Euro. *Cloud cover deviation yearly* is defined as investment day's cloud coverage minus the average of cloud coverage on the focal day from the last five years. *Cloud cover deviation daily* is defined as investment day's cloud coverage minus the average of cloud coverage on the last five days from the focal investment day. The specification is OLS with robust standard errors clustered around campaigns. Table A2 provides the definitions of all variables. *, **, and *** indicate statistical significance at levels of 10%, 5%, and 1%, respectively.

Table 8
Effect of weather on investment across seasons.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Spring	Spring	Summer	Summer	Autumn	Autumn	Winter	Winter
	Dependent variable: Amount (log)							
Cloud cover	−0.107**	−0.115**	−0.186***	−0.137**	−0.153**	−0.098	−0.092	−0.064
	(0.045)	(0.053)	(0.052)	(0.059)	(0.057)	(0.063)	(0.061)	(0.067)
Investor's total prior investments (log)	0.515***	0.470***	0.495***	0.443***	0.508***	0.465***	0.520***	0.460***
	(0.017)	(0.019)	(0.020)	(0.021)	(0.017)	(0.017)	(0.015)	(0.015)
First investment	3.622***	3.213***	3.450***	3.018***	3.668***	3.286***	3.647***	3.126***
	(0.138)	(0.158)	(0.142)	(0.151)	(0.140)	(0.132)	(0.140)	(0.139)
Distance (log)	−0.007	−0.047***	0.006	−0.021	0.006	−0.024**	−0.005	−0.016
	(0.009)	(0.010)	(0.008)	(0.016)	(0.007)	(0.010)	(0.009)	(0.010)
Previous day's total investment (log)	0.033***	0.031***	0.027***	0.024***	0.024***	0.023***	0.029***	0.020***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.005)	(0.005)	(0.007)	(0.006)
Percentage funded	2.575***	2.700***	1.592***	1.418***	2.266***	2.384***	1.856***	1.699***
	(0.407)	(0.528)	(0.519)	(0.464)	(0.375)	(0.336)	(0.282)	(0.297)
Campaign FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	No	Yes	No	Yes	No	Yes	No	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	16,389	16,389	16,653	16,653	19,006	19,006	15,934	15,934
Number of campaigns	56	56	50	50	52	52	55	55
R^2	0.332	0.482	0.360	0.501	0.387	0.529	0.368	0.518
Adj. R^2	0.328	0.389	0.356	0.414	0.384	0.449	0.363	0.424

The dependent variable in all columns is *Amount (log)*, defined as the natural logarithm of investment amount in Euro. The subsample in Models 1 and 2 include only investments in spring. The subsample in Models 3 and 4 include only investments in summer. The subsamples in Models 5 and 6 only investments in autumn. The subsample in Models 7 and 8 include only investments in winter. The specification is OLS with robust standard errors clustered around campaigns. Table A2 provides the definitions of all variables. *, **, and *** indicate statistical significance at levels of 10%, 5%, and 1%, respectively.

Table 9
Seasonal affective disorder as an alternative explanation.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: Amount (log)					
Cloud cover	−0.181***	−0.139***	−0.098***			
	(0.030)	(0.027)	(0.027)			
Clear day				0.138***	0.089***	0.053**
				(0.029)	(0.023)	(0.025)
Length of day	−0.016**	−0.006	−0.007	−0.013	−0.003	−0.005
	(0.008)	(0.008)	(0.006)	(0.008)	(0.007)	(0.006)
Investor's total prior investments (log)		0.506***	0.453***		0.506***	0.454***
		(0.010)	(0.010)		(0.010)	(0.010)
First investment		3.598***	3.139***		3.598***	3.139***
		(0.085)	(0.082)		(0.085)	(0.082)
Distance (log)		0.002	−0.027***		0.002	−0.027***
		(0.005)	(0.006)		(0.005)	(0.006)
Previous day's total investment (log)		0.028***	0.025***		0.028***	0.025***
		(0.003)	(0.003)		(0.003)	(0.003)
Percentage funded		1.513***	1.674***		1.506***	1.669***
		(0.179)	(0.179)		(0.180)	(0.180)
Campaign FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	No	No	Yes	No	No	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	67,981	67,981	67,981	67,981	67,981	67,981
Number of campaigns	102	102	102	102	102	102
R^2	0.159	0.359	0.469	0.159	0.359	0.469
Adj. R^2	0.157	0.358	0.427	0.157	0.358	0.427

The dependent variable in all columns is *Amount (log)*, defined as the natural logarithm of investment amount in Euro. This table repeats all models in Table 2 with one modification; we include *Length of day* as control variable instead of month fixed effects. *Length of day* is measured at the location of the investor. The specification is OLS with robust standard errors clustered around campaigns. Table A2 provides the definitions of all variables. *, **, and *** indicate statistical significance at levels of 10%, 5%, and 1%, respectively.

(Models 1 and 2), summer (Models 3 and 4), autumn (Models 5 and 6), and winter (Models 7 and 8). The results show that while the coefficients of *Cloud cover* are negative in all models, the coefficients are only statistically significant in spring and summer.

The estimates based on seasons (Table 8) provide further support for the mood hypothesis since individuals have higher expectations for cloud coverage in autumn and winter compared with spring and summer. Thus, cloud coverage should have stronger negative effects on the link between cloud cover and contributions to crowdfunding in spring and summer. This is also in line with prior literature (Keller et al., 2005) finding that pleasant weather improves mood during the spring because people have been deprived of such weather during the winter. Thus, our findings support seasonal variations for the effect of sky cloud cover on contribution amounts.

7.3. Does seasonal affective disorder explain the link between cloud cover and investment contributions?

A plausible alternative explanation for the link between cloud cover on investment contributions is the role of seasonal affective disorder (SAD). SAD impacts market participants through depression, and the risk aversion that accompanies depression. The psychology and behavioral economics literature have established the link from SAD (which a literature in psychology has tied to the length of day) to depression, and the link from depression to risk-taking (Kramer and Weber, 2012). For example, Kramer and Weber (2012) use experimental evidence to establish a link between seasonal affective disorder (SAD) and risk attitudes. The SAD-sufferers show stronger preferences for safe choices during the winter than non-SAD-sufferers, and they did not differ from non-SAD-sufferers during the summer. This effect was mediated by depression. To assess this alternative explanation, we include length of day as a proxy for SAD in the regressions instead of month fixed effects. Table 9 presents estimates that redo all models in Table 2. The results indicate that the negative relationship between *Cloud cover* and investment size is robust to including *Length of day*. Additionally, *Length of day* is negatively associated with investment size, but its effect is only statistically significant in Model 1.

7.4. Are results robust to controlling for additional weather-related variables?

For theoretical reasons we have chosen cloud coverage. We assess whether our conclusions hold after controlling for other weather variables that can correlate with cloud coverage. In fact, it is possible that these other factors (such as the maximum temperature in a day) influence mood and risk-taking and excluding them biases our findings. We control for *UV Index*, *Temperature*, and *Humidity*. Table 10 presents the estimates related to *UV Index* in Models 1 and 2, *Temperature* in Models 3 and 4, and *Humidity* in Models 5 and 6. Finally, we include all of these weather variables in the same model (Models 7 and 8). The effect of *Cloud cover* in all models remains negative and statistically significant even after including these control variables. In unreported analyses we included wind speed and obtained similar results.

Table 10
Additional weather related variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: Amount (log)							
Cloud cover	−0.117***		−0.084***		−0.114***		−0.117***	
	(0.031)		(0.030)		(0.031)		(0.035)	
Clear day		0.054**		0.044*		0.052**		0.050*
		(0.025)		(0.024)		(0.025)		(0.026)
UV Index	−0.011	−0.002					−0.014*	−0.008
	(0.007)	(0.006)					(0.007)	(0.007)
Temperature			0.002	0.003**			0.003*	0.004**
			(0.002)	(0.002)			(0.002)	(0.002)
Humidity					0.061	−0.040	0.097	0.022
					(0.095)	(0.086)	(0.096)	(0.092)
Investor's total prior investments (log)	0.454***	0.454***	0.454***	0.455***	0.454***	0.454***	0.455***	0.455***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
First investment	3.135***	3.136***	3.140***	3.140***	3.139***	3.139***	3.140***	3.140***
	(0.080)	(0.080)	(0.082)	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)
Distance (log)	−0.026***	−0.026***	−0.027***	−0.026***	−0.026***	−0.026***	−0.026***	−0.026***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Previous day's total investment (log)	0.025***	0.025***	0.025***	0.026***	0.026***	0.026***	0.026***	0.026***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Percentage funded	1.857***	1.852***	1.688***	1.868***	1.863***	1.863***	1.870***	1.866***
	(0.190)	(0.191)	(0.180)	(0.191)	(0.191)	(0.191)	(0.190)	(0.190)
Campaign FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	67,982	67,982	67,901	67,901	67,978	67,978	67,899	67,899
Number of campaigns	102	102	102	102	102	102	102	102
R^2	0.469	0.469	0.469	0.469	0.469	0.469	0.469	0.469
Adj. R^2	0.428	0.428	0.427	0.428	0.428	0.428	0.428	0.428

The dependent variable in all columns is *Amount (log)*, defined as the natural logarithm of investment amount in Euro. This table repeats Models 3 and 6 in Table 2 while including the following control variables: *UV Index*, *Temperature* and *Humidity*. The specification is OLS with robust standard errors clustered around campaigns. Table A2 provides the definitions of all variables. *, **, and *** indicate statistical significance at levels of 10%, 5%, and 1%, respectively.

Table 11
Transient effect of weather on investment at campaign-city-day level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	City_day_amount (log)							
Cloud cover	−0.186***	−0.103***	−0.161***	−0.101**	−0.155***	−0.093**	−0.151***	−0.093**
	(0.030)	(0.035)	(0.035)	(0.040)	(0.036)	(0.040)	(0.037)	(0.042)
Cloud cover(t-1)			−0.048	0.003	−0.034	−0.002	−0.028	0.008
			(0.041)	(0.043)	(0.041)	(0.044)	(0.043)	(0.045)
Cloud cover (t-2)					−0.019	0.024	0.028	0.047
					(0.046)	(0.050)	(0.053)	(0.057)
Cloud cover (t-3)							−0.064	−0.039
							(0.048)	(0.048)
Distance (log)	−0.067***	−0.059***	−0.062***	−0.056***	−0.060***	−0.057***	−0.060***	−0.064***
	(0.009)	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)	(0.012)
Previous day's total investment (log)	0.046***	0.038***	0.047***	0.037***	0.048***	0.038***	0.049***	0.038***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Percentage funded	4.442***	5.164***	4.378***	5.015***	4.429***	5.004***	4.307***	4.836***
	(0.367)	(0.360)	(0.380)	(0.361)	(0.371)	(0.356)	(0.367)	(0.357)
Campaign FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	No	Yes	No	Yes	No	Yes	No	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	55,881	55,881	49,474	49,474	46,062	46,062	43,264	43,264
Number of campaigns	102	102	102	102	102	102	102	102
R^2	0.160	0.381	0.163	0.391	0.165	0.397	0.167	0.401
Adj. R^2	0.157	0.321	0.160	0.326	0.162	0.329	0.164	0.331

7.5. Do lagged effects of cloud coverage influence investment contributions?

Although we have so far investigated the effect of weather on the current day of investment on contributions, this subsection explores if cloud cover on previous days influences crowdfunding contributions. To assess persistence effects, we include lags of *Cloud cover* for the past three days (in unreported analyses we also include up to five lags) and present the results in Table 11. It appears that the effect of *Cloud cover* is only present on the current day and all lagged variables are not significant. This analysis also shows that weather effects are transient while ruling out alternative explanations such as seasonal affective disorders that supposedly persist over longer periods of time.

8. Conclusion

This paper uses data on financial decisions of crowdfunders to establish a link between mood and (equity) crowdfunding contributions. Previous studies in crowdfunding have studied campaign attributes or other factors underpinning the quality of the investment opportunity, but we focus on investors and what factors drive their behavior. Building on the link between individuals' affective states and their risk-taking behavior from the literature in psychology, we identify positive moods as a key theoretical determinant of contributions in crowdfunding. A key challenge is to identify correlates of mood not affected by the attributes of campaigns or their projections about economic environment. Motivated by large evidence across different scientific fields, a reliable proxy for mood is weather conditions; more specifically, we find that sky cloud cover systematically influences contributions in equity crowdfunding campaigns. We attribute this finding to the link between weather-induced mood and risk preferences. Our paper adds to a growing strand of literature in economics, finance, and accounting that suggests that weather-induced moods influence financial behaviors.

Our study offers several practical implications. First, given how moods influence risk taking in financial decision making, crowdfunders should not underestimate factors that influence their moods including weather. While we don't directly establish the long-term performance of investment decisions influenced by weather, if investors' moods contain no information about the investment opportunity (say, the projected cash flows), then they could be a source of bias under conditions of uncertainty. The good news is that not all environments or investors are the same: our evidence shows that more experienced crowdfunders are less sensitive to mood induced risk-taking, and additionally these effects are less under less uncertainty. Second, while entrepreneurs cannot fully predict the weather to strategically time the campaign launch to maximize fundraising success, there are a number of strategies that they can devise to offset the adverse effects of cloudy days; these include targeting more experienced investors, and engaging in campaigns at a later stage of venture development if possible. Additionally, in autumn or winter, investors appear insensitive to cloud cover in their contributions to campaigns. On cloudy days, entrepreneurs can also increase their marketing activities in ways that improve prospective investors' moods. Finally, from a policy perspective, if there are concerns that crowdfunders are driven by moods or other motivations like thrill seeking (Demir et al., 2019) in some contexts more than others, and such behavior is detrimental to investors, policy makers can introduce frictions in the process of crowdfunding - e.g., by eliciting interest in a campaign days in advance of allowing capital commitments (Cumming et al., 2020). We hope our research inspires scholars to pursue studying the effects of investors' moods (primed by other stimuli) on crowdfunding behavior and their long-term implications.

The dependent variable in all columns is *Amount (log)*, defined as the natural logarithm of investment amount in Euro. This table repeats Models 2 and 3 in Table 2 while including up to three lags of *Cloud cover* to the models. Specification is OLS with robust standard errors clustered around campaigns. Table A2 provides the definitions of all variables. *, **, and *** indicate statistical significance at levels of 10%, 5%, and 1%, respectively.

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Appendix A

Table A1
Weather over time.

	Mean	Sd.	Mean	Sd.
Variable	Cloud cover		Clear day	
Month	Panel A			
1	0.699	0.197	0.026	0.160
2	0.649	0.218	0.039	0.193
3	0.578	0.248	0.084	0.277
4	0.570	0.223	0.056	0.230
5	0.597	0.207	0.038	0.191
6	0.551	0.204	0.051	0.221
7	0.524	0.215	0.080	0.271
8	0.514	0.225	0.082	0.274
9	0.536	0.231	0.083	0.275

(*continued on next page*)

Table A1 (*continued*)

Variable	Mean	Sd.	Mean	Sd.
	Cloud cover		Clear day	
Month	Panel A			
10	0.632	0.208	0.034	0.180
11	0.692	0.194	0.020	0.138
12	0.703	0.202	0.022	0.145
Total	0.609	0.224	0.049	0.217
Year	Panel B			
2012	0.619	0.217	0.030	0.170
2013	0.616	0.221	0.052	0.222
2014	0.606	0.217	0.047	0.211
2015	0.601	0.228	0.052	0.222
2016	0.611	0.228	0.054	0.226
2017	0.619	0.225	0.042	0.200
2018	0.586	0.227	0.057	0.233
2019 (till March)	0.706	0.177	0.031	0.174
Total	0.609	0.224	0.049	0.217

This table presents summary statistics for weather variables (*Cloud cover* and *Clear day*) over time.

Table A2
Variable definitions.

Variable	Definition
Panel A: investment level	
Amount (log)	Natural logarithm of investment amount in Euro
Cloud coverage	The percentage of sky occluded by clouds, between 0 and 1, inclusive.
Clear day	A dummy variable that is equal to one if a meteorologist categorized the weather condition as clear day based on Dark Sky API.
Investor's total prior investments (log)	Natural logarithm of all prior investments of an individual (plus one) in Euro.
First investment	A dummy variable that is equal to one if it is the first time that investor makes an investment, and zero otherwise.
Distance (log)	Natural logarithm of distance in kilometers (plus one) between the investor's location and the headquarter of venture running the campaign.
Previous day's total investment (log)	Natural logarithm of all investments in the last day in a campaign.
Percentage funded	Total amount of raised funding right before the focal investment over target goal.
Campaign FE	A set of 102 dummies for each campaign.
City FE	A set of dummies representing investor's city.
Day of Week FE	Seven dummy variables for each day of the week.
Day of month FE	Thirty one dummy variables for each day of a month
Month FE	Twelve dummy variables for each month of a year
Year FE	Eight dummy variable for year 2012 till 2019.
Female	A dummy variable that is equal to one if investor is female and zero if investor is male.
Investment experience	Number of prior investments made by the investor.
Cloud coverage deviation yearly	Investment day's cloud coverage minus the average of cloud coverage on the focal day from the last five years.
Cloud coverage deviation daily	Investment day's cloud coverage minus the average of cloud coverage on the last five days from the focal investment day.
Cloud coverage deviation weighted yearly	Investment day's cloud coverage minus the weighted average of cloud coverage on the focal day from the last five years.
Cloud coverage deviation weighted daily	Investment day's cloud coverage minus the weighted average of cloud coverage on the last five days from the focal investment day.
Change in cloud cover	Investment day's cloud coverage minus cloud coverage from the previous day of the focal investment.
Length of day	The time between the sunset and sunrise in hours at investor location.
UV Index	The strength of sunburn-producing ultraviolet (UV)Â radiation, between 0 and 12, inclusive.
Temperature	The highest temperature measured on a day in celsius.
Humidity	The relative humidity, between 0 and 1, inclusive.
Panel B: city-campaign-day level	
City_date_amount (log)	Natural logarithm of total amount of all investments from one city in a campaign on a day in Euro.
City_date_count (log)	Natural logarithm of total number of investments from one city in a campaign on a day.
Panel C: campaign characteristics	
Target Goal	Total capital requirement of a campaign.
Share Offered	Percentage of venture equity offered during the campaign.
Growth stage	Dummy variable that is equal to one if the venture seeking funding is in growth stage, and zero otherwise.
Venture loan	Dummy variable that is equal to one if the offering is loan, and it is set to zero if the campaign is an equity offering.
Berlin	A dummy variable that is equal to one if the venture is in Berlin, Germany.

Table A3
Including female and investment experience as control variables without interaction terms.

	(1)	(2)	(3)	(4)	(5)	(6)

(*continued on next page*)

Table A3 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: Amount (log)						
Dependent variable: Amount (log)						
Cloud cover	−0.147***	−0.105***	−0.091***	−0.076***	−0.091***	−0.076***
	(0.027)	(0.027)	(0.024)	(0.026)	(0.024)	(0.026)
Female	−0.048	−0.087**			−0.067**	−0.096***
	(0.034)	(0.037)			(0.032)	(0.035)
Investment exprience			−0.077***	−0.073***	−0.077***	−0.073***
			(0.003)	(0.003)	(0.003)	(0.003)
Investor's total prior investments (log)	0.506***	0.453***	0.676***	0.606***	0.676***	0.605***
	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
First investment	3.604***	3.144***	4.171***	3.713***	4.172***	3.714***
	(0.085)	(0.082)	(0.082)	(0.081)	(0.082)	(0.081)
Distance (log)	0.002	−0.026***	0.002	−0.020***	0.002	−0.020***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Previous day's total investment (log)	0.028***	0.025***	0.021***	0.020***	0.021***	0.020***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Percentage funded	1.516***	1.683***	1.835***	1.866***	1.838***	1.869***
	(0.176)	(0.172)	(0.162)	(0.161)	(0.161)	(0.160)
Campaign FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	No	Yes	No	Yes	No	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of month FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	67,982	67,982	67,982	67,982	67,982	67,982
Number of campaigns	102	102	102	102	102	102
R^2	0.360	0.469	0.480	0.553	0.480	0.553
Adj. R^2	0.359	0.428	0.478	0.518	0.478	0.518

The dependent variable in all columns is *Amount (log)*, defined as the natural logarithm of investment amount in Euro. The specification is OLS with robust standard errors clustered around campaigns. Table A2 provides the definitions of all variables. *, **, and *** indicate statistical significance at levels of 10%, 5%, and 1%, respectively.

Table A4
Effect of deviation from expected cloud coverage on investment size.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: Amount (log)						
Cloud cover deviation weighted yearly	−0.076**	−0.060*	−0.077**			
	(0.037)	(0.031)	(0.034)			
Cloud cover deviation weighted daily				−0.090**	−0.080**	−0.090***
				(0.039)	(0.034)	(0.033)
Investor's total prior investments (log)		0.511***	0.449***		0.506***	0.443***
		(0.010)	(0.010)		(0.011)	(0.011)
First investment		3.612***	3.082***		3.596***	3.067***
		(0.082)	(0.079)		(0.086)	(0.082)
Distance (log)		0.001	−0.038***		−0.003	−0.035***
		(0.007)	(0.008)		(0.006)	(0.007)
Previous day's total investment (log)		0.034***	0.028***		0.029***	0.022***
		(0.004)	(0.004)		(0.004)	(0.003)
Percentage funded		1.514***	1.594***		1.451***	1.556***
		(0.210)	(0.205)		(0.212)	(0.207)
Campaign FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	No	No	Yes	No	No	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of month FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	44,949	44,949	44,949	45,703	45,703	45,703
Number of campaigns	102	102	102	102	102	102
R^2	0.156	0.360	0.489	0.169	0.368	0.499
Adj. R^2	0.153	0.358	0.436	0.166	0.366	0.446

The dependent variable in all columns is *Amount (log)*, defined as the natural logarithm of investment amount in Euro. *Cloud cover deviation weighted yearly* is defined as investment day's cloud coverage minus the weighted average of cloud coverage on the focal day from the last five years. *Cloud cover deviation weighted daily* is defined as investment day's cloud coverage minus the weighted average of cloud coverage on the last five days from the focal investment day. The specification is OLS with robust standard errors clustered around campaigns. Table A2 provides the definitions of all variables. *, **, and *** indicate statistical significance at levels of 10%, 5%, and 1%, respectively.

Table A5
Effect of deviation from the previous day's cloud coverage on investment size.

	(1)	(2)	(3)
Dependent variable: Amount (log)			
Change in cloud cover	−0.071**	−0.060**	−0.080***
	(0.031)	(0.028)	(0.029)
Investor's total prior investments (log)		0.506***	0.451***
		(0.011)	(0.011)
First investment		3.603***	3.127***
		(0.087)	(0.084)
Distance (log)		0.004	−0.024***
		(0.006)	(0.006)
Previous day's total investment (log)		0.028***	0.023***
		(0.003)	(0.003)
Percentage funded		1.491***	1.643***
		(0.194)	(0.187)
Campaign FE	Yes	Yes	Yes
City FE	No	No	Yes
Day of Week FE	Yes	Yes	Yes
Day of month FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
N	59,547	59,547	59,547
Number of campaigns	102	102	102
R^2	0.160	0.361	0.477
Adj. R^2	0.158	0.360	0.432

The dependent variable in all columns is *Amount (log)*, defined as the natural logarithm of investment amount in Euro. *Change in cloud cover* is defined as investment day's cloud coverage minus cloud coverage for previous investment day's cloud coverage. The specification is OLS with robust standard errors clustered around campaigns. Table A2 provides the definitions of all variables. *, **, and *** indicate statistical significance at levels of 10%, 5%, and 1%, respectively.

Table A6
Investment size across seasons.

Season	Mean	S.D.	p10	p25	p50	p75	p90
Spring	5.001	1.708	2.398	3.932	5.017	6.217	6.909
Summer	5.165	1.620	3.045	4.025	5.303	6.217	7.004
Autumn	5.305	1.693	3.045	4.511	5.303	6.321	7.601
Winter	5.025	1.721	2.398	3.932	5.017	6.217	6.909
Total	5.132	1.690	2.773	3.932	5.303	6.217	7.171

This table presents summary statistics of average investment size across seasons.

References

Ahlers, G.K., Cumming, D., Günther, C., Schweizer, D., 2015. Signaling in Equity Crowdfunding. Entrepreneurship Theory and Practice, 39, pp. 955–980.
Amit, R., Brander, J., Zott, C., 1998. Why do venture capital firms exist? Theory and Canadian evidence. J. Bus. Ventur. 13, 441–466.
Bassi, A., Colacito, R., Fulghieri, P., 2013. 'o sole mio: an experimental analysis of weather and risk attitudes in financial decisions. Rev. Financ. Stud. 26, 1824–1852.
Benedetti, F., Colombo, C., Pontiggia, A., Bernasconi, A., Florita, M., Smeraldi, E., 2003. Morning light treatment hastens the antidepressant effect of citalopram: a placebo-controlled trial. J. Clin. Psychiatry 64, 648–653.
Bergsma, K., Jiang, D., 2016. Cultural new year holidays and stock returns around the world. Financ. Manag. 45, 3–35.
Bertoni, F., Colombo, M.G., Grilli, L., 2011. Venture capital financing and the growth of high-tech start-ups: disentangling treatment from selection effects. Res. Policy 40, 1028–1043.
Block, J., Hornuf, L., Moritz, A., 2018. Which updates during an equity crowdfunding campaign increase crowd participation? Small Bus. Econ. 50, 3–27.
Busenitz, L.W., Barney, J.B., 1997. Differences between entrepreneurs and managers in large organizations: biases and heuristics in strategic decision-making. J. Bus. Ventur. 12, 9–30.
Bushee, B.J., Friedman, H.L., 2015. Disclosure standards and the sensitivity of returns to mood. Rev. Financ. Stud. 29, 787–822.
Busse, M.R., Pope, D.G., Pope, J.C., Silva-Risso, J., 2015. The psychological effect of weather on car purchases. Q. J. Econ. 130, 371–414.
Byrnes, J.P., Miller, D.C., Schafer, W.D., 1999. Gender differences in risk taking: a meta-analysis. Psychol. Bull. 125, 367.
Charness, G., Gneezy, U., 2012. Strong evidence for gender differences in risk taking. J. Econ. Behav. Organ. 83, 50–58.
Chhaochharia, V., Kim, D., Korniotis, G.M., Kumar, A., 2019. Mood, firm behavior, and aggregate economic outcomes. J. Financ. Econ. 132, 427–450.
Cholakova, M., Clarysse, B., 2015. Does the possibility to make equity investments in crowdfunding projects crowd out reward-based investments? Entrepreneurship Theor. Pract. 39, 145–172.
Chou, K.-L., Lee, T., Ho, A.H., 2007. Does mood state change risk taking tendency in older adults? Psychol. Aging 22, 310.
Claustrat, B., Leston, J., 2015. Melatonin: physiological effects in humans. Neurochirurgie 61, 77–84.
Clore, G.L., Schwarz, N., Conway, M., 1994. Affective causes and consequences of social information processing. In: Handbook of Social Cognition, 1, pp. 323–417.
Colombo, M.G., Franzoni, C., Rossi-Lamastra, C., 2015. Internal social capital and the attraction of early contributions in crowdfunding. Entrepreneurship Theor. Pract. 39, 75–100.
Conlin, M., O'Donoghue, T., Vogelsang, T.J., 2007. Projection bias in catalog orders. Am. Econ. Rev. 97, 1217–1249.
Cooper, A.C., Woo, C.Y., Dunkelberg, W.C., 1988. Entrepreneurs' perceived chances for success. J. Bus. Ventur. 3, 97–108.
Cortés, K., Duchin, R., Sosyura, D., 2016. Clouded judgment: the role of sentiment in credit origination. J. Financ. Econ. 121, 392–413.

Croson, R., Gneezy, U., 2009. Gender differences in preferences. J. Econ. Lit. 47, 448–474.
Crowley, S.J., Lee, C., Tseng, C.Y., Fogg, L.F., Eastman, C.I., 2003. Combinations of bright light, scheduled dark, sunglasses, and melatonin to facilitate circadian entrainment to night shift work. J. Biol. Rhythm. 18, 513–523.
Cumming, D., Meoli, M., Vismara, S., 2018. Does equity crowdfunding democratize entrepreneurial finance? Small Bus. Econ. 1–20.
Cumming, D., Meoli, M., Vismara, S., 2019. Investors' choices between cash and voting rights: evidence from dual-class equity crowdfunding. Res. Policy 48 (8).
Cumming, D., Hervé, F., Manthé, E., Schwienbacher, A., 2020. Testing-the-waters policy with hypothetical investment: evidence from equity crowdfunding. Entrepreneurship Theor. Pract. p. 1042258720932522.
Dehaan, E., Madsen, J., Piotroski, J.D., 2017. Do weather-induced moods affect the processing of earnings news? J. Account. Res. 55, 509–550.
Demir, T., Mohammadi, A., Shafi, K., 2019. Crowdfunding as Gambling: Evidence From Repeated Natural Experiments.
Dichev, I.D., Janes, T.D., 2003. Lunar cycle effects in stock returns. J. Priv. Equity 6, 8–29.
Drake, M.S., Gee, K.H., Thornock, J.R., 2016. March market madness: the impact of value-irrelevant events on the market pricing of earnings news. Contemp. Account. Res. 33, 172–203.
Eckel, C.C., Grossman, P.J., 2008. Men, women and risk aversion: experimental evidence. In: Handbook of Experimental Economics Results, 1, pp. 1061–1073.
Edmans, A., Garcia, D., Norli, Ø., 2007. Sports sentiment and stock returns. J. Financ. 62, 1967–1998.
Faccio, M., Marchica, M.-T., Mura, R., 2016. Ceo gender, corporate risk-taking, and the efficiency of capital allocation. J. Corp. Finan. 39, 193–209.
Florida, R., 2005. Cities and the Creative Class. Routledge.
Goetzmann, W.N., Zhu, N., 2005. Rain or shine: where is the weather effect? Eur. Financ. Manag. 11, 559–578.
Goetzmann, W.N., Kim, D., Kumar, A., Wang, Q., 2014. Weather-induced mood, institutional investors, and stock returns. Rev. Financ. Stud. 28, 73–111.
Grable, J.E., Roszkowski, M.J., 2008. The influence of mood on the willingness to take financial risks. J. Risk Res. 11, 905–923.
Greifeneder, R., Bless, H., 2007. Relying on accessible content versus accessibility experiences: the case of processing capacity. Soc. Cogn. 25, 853–881.
Guenther, C., Johan, S., Schweizer, D., 2018. Is the crowd sensitive to distance?—how investment decisions differ by investor type. Small Bus. Econ. 50, 289–305.
Harris, J.D., Sapienza, H.J., Bowie, N.E., 2009. Ethics and entrepreneurship. J. Bus. Ventur. 24, 407–418.
Hegde, D., Tumlinson, J., 2014. Does social proximity enhance business partnerships? Theory and evidence from ethnicity's role in us venture capital. Manag. Sci. 60, 2355–2380.
Hervé, F., Manthé, E., Sannajust, A., Schwienbacher, A., 2019. Determinants of individual investment decisions in investment-based crowdfunding. J. Bus. Financ. Acc. 46, 762–783.
Hirshleifer, D., Shumway, T., 2003. Good day sunshine: stock returns and the weather. J. Financ. 58, 1009–1032.
Hornuf, L., Schmitt, M., 2016. Does a Local Bias Exist in Equity Crowdfunding?. In: Max Planck Institute for Innovation & Competition Research Paper.
Hornuf, L., Schwienbacher, A., 2018. Market mechanisms and funding dynamics in equity crowdfunding. J. Corp. Finan. 50, 556–574.
Howarth, E., Hoffman, M.S., 1984. A multidimensional approach to the relationship between mood and weather. Br. J. Psychol. 75, 15–23.
Isbell, L.M., Wyer Jr., R.S., 1999. Correcting for mood-induced bias in the evaluation of political candidates: the roles of intrinsic and extrinsic motivation. Personal. Soc. Psychol. Bull. 25, 237–249.
Kamstra, M.J., Kramer, L.A., Levi, M.D., 2000. Losing sleep at the market: the daylight saving anomaly. Am. Econ. Rev. 90, 1005–1011.
Kamstra, M.J., Kramer, L.A., Levi, M.D., 2003. Winter blues: a sad stock market cycle. Am. Econ. Rev. 93, 324–343.
Kamstra, M.J., Kramer, L.A., Levi, M.D., Wermers, R., 2017. Seasonal asset allocation: evidence from mutual fund flows. J. Financ. Quant. Anal. 52, 71–109.
Kaplanski, G., Levy, H., 2010. Sentiment and stock prices: the case of aviation disasters. J. Financ. Econ. 95, 174–201.
Keller, M.C., Fredrickson, B.L., Ybarra, O., Côté, S., Johnson, K., Mikels, J., Conway, A., Wager, T., 2005. A warm heart and a clear head: the contingent effects of weather on mood and cognition. Psychol. Sci. 16, 724–731.
Kleinert, S., Volkmann, C., Grünhagen, M., 2018. Third-party signals in equity crowdfunding: the role of prior financing. Small Bus. Econ. 1–25.
Kovács, B., 2017. Too hot to reject: the effect of weather variations on the patent examination process at the United States patent and trademark office. Res. Policy 46, 1824–1835.
Kramer, L.A., Weber, J.M., 2012. This is your portfolio on winter: seasonal affective disorder and risk aversion in financial decision making. Soc. Psychol. Personal. Sci. 3, 193–199.
Kripke, D.F., 1998. Light treatment for nonseasonal depression: speed, efficacy, and combined treatment. J. Affect. Disord. 49, 109–117.
Kuhnen, C.M., Knutson, B., 2011. The influence of affect on beliefs, preferences, and financial decisions. J. Financ. Quant. Anal. 46, 605–626.
Lam, R.W., Levitt, A.J., Levitan, R.D., Enns, M.W., Morehouse, R., Michalak, E.E., Tam, E.M., 2006. The can-sad study: a randomized controlled trial of the effectiveness of light therapy and fluoxetine in patients with winter seasonal affective disorder. Am. J. Psychiatr. 163, 805–812.
Lambert, G.W., Reid, C., Kaye, D.M., Jennings, G., Esler, M.D., 2002. Effect of sunlight and season on serotonin turnover in the brain. Lancet 360, 1840–1842.
Li, C., Luo, X., Zhang, C., Wang, X., 2017. Sunny, rainy, and cloudy with a chance of mobile promotion effectiveness. Mark. Sci. 36, 762–779.
Loewenstein, G.F., Weber, E.U., Hsee, C.K., Welch, N., 2001. Risk as feelings. Psychol. Bull. 127, 267.
Loughran, T., Schultz, P., 2004. Weather, stock returns, and the impact of localized trading behavior. J. Financ. Quant. Anal. 39, 343–364.
Lucey, B.M., 2010. Lunar seasonality in precious metal returns? Appl. Econ. Lett. 17, 835–838.
Lukkarinen, A., Teich, J.E., Wallenius, H., Wallenius, J., 2016. Success drivers of online equity crowdfunding campaigns. Decis. Support. Syst. 87, 26–38.
Mohammadi, A., Shafi, K., 2018. Gender differences in the contribution patterns of equity-crowdfunding investors. Small Bus. Econ. 50, 275–287.
Ottati, V.C., Isbell, L.M., 1996. Effects on mood during exposure to target information on subsequently reported judgments: an on-line model of misattribution and correction. J. Pers. Soc. Psychol. 71, 39.
Parrott, W.G., Sabini, J., 1990. Mood and memory under natural conditions: evidence for mood incongruent recall. J. Pers. Soc. Psychol. 59, 321.
Piva, E., Rossi-Lamastra, C., 2018. Human capital signals and entrepreneurs' success in equity crowdfunding. Small Bus. Econ. 51, 667–686.
Powell, M., Ansic, D., 1997. Gender differences in risk behaviour in financial decision-making: an experimental analysis. J. Econ. Psychol. 18, 605–628.
Praschak-Rieder, N., Willeit, M., Wilson, A.A., Houle, S., Meyer, J.H., 2008. Seasonal variation in human brain serotonin transporter binding. Arch. Gen. Psychiatry 65, 1072–1078.
Prasko, J., 2008. Bright light therapy. Neuro endocrinology letters, 29, pp. 33–64.
Ralcheva, A., Roosenboom, P., 2018. Forecasting success in equity crowdfunding. Small Bus. Econ. 1–18.
Rick, S., Loewenstein, G., 2008. The role of emotion in economic behavior. In: Handbook of Emotions, 3, pp. 138–158.
Rider, C.I., 2012. How employees' prior affiliations constrain organizational network change: a study of u.s. venture capital and private equity. Adm. Sci. Q. 57, 453–483.
Rind, B., 1996. Effect of beliefs about weather conditions on tipping. J. Appl. Soc. Psychol. 26, 137–147.
Rosenthal, N.E., Sack, D.A., Gillin, J.C., Lewy, A.J., Goodwin, F.K., Davenport, Y., Mueller, P.S., Newsome, D.A., Wehr, T.A., 1984. Seasonal affective disorder: a description of the syndrome and preliminary findings with light therapy. Arch. Gen. Psychiatry 41, 72–80.
Sanassi, L.A., 2014. Seasonal affective disorder: is there light at the end of the tunnel? J. Am. Acad. PAs 27, 18–22.
Saunders, E.M., 1993. Stock prices and wall street weather. Am. Econ. Rev. 83, 1337–1345.
Schoonhoven, C.B., Eisenhardt, K.M., Lyman, K., 1990. Speeding products to market: waiting time to first product introduction in new firms. Adm. Sci. Q. 177–207.
Schwarz, N., Clore, G.L., 1983. Mood, misattribution, and judgments of well-being: informative and directive functions of affective states. J. Pers. Soc. Psychol. 45, 513.
Sedikides, C., 1995. Central and peripheral self-conceptions are differentially influenced by mood: tests of the differential sensitivity hypothesis. J. Pers. Soc. Psychol. 69, 759.
Shafi, K., 2019. Investors' evaluation criteria in equity crowdfunding. Small Bus. Econ.
Shafi, K., Mohammadi, A., Johan, S.A., 2020. Investment ties gone awry. Acad. Manag. J. 63, 295–327.
Siemer, M., Reisenzein, R., 1998. Effects of mood on evaluative judgements: influence of reduced processing capacity and mood salience. Cognit. Emot. 12, 783–805.

Simonsohn, U., 2009. Weather to go to college. Econ. J. 120, 270–280.
Sorenson, O., Stuart, T.E., 2001. Syndication networks and the spatial distribution of venture capital investments. Am. J. Sociol. 106, 1546–1588.
Spindelegger, C., Stein, P., Wadsak, W., Fink, M., Mitterhauser, M., Moser, U., Savli, M., Mien, L.-K., Akimova, E., Hahn, A., et al., 2012. Light-dependent alteration of serotonin-1a receptor binding in cortical and subcortical limbic regions in the human brain. World J. Biol. Psychiatry 13, 413–422.
Stuart, T.E., Hoang, H., Hybels, R.C., 1999. Interorganizational endorsements and the performance of entrepreneurial ventures. Adm. Sci. Q. 44, 315–349.
Sunden, A.E., Surette, B.J., 1998. Gender differences in the allocation of assets in retirement savings plans. Am. Econ. Rev. 88, 207–211.
Vismara, S., 2016a. Equity retention and social network theory in equity crowdfunding. Small Bus. Econ. 46, 579–590.
Vismara, S., 2016b. Information cascades among investors in equity crowdfunding. In: Entrepreneurship Theory and Practice.
Vulkan, N., Åstebro, T., Sierra, M.F., 2016. Equity crowdfunding: a new phenomena. J. Bus. Ventur. Insights 5, 37–49.
Walthoff-Borm, X., Schwienbacher, A., Vanacker, T., 2018. Equity crowdfunding: first resort or last resort? J. Bus. Ventur. 33, 513–533.
Wang, Y.A., Young, M., 2019. Terrorist attacks and investor risk preference: Evidence from mutual fund flows. J. Financ. Econ. 137 (2). Forthcoming.
Wyer Jr., R.S., Clore, G.L., Isbell, L.M., 1999. Affect and information processing. In: Advances in Experimental Social Psychology, 31. Elsevier, pp. 1–77.
Yuen, K.S., Lee, T.M., 2003. Could mood state affect risk-taking decisions? J. Affect. Disord. 75, 11–18.
Zhang, B., Ziegler, T., Mammadova, L., Johanson, D., Gray, M., Yerolemou, N., 2018. The 5th uk alternative finance industry report. In: Tech. Rep. The Cambridge Centre for Alternative Finance.