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Clouded judgment: The role of sentiment in credit origination☆

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ABSTRACT

Using daily fluctuations in local sunshine as an instrument for sentiment, we study its effect on day-to-day decisions of lower-level financial officers. Positive sentiment is associated with higher credit approvals, and negative sentiment has the opposite effect of a larger magnitude. These effects are stronger when financial decisions require more discretion, when reviews are less automated, and when capital constraints are less binding. The variation in approval rates affects ex post financial performance and produces significant real effects. Our analysis of the economic channels suggests that sentiment influences managers' risk tolerance and subjective judgment.

1. Introduction

Corporate outcomes depend on daily financial decisions, many of which are made by managers outside the executive suite and away from the headquarters. Because these decisions nearly always involve personal judgment, they may be affected by the agent's psychological factors, such as fluctuations in mood and emotional state, broadly referred to as sentiment.

Given the inherent subjectivity in corporate decisions, understanding the role of sentiment is important. At the firm level, sentiment may increase or hinder an agent's productivity and alter the assessment of investment projects. For example, Graham, Harvey, and Puri (2015) provide survey evidence that up to one-half of managers rely on their 'gut feel' in investment decisions. At the aggregate level, sentiment may propagate across agents and generate spillovers across markets (Baker, Wurgler, and Yuan, 2012). For example, Shiller (2015) attributes the recent financial crisis to positive sentiment in the financial sector which skewed managerial expectations and overextended financial firms.

Despite the potential importance of these effects, clean evidence on the role of sentiment in corporate decisions is difficult to obtain. First, day-to-day financial decisions are usually unobservable. Second, even if they could be traced, it is difficult to evaluate their outcomes without knowing the opportunity set—namely, the options that were

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considered but rejected. Third, while sentiment is one of the most volatile personal traits, it is hard to measure at the time of the agent's decision and to separate from the confounding economic factors.

Our paper provides micro evidence on the role of sentiment in the day-to-day decisions of lower-level financial officers. To address identification challenges, we focus on a large number of regular, well-understood decisions at financial firms, namely, credit approvals. In this setting, the decision is standardized, the opportunity set is observable, and the ex post outcome is clear. With over $1 trillion in annual transaction volume, this is an economically important market with significant real effects.

As a source of exogenous variation in sentiment that matches the frequency of financial decisions, while being uncorrelated with information, we exploit daily variation in local sunshine across over 2,000 counties in 1998–2010. This identification strategy is grounded in prior evidence on the effect of sunshine on an agent's mood from psychology (Schwarz and Clore, 1983), experimental economics (Bassi, Colacito, and Fulghieri, 2013), and financial markets (Hirshleifer and Shumway, 2003; Goetzmann, Kim, Kumar, and Wang, 2015).

Our main finding is that positive sentiment, attributable to daily variation in local sunshine, leads to higher credit approvals, and negative sentiment generates the opposite effect. Using hourly data on cloud cover for each county-day, we 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. These estimates account for county$*$month fixed effects which absorb monthly variation in economic fundamentals unique to each county, such as investment opportunities, competition, and managerial skills and incentives. Thus, our estimates reflect changes in managerial decisions relative to the baseline average observed over the same month, for the same set of firms, and in the same geographic location. These estimates also control for the observable fundamentals of loan applications reviewed on a given county-day, including household income, leverage, and demographics.

The variation in credit approvals in response to the sentiment primer has significant real effects. A rough estimate of the extra credit approved on one perfectly sunny day relative to one fully overcast day is about $150 million nationwide or $91,000 per county-day. These estimates are very similar whether we use raw or seasonally adjusted measures of local sunshine as a source of variation in sentiment.

In the cross-section of loans, the effect of sentiment increases when financial officers have more discretion. For example, sentiment has a stronger effect on the approvals of applications by low-income and medium-income households, which require more judgment. In contrast, the effect of sentiment disappears when the decision is clear-cut and when pre-approvals are common—namely, for high-quality applications from households earning over $100,000 per year.

In the cross-section of firms, the effect is stronger for smaller, local firms. At such firms, approval decisions are typically less automated, and all of the managerial actions are confined to the firm's small geographic domain, thus allowing for a more precise estimation of sentiment proxies. In contrast, the sentiment effect drops by up to one-half for large, national firms where managerial decisions are more standardized and where nonlocal influence is more likely.

In the time-series analysis, we find that the economic importance of sentiment varies across business cycles. For example, the effect of daily variation in sentiment on officers' decisions more than doubles during the credit boom in the early 2000s. This evidence suggests that sentiment has a stronger effect on managerial decisions when capital constraints are less binding and when monitoring is loose.

Next, to disentangle the effect of managerial discretion from variation in loan characteristics, we provide evidence on the relation between daily sunshine and loan pricing—an important decision variable determined by computerized algorithms. This outcome variable seeks to capture all of the loan's hard data, both public and private, but requires little discretionary input from the officer.

We find no relation between daily sunshine and loan pricing. This evidence demonstrates that the empirical link between the sentiment proxy and credit extension is confined to discretionary outcome variables and does not show up in automated decision outcomes for the same financial products. This dichotomy shows that the relation between sentiment and daily approvals is not driven by an omitted risk characteristic of the underlying loan, which would likely affect both discretionary and automated decisions that use the same input data. Another important conclusion is that higher approval rates on sunny days are not offset by higher interest rates and represent a measurable shift in credit outcomes.

Next, we evaluate the ex post performance of loans approved on sunny and cloudy days. The evidence shows that loans approved on sunny days experience significantly higher defaults. In particular, a one standard deviation reduction in the deseasoned cloud cover on the day of the loan approval is associated with a 2.7% higher loan default rate, controlling for observable loan characteristics. While the variation in weather captures only a fraction of the daily variation in agents' moods, these estimates show that correlated mood changes produce significant real consequences.

In our final analysis, we consider several non-mutually exclusive channels through which the variation in sunshine may affect officers' decisions. The first channel—risk tolerance—suggests that managers in a good mood show higher risk tolerance and approve a greater fraction of risky loans. Loewenstein, Weber, Hsee, and Welch (2001) theoretically demonstrate that an individual's mood affects risk-taking behavior, and several recent studies find support for this hypothesis in an experimental setting. In a controlled experiment, Bassi, Colacito, and Fulghieri (2013) find that subjects report more positive mood states on sunny days and, when presented with a choice of lottery payoffs, exhibit higher risk tolerance. In another experiment, Kramer and Weber (2012) find that an individual's tolerance to financial risks increases with the amount of sunlight and connect their findings to the link between emotional state and risk aversion.

Our evidence suggests that the risk tolerance channel contributes to the behavior of financial officers. Using salient measures of loan risk, available to the officer at the time of application review, we find that an increase in local sunshine is associated with riskier lending. A change in the deseasoned cloud cover from the score of 8 (overcast) to 0 (perfectly sunny) on the day of the loan approval is associated with a 108 basis-point increase in the loan-to-value ratio and a 3.4 point drop in the credit score of approved loans. The salience of these risk measures at the time of loan approval suggests that officers show higher risk tolerance on positive sentiment days.

The second channel—mood attribution—posits that a positive (negative) mood generates an upward (downward) bias in the subjective assessment of application quality. For example, an officer in a good mood may evaluate the same loan data more favorably, and such assessments can lead to higher loan approvals. This channel is grounded in the evidence from psychology that subjects project their moods from one setting (weather) onto unrelated economic tasks, such as assessments of quality, satisfaction, and economic outcomes.[1] When primed by positive states, agents also show greater confidence in their subjective judgments and a stronger reliance on personal discretion in their decisions.

The evidence suggests that the mood attribution channel is likely operative in our setting. When we investigate the reasons stated by loan officers for their decisions, we find that a loan with the same quantitative measures of risk is less likely to be rejected for subjective reasons (discussed in the empirical section) on sunny days, compared to an observationally similar loan reviewed in the same county during the same month. In other words, an increase in local sunshine corresponds to a decline in the fraction of loans denied for subjective reasons, possibly because an officer interprets the same information more favorably when primed with a positive mood stimulus.

Second, while loans approved on sunny days are observably riskier, consistent with higher risk tolerance, they default significantly more often than would be expected based on their observable risk characteristics. This result appears consistent with an upward bias in the assessment of loan quality over and above the available risk characteristics.

The third channel—allocation of effort—posits that variation in sunshine affects managers' productivity or leads them to selectively review particular applications. For example, if managers incur disutility from reporting negative outcomes on positive sentiment days, they may selectively review stronger applications on sunny days and postpone their rejections to cloudy days. Alternatively, sunshine may affect managerial effort spent on application reviews. If managers allocate less time to application reviews on sunny days, they may review a greater fraction of quick-to-approve loans to free up time for an early departure, thus increasing the average approval rate.

We find little support for this channel. The evidence shows no discernible relation between daily variation in local sunshine and the volume or quality of applications reviewed. We also find no evidence that an increase in loan approvals on sunny days is followed by an abnormal drop in loan approvals over the next several days, as would be expected if managers selectively approved stronger applications, while creating a backlog of denials that would be cleared later. Similarly, we do not find that a decline in loan approvals on cloudy days is followed by an abnormal increase in loan approvals.

In another test of the effort allocation channel, we investigate selection of applications on unobservable measures of quality. For example, a loan officer may choose to review applications with negative soft information on overcast days, resulting in a lower approval rate. This practice will create a backlog of applications with positive soft information that would be approved over the next several days. If these unobservable characteristics are important for loan performance, they should be ultimately reflected in loan defaults. Therefore, under such a scenario, loans approved over the next several days after an overcast day should be unobservably better and less likely to default. In contrast, we find that daily measures of sunshine are unrelated to the average default rate of loans approved in the same county over subsequent days, an outcome inconsistent with selection on unobservables.

Our findings have important implications. First, changes in an agent's mood influence important daily decisions at financial firms. These effects arise even when trained financial experts repeatedly evaluate standardized projects, have access to verified data, and observe the outcomes of their decisions. Second, when common psychological factors drive correlated mood changes across decision agents, they produce significant real consequences. Third, the mechanism underlying the effect of mood on economic decisions is likely linked to changes in risk tolerance and subjective judgment.

The central contribution of this article is to provide micro evidence on the effect of daily sentiment on routine corporate decisions and to evaluate its real outcomes. To our knowledge, this paper is one of the first to investigate and contrast a number of channels through which the mood of lower-level financial officers affects their decisions.

2. Related literature

Our paper is part of the literature in behavioral corporate finance that studies the effect of psychological factors on economic decisions, a strand of work surveyed in Baker and Wurgler (2012). Prior evidence shows that managerial decisions are affected by a number of psychological traits. So far, the literature has focused mostly on time-persistent traits, such as confidence (Malmendier and Tate, 2005, 2008; Gervais, Heaton, and Odean, 2011), extraversion (Green, Jame, and Lock, 2015), and propensity to anchoring (Dougal, Engelberg, Parsons, and Van Wesep, 2015).

[1] For example, Schwarz and Clore (1983), Wann et al. (1994), and Rind (1996), among many others.

While these long-run characteristics determine a distinct managerial style, day-to-day decisions vary for the same managers and comparable information sets. For example, about a half of surveyed managers admit that they approve or deny projects based on a 'gut feel,' a subjective assessment at the time of the decision (Graham, Harvey, and Puri, 2015). Evidence in psychology suggests that an agent's mood is one of the most powerful high-frequency factors that influence subjective judgments. Our paper studies subjective decisions on millions of standardized projects and shows how managers adjust their decisions in response to mood primers, while most other characteristics remain constant.

Prior work in behavioral corporate finance has focused mostly on financial policies of the upper management, such as leverage (Malmendier, Tate, and Yan, 2011; Dittmar and Duchin, 2016), financing (Green, Hwang, and Wang, 2015), investment (Gervais, 2010), acquisitions (Ahern, Daminelli, and Fracassi, 2015), and research and development (Hirshleifer, Low, and Teoh, 2012). While these strategic choices are made in the executive suite, their implementation depends on the decisions of managers much further down in the hierarchy. For example, investment budgets ultimately trickle down to department managers who allocate them across projects. Similarly, while the top management at financial firms determines the overall credit policy, the quality of credit origination depends on the decisions of thousands of loan officers. In contrast to the focus on the infrequent policy changes by the top management, we provide evidence on the daily decisions of lower-level officers that underpin their execution.

Our paper also adds to the emerging literature on the role of behavioral factors in credit origination. Engelberg, Gao, and Parsons (2012) find that personal connections between firm employees and bank managers are associated with more favorable lending terms, such as larger loan amounts and less restrictive covenants. Using an electronic peer-to-peer lending market, Duarte, Siegel, and Young (2012) provide evidence that micro-lending decisions are affected by the creditor's perception of the borrower's trustworthiness and physical appearance. In a field experiment in India, Chen, Moskowitz, and Shue (2015) find that loan officers underestimate the likelihood of sequential streaks under the law of small numbers. Our paper extends this literature by studying the role of loan officers' moods in one of the most liquid and competitive credit markets. In contrast to a focus on idiosyncratic characteristics which may cancel out in the aggregate, we show that changes in mood can be correlated across agents and geographic markets and demonstrate that such correlated changes produce significant real effects.

3. Empirical design and data

This section motivates our focus on sunshine as a primer of mood and serves as a starting point for evaluating its relevance and exogeneity. We also provide institutional details on the loan approval process, loan officers, and their decision outcomes.

3.1. Sunshine as a mood primer

We exploit variation in local sunshine as a driver of an agent's mood. This approach is motivated by a robust monotonic relation between sunshine and mood documented in multiple contexts in psychology, neurobiology, medicine, and experimental economics. In this subsection, we briefly discuss this evidence as a first step in assessing the relevance of sunshine as a primer for managerial mood and evaluate other properties of this instrument.

The effect of daily sunshine on mood has been established and replicated in a variety of research settings in social psychology and experimental economics over the past few decades. In early work, Persinger (1975) and Cunningham (1979) show that sunshine is positively correlated with self-reported mood, and Schwarz and Clore (1983) find that subjects queried on sunny days report happier moods and greater life satisfaction than those queried on overcast days. Parrott and Sabini (1990) demonstrate that subjects' exposure to clear and cloudy skies serves as an effective way of eliciting happy and sad moods, respectively. More recently, Scott (2007) examines how subjects' daily moods vary with daily local sunshine over several weeks and concludes that "sunshine was identified as the crucial factor for mood adjustment." Bassi, Colacito, and Fulghieri (2013) randomly assign subjects to experimental sessions held on sunny and overcast days and find that sunshine leads to significantly more positive self-reported mood.

Sunshine is the most robust environmental mood primer. It produces a large and monotonic effect on mood. Persinger and Levesque (1983) show that weather conditions explain about 40% of daily variation in mood and find that sunshine has the strongest immediate effect. Howarth and Hoffman (1984) examine eight weather variables and find that the number of hours of sunshine is the only one related to optimism scores. Rind (1996) conducts a study in which subjects are exposed to multiple weather conditions and finds that sunshine influences self-reported mood and subjects' behavior, but other environmental factors such as temperature and precipitation have no incremental effect. Saunders (1993) reaches a similar conclusion in a study of the effect of weather on stock prices after considering other environmental factors, such as temperature, precipitation, humidity, and wind.

Research in neurobiology reveals the mechanism that underlies the robust relation between sunshine and human mood. Among recent studies, Lambert, Reid, Kaye, Jennings, and Esler (2002), Praschak-Rieder, Willeit, Wilson, Houle, and Meyer (2008), and Spindelegger, Stein, Wadsak, Fink, Mitterhauser, Moser, Savli, Mien, Akimova, Hahn, Willeit, Kletter, Kasper, and Lanzenberger (2012) provide evidence that sunlight increases the release of serotonin, a monoamine neurotransmitter associated with happiness and elevated emotional states. The significance of this effect is illustrated by the fact that many antidepressant medications target the secretion of serotonin in order to treat mood disorders and depression. In contrast, a drop in sunlight triggers the production of melatonin, a hormone secreted by the pineal gland in the brain and associated with depression, fatigue, and sleepiness. Exposure to sunlight halts the secretion of melatonin. Crowley, Lee, Tseng, Fogg, and Eastman (2003) and Claustrat and Leston (2015) provide recent evidence on the effect of sunlight on melatonin secretion.

The efficacy of sunlight as a mood stimulus is also demonstrated by research in medicine, which shows that the administration of sunlight, or light therapy, is an effective mood altering treatment. In controlled-trial comparisons, light therapy has been found as effective as antidepressants in treating mood disorders, while providing a quicker therapeutic effect (Lam, Levitt, Levitan, Enns, Morehouse, Michalak, and Tam 2006). When combined with antidepressants, exposure to sunlight strengthens and accelerates patients' mood adjustments (Benedetti, Colombo, Pontiggia, Bernasconi, Florita, and Smeraldi, 2003). Recent clinical work suggests light therapy as the first-line treatment for many types of mood disturbances and depressive disorders, citing its efficacy and few side effects (Prasko, 2008; Sanassi, 2014).

In addition to serving as a powerful mood stimulus, sunshine has several other useful properties for identification. First, changes in sunshine are plausibly orthogonal to economic fundamentals. Second, variation in sunshine is measured at a frequency that closely matches the frequency of economic decisions in our setting. By exploiting daily variation in sunshine, our empirical design holds constant other drivers of economic decisions which remain invariant in the short run, such as firm policies, market fundamentals, managerial incentives and expertise, and many others. Third, in contrast to national measures of sentiment that assume market-wide homogeneity, this proxy affords rich cross-sectional variation across geographic regions on any given day.

Combined together, these properties generate an exogenous, high-frequency driver of mood unique to each geographic market. In contrast to measures of sentiment inferred from various forms of economic activity (surveyed in Baker and Wurgler, 2007; Da, Engelberg, and Gao, 2015), this approach allows us to separate the effect of mood on economic outcomes from the reverse relation—the effect of economic conditions on mood. This distinction is important because causality could run in both directions. For example, Karabulut (2013) argues that investor sentiment inferred from social media drives stock returns, while Cowgill and Zitzewitz (2013) suggest that causality runs in the opposite way—namely, a firm's stock return drives the mood of its employees. Finally, in contrast to sentiment proxies inferred from observable activities, in which the driver of mood is typically unknown, our empirical design isolates the identifying source of its variation—namely, an exogenous environmental factor.

3.2. Weather data

We obtain data on local weather from the Integrated Surface Database of the National Oceanic and Atmospheric Administration (NOAA), a federal agency tasked with monitoring the oceans and the atmosphere. The NOAA database contains hourly weather observations from over 35,000 weather stations in the U.S. and abroad, of which 14,000 stations are active. Using the geographic coordinates of each weather station, we map stations to U.S. counties by selecting the weather station closest to the geographic center of the county. To ensure precise measurement of weather conditions, we exclude 73 counties (2.4% of all counties) located more than 50 miles from the nearest weather station. The average (median) distance from the county center to the nearest weather station is 19 (18) miles.

Cloud cover conditions are reported hourly on a nine-point scale, ranging from 0 (clear) to 8 (overcast). To construct our first measure of cloudiness, *Cloud cover*, we use the mean score of cloud cover between 8 a.m. and 4 p.m. (local time) at each weather station, following the approach in Loughran and Schultz (2004). Table 1, Panel A, shows that the average (median) *Cloud cover* is 3.4 (2.8). The data reveal large time-series variation: in the average county-month, the standard deviation of *Cloud cover* is 3.1, a magnitude comparable to the mean.

In addition to the average cloud cover, we introduce two indicator variables, *Sunny* and *Overcast*, which correspond to county-days with perfectly clear skies (daily *Cloud cover* = 0) and fully overcast skies (daily *Cloud cover* = 8), respectively. These variables test for asymmetry in the effect of positive and negative primers of mood. This research design is motivated by evidence in psychology that subjects respond more strongly to negative changes in mood than to positive changes of similar magnitude (e.g., Baumeister, Bratslavsky, Finkenauer, and Vohs, 2001). This prediction also follows from the prospect theory of Kahneman and Tversky (1979). In particular, if the average cloud cover serves as a reference point for a given day, drops below the reference point are expected to generate larger economic effects than comparable increases above the reference point. Panel A shows that about one-quarter of county-days are perfectly sunny or fully overcast between 8 a.m. and 4 p.m. These indicators provide consistent primers of mood, whether the manager observes the weather on the way to work, during his workday, or during the lunch break.

Our final measure of sunshine, *Deseasoned cloud cover (DCC)*, removes seasonal variation in weather specific to a given location. This measure is motivated by two factors. First, it separates changes in weather from seasonal variation in daylight associated with seasonal affective disorder, a factor that has been shown to alter subjects' risk tolerance in experimental settings (Kramer and Weber, 2012) and financial markets (Kamstra, Kramer, and Levi, 2003;Kamstra, Kramer, Levi, and Wermers, 2016). Second, by deseasoning our measure of cloud cover, we remove the effect of predictable intra-year economic cycles, such as seasonality in earnings, home sales, and credit demand. Following the intuition in Hirshleifer and Shumway (2003), we compute daily *DCC* by subtracting the average cloud cover observed in the same county during the same workweek of the year over the trailing three years. For example, to compute *DCC* on May 10, 2010 in Chicago, we record the actual *Cloud cover* on that day and then subtract the average *Cloud cover* in Chicago that was observed during the same (20th) workweek of the year over the trailing three years. The average cloud cover for the same time of the year in the near past provides a stable estimate of

Table 1
Summary statistics.
This table reports summary statistics for the main sample, which comprises mortgage applications reviewed in 1998–2010 by 7,748 FDIC-insured depository institutions subject to mandatory reporting under the Home Mortgage Disclosure Act (HMDA). The reported figures are sample-wide statistics unless stated otherwise. Panel A reports weather conditions based on data from the National Oceanic and Atmospheric Administration. Panel B covers loan officers and financial firms. Data on loan officers' compensation are from the Bureau of Labor Statistics for 2010. Data on financial firms are from Call Reports and CRSP. Data on bank branches are from the FDIC Summary of Deposits. Panel C shows summary statistics for loan applications. Data on loan applications are from the confidential version of the HMDA loan application registry obtained from the Federal Reserve Board. Data on loan interest rates, loan-to-value ratios, default rates, low-documentation borrowers, and FICO scores are reported for originated loans and come from LPS Applied Analytics. Variable definitions appear in Appendix A.

	Mean	25th percentile	Median	75th percentile	Standard deviation
Panel A: Weather conditions					
Distance to nearest weather station (miles)	19.38	8.52	17.70	27.32	11.63
Cloud cover (scale of 0–8)	3.44	0.00	2.78	6.86	3.14
Overcast indicator	0.27	0.00	0.00	1.00	0.44
Sunny indicator	0.26	0.00	0.00	1.00	0.44
Deseasoned cloud cover (DCC)	−0.04	−2.52	−0.53	2.48	3.08
Panel B: Firms and loan officers					
Loan officer compensation ($ per year)	65,900	40,340	56,490	80,140	32,809
Firm book assets ($ mil.)	2,011	99	201	457	28,500
Number of branches per firm	35	3	7	15	211
Publicly traded indicator (%)	7.6	0.0	0.0	0.0	0.4
Market value of equity ($ mil.)	2,374	38	116	443	13,300
Panel C: Borrower and loan characteristics					
Borrower income ($ per year)	85,726	46,000	66,333	97,000	104,294
Loan amount ($)	207,912	76,000	140,000	250,000	352,319
Debt-to-income ratio (DTI, %)	194.6	130.9	188.7	254.8	134.5
Fraction of minority applicants (%)	30.3	14.3	25.0	50.0	19.0
Fraction of low-documentation applicants (%)	23.3	10.5	19.0	33.3	17.7
Days from application submission to review	40	9	28	52	48
Applications reviewed per county-day	35.1	7.8	14.1	27.8	190.5
Loan approval rate (%)	65.11	58.95	65.73	72.30	10.93
Loan interest rate (%)	6.16	5.50	6.26	7.00	1.33
Loan-to-value ratio (LTV, %)	83.7	77.7	84.7	92.8	12.0
FICO score	707	676	712	744	54
Loan default rate (%)	2.60	0.50	1.19	8.72	8.91

normal weather conditions in a given location. As a result, *DCC* can be interpreted as abnormal cloud cover relative to the expected weather conditions during a given time of the year. Panel A shows that the average value of *DCC* is very close to zero, as expected from variable construction. Yet, the variable shows a large standard deviation of 3.1, a value comparable to the average daily cloud cover (3.4). This demonstrates that a large fraction of variation in daily sunshine cannot be easily predicted from seasonal patterns, a property that supports the exogeneity of the mood primer.

3.3. Loan officers and the loan review process

Our empirical analysis focuses on reviews of routine loans with well-standardized risk characteristics—namely, residential mortgages. The review process begins when a potential borrower submits a mortgage application. The application is then assigned to a loan officer at the branch where the application is submitted. A typical branch employs one or two loan officers, and the average number of loan officers per branch is 1.34 (untabulated).[2]

After the application is screened for completeness, the loan officer initiates the data verification process, which usually takes several weeks. During this period, the officer obtains information on the borrower's credit history, financial obligations, legal compliance, and employment records. Because this information comes from multiple sources, such as credit bureaus, state and federal agencies, and internal records, there is a significant time lag between the date of application submission and the date of application review. The duration of this time lag depends on a largely exogenous factor, namely, the combined response time of outside agencies which provide the information requested. The large temporal gap between the date of application submission and the date of application review, unique to each application, allows us to separate the effect of sentiment on credit supply (loan approvals) from the effect of sentiment on credit demand (mortgage applications).

After all the data have arrived, the application becomes complete and undergoes a formal review. To arrive at a decision, the officer may take into account hard and soft information, use personal judgment, and rely on financial software. Our discussions with loan officers indicate that this review nearly always takes less than one day. Because loan officers hold decision rights and use personal judgment, their decisions—like most corporate decisions—involve discretion. Recent work confirms that loan officers

[2] Specifically, in 2010, there are 132,230 mortgage officers at depository institutions (Bureau of Labor Statistics) working at 98,519 bank branches (Federal Deposit Insurance Corporation (FDIC) Summary of Deposits).

hold decision rights and exercise discretion in mortgage approvals (Tzioumis and Gee, 2013).

The compensation of a loan officer depends on the number of loans originated and their subsequent performance. The typical loan officer is rewarded for originating well-performing loans and penalized for loan defaults. These performance incentives are important, as evidenced by the large cross-sectional variation in the realized compensation of loan officers. Table 1, Panel B, shows aggregate compensation data from the Bureau of Labor Statistics for 2010. The average (median) loan officer earns $65,900 ($56,490) per year. The 25th and 75th compensation percentiles are $40,340 and $80,140, respectively. Consistent with the important role of performance incentives, the cross-sectional interquartile range ($39,800) is about three quarters of the median.

Loan officers are educated and certified financial managers. They must obtain a Mortgage Loan Originator license, which has to be renewed annually. To obtain a license, an officer must satisfy education and coursework requirements, pass an examination, and complete background checks. In addition, many officers undergo additional certification and training programs via the American Bankers Association and the Mortgage Bankers Association.

To summarize, loan officers provide a useful laboratory setting for studying the decisions of lower-level corporate officers because they hold decision rights, rely on personal discretion, have performance incentives, and possess financial knowledge.

3.4. Loan data and sample construction

Our main data set is the confidential version of the Home Mortgage Disclosure Act (HMDA) loan application registry obtained from the Board of Governors of the Federal Reserve System. This administrative data set, based on mandatory reporting to financial regulators, covers all mortgage applications reviewed by qualified financial firms.[3] To be included in the data, a firm must have at least one office branch in any metropolitan statistical area and meet the minimum size threshold. In 2004, the median sample year, this reporting threshold is $33 million in book assets, equivalent to the 14th size percentile of FDIC-insured depository institutions. Because of the low reporting threshold, the data set covers the majority of lenders, both publicly traded and privately held, and accounts for about 90% of the U.S. mortgage market. Table 1, Panel B, provides summary statistics for the 7,748 financial firms in our sample. The average firm owns book assets worth $2 billion and operates 35 branches. 7.6% of firms are publicly traded, and the average equity value of a public firm is $2.4 billion.

For each loan application, the data set provides borrower characteristics (e.g., income and race), loan attributes (e.g., loan amount and purpose), property characteristics (e.g., type and location at the level of a U.S. census tract), and the decision on the loan application (e.g., approved, denied, or closed for incompleteness). Our confidential version of the database also provides the date when the application is submitted and the date when the decision action is taken. If the decision action is a denial, the data set typically provides the loan officer's stated reason for denial. While the data reveal the identity of the loan officer's firm, the identity and personal characteristics of the loan officer are not reported.

To trace the performance of approved loans, we use Lender Processing Services (LPS) Applied Analytics, a data set compiled by Black Knight Financial Services Group. These data provide loan-level monthly status updates, including information on repayments, delinquencies, and loan modifications. The information comes from loan servicers and covers approximately two-thirds of the mortgage market, according to the estimates from the data provider. For each originated loan, the data include risk characteristics (e.g., FICO score and loan-to-value ratio), loan pricing information (e.g., loan amount, maturity, and interest rate), and property characteristics (e.g., appraised amount, geographic location, and property type). The data set also provides information on the date of loan origination and the identity of the financial firm approving the loan. Because this database focuses on loan performance, the data cover only originated loans.

To construct our sample, we begin with the universe of all HMDA loan applications submitted in 1998–2010 to FDIC-insured depository institutions included in the FDIC Summary of Deposits (SOD). Our sample starts in 1998 because data on loan performance are sparse in earlier years. To screen out possible data errors, we drop observations with missing decision action dates or decision action dates that fall on non-workdays. We also drop applications that were closed for incompleteness or withdrawn by the applicant before a decision was made. Finally, using the annual SOD panel on the locations of all bank branches, we drop loan applications filed with lenders that do not have a branch in the county of the mortgage property. These observations comprise broker-originated applications sent to external processing centers in which the location of the loan officer cannot be inferred from the property location.[4]

Table 1, Panel C, provides summary statistics on loan applications. The median borrower earns about $66,000 per year and applies for a $140,000 mortgage. The debt-to-income ratio, a measure of loan risk, has a mean of 195% and a standard deviation of 135%, revealing large cross-sectional variation. The average (median) period between the date of application submission and the decision action date is 40 (28) days, and the standard deviation is 48 days, consistent with the discussed variation in agency response times during data verification. On the average county-day, 35 applications are reviewed, and the average application approval rate is 65.1%.

The bottom rows of Panel C report data on originated loans. The average loan is issued to a borrower with a FICO score of 707, has a loan-to-value ratio of 84%, and carries an annual interest rate of 6.16%. Among the originated

[3] For a detailed description of the HMDA data set, see Duchin and Sosyura (2014).

[4] Cortés (2014) provides additional details on identifying these nonlocal lenders.

loans, 2.6% experience default (defined as a 90-day delinquency or foreclosure) within two years of origination.

4. Main results

This section studies how the variation in daily sunshine affects the decisions of loan officers and their subsequent outcomes. We begin with an analysis of loan approvals, proceed with an investigation of loan pricing, and conclude with an examination of loan performance and real effects.

4.1. Loan approvals

This subsection studies the effect of sunshine on loan approvals. We first discuss the empirical model, then provide univariate regression evidence, and continue with multivariate analysis.

To examine the effect of local sunshine on loan approvals, we estimate a linear fixed effects model explaining daily loan approval rates in each county. The dependent variable—the loan approval rate (in percent)—is the ratio of the number of loan applications approved to the number of loan applications reviewed, a definition that accounts for daily variation in loan officers' workloads. The main independent variable of interest is a measure of sunshine on a given county-day, which serves as a primer of mood.

To account for daily variation in the quality of applications reviewed, control variables include the average borrower income, the average debt-to-income ratio of applications reviewed (in percent), and the fraction of applications from minority borrowers (in percent). The debt-to-income ratio captures a borrower's ability to service the loan from regular earnings and serves as a common measure of loan risk in the mortgage industry.[5] To account for cross-county heterogeneity in borrower risk characteristics and changes in economic conditions over time, all regressions include county∗month fixed effects. This specification captures all changes in economic variables that operate at a monthly frequency, such as changes in employment, real estate prices, and seasonal business patterns. With the inclusion of these fixed effects, the coefficients on the main variables of interest can be interpreted as changes in loan approval rates in response to variation in local sunshine relative to the average approval rate for applications of similar quality observed in the same county over the same month.

The unit of observation is a county-day. This aggregation method allows for arbitrary correlations in loan approvals between applications from the same county and mitigates the influence of outliers. To account for within-county serial correlation in the error term, standard errors are clustered by county.

Table 2, Panel A, shows univariate evidence that local sunshine is associated with higher loan approvals. This conclusion persists across all measures of sunshine, with point estimates reliably significant at the 1% level and economically important. According to the point estimate in column 1, a one-unit decrease in *Cloud cover* (measured on the scale from 0 to 8) is associated with a 16.5 basis-point increase in the local loan approval rate. Based on this estimate, a decrease in *Cloud cover* from the score of 8 (overcast) to 0 (clear skies) corresponds to a 132 basis-point increase in the loan approval rate.

Columns 2 and 3 reveal some asymmetry in economic magnitudes between positive and negative primers of mood. On days with perfectly clear skies (the indicator *Sunny*), the loan approval rate increases by 53 basis points (bps), but on days with fully overcast skies (the indicator *Overcast*), the approval rate drops by 117 bps relative to the average loan approval rate in the same county over the same month. These results are consistent with prior evidence in psychology, medicine, and experimental economics that negative primers of mood produce economically larger effects.[6] Relative to the average approval rate of 65%, these estimates correspond to economically significant marginal effects of 0.82% and 1.77%, respectively. Observed in a deep and competitive loan market, these effects are associated with economically large changes in originated credit. For example, based on the average daily volume of 57,000 applications and the average loan amount of \$207,912, a rough estimate of the extra credit approved on one perfectly sunny day (*Cloud cover* = 0) relative to one fully overcast day (*Cloud cover* = 8) nationwide is about \$156 million.[7] Column 4 shows that the effect of sunshine holds robustly after accounting for seasonal variation in weather, captured by the deseasoned measure *DCC*. A decrease in *DCC* from the score of 8 to 0 corresponds to a 129 bps increase in the loan approval rate. This effect is economically comparable to that of the unadjusted measure of cloud cover, suggesting that the results are driven by daily variation in local sunshine over and above seasonal patterns.

Table 2, Panel B, shows multivariate evidence on the effect of sunshine on loan approvals with a full system of controls and fixed effects. The economic magnitude and statistical significance of the effect of sunshine on loan approvals remains virtually unchanged after introducing controls for borrower income, demographics, and loan risk, in addition to county∗month fixed effects. For example, the point estimates on *Cloud cover* and *DCC* (coefficients = −0.160 and −0.156, respectively), are nearly identical to those observed in the univariate regressions in Panel A (coefficients = −0.165 and −0.161, respectively). This evidence suggests that daily variation in weather is uncorrelated with the characteristics of loan applications that become ready for review. This empirical pattern supports the exogeneity of the mood primer. Based on the

[5] For example, the debt-to-income ratio is the main criterion used by the regulators to evaluate borrower risk and eligibility for federal assistance programs, such as the Federal Home Affordable Modification Program. An advantage of this measure is its availability for all applications. In the analysis of loan performance, we use FICO scores (available only for originated loans).

[6] See, for example, Baumeister et al. (2001) and the references therein.

[7] This estimate is calculated as follows: based on column 1 of Table 2, Panel A, a change in *Cloud cover* from 8 to 0 is associated with an increase of 0.165∗8 = 1.32% in the daily application approval rate. Nationwide, this number implies the approval of 57,000∗0.0132 = 752 more applications on a given day, or 752∗207,912 = \$156.3 million in extra credit origination.

Table 2
Loan approvals.
This table studies the relation between local weather conditions and loan approvals. The dependent variable is the loan approval rate (in percent), defined as the ratio of the number of loan applications approved to the number of loan applications reviewed on a given county-day. The main variable of interest is one of the measures of local cloud cover on the county-day when a decision on a loan application is made. Panels A and B show univariate and multivariate regressions, respectively. *Debt-to-income* is the ratio of the requested loan amount to borrower income, stated in percent. *Income* is the annual income of the borrower, stated in thousands of dollars. *Fraction of minority applicants* is the ratio of applications from non-white borrowers to all applications reviewed on a given county-day, stated in percent. Other variable definitions appear in Appendix A. The unit of observation is a county-day. All regressions include county∗month fixed effects. Standard errors (in parentheses) are clustered by county. Significance levels are indicated as follows: *=10%, **=5%, ***=1%. See Table 1 for sample descriptive characteristics.

Model	(1)	(2)	(3)	(4)
Panel A: Univariate regressions				
Cloud cover	−0.165***			
	(0.00933)			
Overcast		−1.169***		
		(0.0685)		
Sunny			0.525***	
			(0.0679)	
Deseasoned cloud cover				−0.161***
				(0.00997)
County∗month fixed effects	Yes	Yes	Yes	Yes
Observations	3,223,181	3,223,181	3,223,181	2,924,420
R-squared	0.164	0.164	0.164	0.163
Panel B: Multivariate regressions				
Cloud cover	−0.160***			
	(0.009)			
Overcast		−1.128***		
		(0.067)		
Sunny			0.520***	
			(0.067)	
Deseasoned cloud cover				−0.156***
				(0.010)
Debt-to-income	−0.060**	−0.060**	−0.060**	−0.060**
	(0.024)	(0.024)	(0.024)	(0.024)
Income	1.920***	1.920***	1.920***	1.800***
	(0.318)	(0.319)	(0.318)	(0.328)
Fraction of minority applicants	−0.084***	−0.084***	−0.084***	−0.084***
	(0.004)	(0.004)	(0.004)	(0004)
County∗month fixed effects	Yes	Yes	Yes	Yes
Observations	3,223,181	3,223,181	3,223,181	2,924,420
R-squared	0.192	0.192	0.191	0.191

point estimates in columns 2 and 3, loan approval rates increase by 52 bps on sunny days and drop by 113 bps on cloudy days. Based on the point estimate in column 4, an 8-unit reduction in *DCC* corresponds to a 125 bps increase in the loan approval rate, equivalent to $147.9 million in extra credit for one day nationwide or 90,816 per county-day.[8] Given the large daily volatility in sunshine within any given season indicated by the standard deviation of *DCC*, these estimates suggest large economic effects over longer horizons.

Control variables show the expected relations between loan risk characteristics, borrower demographics, and loan approvals. Loans with a higher credit risk are less likely to be approved, as shown by the negative coefficient on the debt-to-income ratio (*DTI*), which is statistically significant at the 1% level. Based on point estimates in columns 1–4, an increase in *DTI* from the 25th percentile (131%) to the 75th percentile (255%) reduces the approval rate by 7.4 percentage points.[9] This estimate puts in perspective the economic significance of the effect of cloud cover. Based on the point estimate in column 4, an increase in *DCC* from the 25th percentile (−2.52) to the 75th percentile (2.48) is associated with a reduction in the approval rate of 78 bps.[10] Thus, the effect of the daily-changing measure of sunshine is comparable to about one-ninth of the effect

[8] This estimate is calculated as follows: based on column 4 of Table 2, Panel B, an 8-point change in *DCC* is associated with an increase of $0.156*8 = 1.248\%$ in the daily application approval rate. Nationwide, this number implies the approval of $57{,}000*0.01248 = 711.4$ more applications on a given day, or $711.4*207{,}912 = \$147.9$ million in extra credit approval. For the average county-day with 35 applications reviewed and total requested loan amount of $35*207{,}912 = \$7{,}276{,}920$, the 1.248 percent increase in the loan approval rate corresponds to an increase of credit of $7{,}276{,}920*0.01248 = \$90{,}816$.

[9] This estimate is calculated as follows: $(255-131\%)*0.06 = 7.44\%$.

[10] This estimate is calculated as follows: $(2.48-(-2.52))*0.156 = 0.78\%$.

of a time-persistent, fundamental driver of loan approvals. The data also reveal the importance of borrower characteristics for loan approvals. The bottom rows of the table show that lower-income and minority borrowers are less likely to be approved.

In summary, daily variation in local sunshine has an economically important effect on loan approvals. This effect holds after accounting for the quality of borrowers, changes in economic conditions, and seasonal patterns. A decrease in sunshine has a larger effect on loan approvals than a comparable increase, consistent with a stronger effect of negative mood primers.

4.2. Cross-sectional and time-series evidence

If sunshine influences loan officers' subjective decisions, this effect should be stronger when officers exercise more discretion. In this subsection, we test this hypothesis by studying how the effect of sunshine varies across financial institutions, credit cycles, and loan types.

In Table 3, we compare loan approvals at local community banks (Panel A) and large national banks (Panel B). Using the Federal Reserve's classification, we define community banks as banks that hold book assets of less than $2 billion. In these smaller banks, loan approval decisions are typically less automated. In addition, because community banks operate within a small geographic region, all of their managers are located in the same area and are affected by similar environmental factors. In Panel B, we present evidence on financial institutions at the opposite end of the size spectrum—namely, large national banks, defined as those that operate in multiple states and hold book assets worth over $80 billion.

Table 3 shows that that local sunshine is positively related to loan approval rates for both groups of financial institutions. The coefficients on all measures of cloud cover across both panels are statistically significant at the 1% level and have the expected signs. A comparison of the point estimates indicates that the effect on loan approvals is larger at community banks than at national banks across all four measures of cloud cover. The difference in coefficient estimates between the two groups of banks is statistically significant at the 1% level (untabulated) and economically important. For example, an interquartile range decline (5.0 points) in the seasonally adjusted daily cloud cover, *DCC*, corresponds to an 80 bps increase in the approval rate at community banks, nearly twice the 41 bps increase observed at national banks for the same change in cloud cover. These results are consistent with greater managerial discretion and more localized decision-making at community banks.

If variation in sunshine influences loan officers' discretion, this effect should be stronger when monitoring is loose and capital constraints are less binding. Table 4 tests this hypothesis by focusing on the recent housing boom, a period characterized by weaker monitoring, greater credit availability, and significant lender discretion. To test for the differential effect of sunshine on loan approvals during the housing boom, we interact the measures of cloud cover with the binary indicator *Housing boom*, which is equal to one in 2002–2004 and zero otherwise. To ensure that the period of interest is unaffected by the early signs of overheating in the housing market, we conservatively close the time window at the end of 2004, the year when survey-based home buyer expectations and home builder expectations both reached their peaks before starting to decline (Case, Shiller, and Thompson, 2012). With the inclusion of county$*$month fixed effects, the indicator *Housing boom* is absorbed, and the main variables of interest are its interaction terms with the daily measures of local cloud cover.

Table 4 shows that the effect of sunshine on loan approvals is significantly stronger during the housing boom. For three of the four measures of cloud cover (with the exception of the indicator *Sunny*), the interaction terms between the measures of sunshine and the housing boom indicator are reliably significant at the 1% level and have the expected signs. The point estimates on the interaction term suggest that the effect of cloud cover on loan approvals more than doubles during the housing boom. For example, column 2 shows that the loan approval rate is 87 bps lower on fully overcast days than on other days in the same county-month, and this effect increases to 192 bps during the housing boom. Similar conclusions with comparable economic magnitudes emerge from the analysis of raw and de-seasoned measures of cloud cover. This evidence is consistent with the interpretation that a primer of mood has a larger effect on managerial decisions during an expansionary credit cycle when managers are afforded more discretion. This finding also parallels recent evidence in other corporate settings that managerial monitoring weakens during upward economic cycles (Jenter and Kanaan, 2015).

In Table 5, we examine how the effect of sunshine on mortgage approvals varies in the cross-section of borrowers. If sunshine influences managerial judgment, its effect should be stronger when managerial decisions are more subjective, and it should be weaker when loan approvals are clear-cut. To test this hypothesis, we sort loan applications into three groups according to household income and estimate the loan approval regressions separately in each group. Income groups are based on the following thresholds: (a) low income (below $30,000), (b) medium income ($30,000–$100,000), and (c) high income (over $100,000), which are examined in Panels A, B, and C, respectively.

Across all measures of cloud cover, daily variation in sunshine affects loan approvals only for low-income and medium-income loan applications—the categories over which loan officers have more discretion. In contrast, in the group of high-income borrowers, where loan approvals are typically clear-cut, the effect of cloud cover has near-zero point estimates, which are never statistically significant across all measures. A comparison of the economic magnitudes reveals that the effect of sunshine is stronger in the subsample of medium-income borrowers than in the subsample of borrowers in the lowest income tercile. One interpretation of this result is that sunshine influences loan officers' decisions on the most subjective loan applications in which the decision is unclear a priori. In contrast, this influence diminishes in the subsample of the likely rejects and disappears in the subsample of clear-cut approvals.

In summary, the results in this subsection suggest that the effect of sunshine on loan approvals is linked to loan

Table 3
Cross-sectional evidence: firms.
This table studies the relation between local weather and loan approvals at community banks (Panel A) and national banks (Panel B). The dependent variable is the loan approval rate, defined as the ratio of the number of loan applications approved to the number of loan applications reviewed on a given county-day and expressed in percent. Community banks comprise banks that hold book assets of less than $2 billion. National banks comprise banks that operate in multiple states and hold book assets of at least $80 billion. *Debt-to-income* is the ratio of the requested loan amount to borrower income, stated in percent. *Income* is the annual income of the borrower, stated in thousands of dollars. *Fraction of minority applicants* is the ratio of applications from non-white borrowers to all applications reviewed on a given county-day, stated in percent. Variable definitions appear in Appendix A. The unit of observation is a county-day. All regressions include county∗month fixed effects. Standard errors (in parentheses) are clustered by county. Significance levels are indicated as follows: *=10%, **=5%, ***=1%. See Table 1 for sample descriptive characteristics.

Model	(1)	(2)	(3)	(4)
Panel A: Community banks				
Cloud cover	−0.152***			
	(0.013)			
Overcast		−1.062***		
		(0.087)		
Sunny			0.451***	
			(0.089)	
Deseasoned cloud cover				−0.160***
				(0.013)
Debt-to-income	−0.044*	−0.044*	−0.044*	−0.038
	(0.024)	(0.024)	(0.024)	(0.025)
Income	1.340***	1.350***	1.340***	1.330***
	(0.301)	(0.300)	(0.301)	(0.306)
Fraction of minority applicants	−0.079***	−0.079***	−0.079***	−0.079***
	(0.004)	(0.004)	(0.004)	(0.004)
County∗month fixed effects	Yes	Yes	Yes	Yes
Observations	1,911,437	1,911,437	1,911,437	1,734,071
R-squared	0.225	0.225	0.225	0.225
Panel B: National banks				
Cloud cover	−0.098***			
	(0.014)			
Overcast		−0.719***		
		(0.098)		
Sunny			0.417***	
			(0.101)	
Deseasoned cloud cover				−0.081***
				(0.015)
Debt-to-income	−0.027	−0.027	−0.026	−0.019
	(0.037)	(0.037)	(0.037)	(0.038)
Income	2.170***	2.170***	2.170***	1.970***
	(0.418)	(0.418)	(0.418)	(0.436)
Fraction of minority applicants	−0.089***	−0.089***	−0.089***	−0.089***
	(0.004)	(0.004)	(0.004)	(0.004)
County∗month fixed effects	Yes	Yes	Yes	Yes
Observations	1,393,742	1,393,742	1,393,742	1,270,139
R-squared	0.236	0.236	0.236	0.235

officers' discretion. This effect is driven by medium- and low-income loan applications that require subjective judgment. The effect of sunshine is more pronounced during periods of loose capital constraints and at small community banks where loan approvals are less automated.

4.3. Loan pricing

In this subsection, we study the relation between local sunshine and loan interest rates. The analysis of interest rates is important because even the lowest-quality loans may have a positive net present value, as long as the lender charges the borrower an appropriate yield premium commensurate with loan risk.

Previous literature suggests that loan pricing is driven primarily by computerized bank algorithms that rely on hard loan data, such as the borrower's FICO score, loan-to-value ratio, and documentation level (Rajan, Seru, and Vig, 2015). A key feature of the loan pricing process is that it is typically centralized at the firm level, and loans are priced with relatively little input from the loan officer. Our conversations with banking regulators and loan officers confirm that loan officers typically have little input into the pricing of mortgages. At the same time, loan pricing algorithms seek to incorporate all of the hard information,

Table 4
Time-series variation: the housing boom.

This table studies how the relation between local weather and loan approvals varies across business cycles. The dependent variable is the loan approval rate, defined as the ratio of the number of loan applications approved to the number of loan applications reviewed on a given county-day and expressed in percent. The main variable of interest is the interaction term of local cloud cover with the binary indicator *Housing boom*, which denotes the period 2002–2004 when home buyer expectations and home builder expectations reached their peaks. All regressions include county∗month fixed effects, which absorb the time-series indicator *Housing boom*. Control variables include the average debt-to-income ratio of applications reviewed, the average borrower income, and the fraction of applications from minority borrowers, which are defined in Appendix A. Standard errors (in parentheses) are clustered by county. Significance levels are indicated as follows: *=10%, **=5%, ***=1%. See Table 1 for sample descriptive characteristics.

Model	(1)	(2)	(3)	(4)
Cloud cover	−0.128***			
	(0.010)			
Housing boom × Cloud cover	−0.135***			
	(0.020)			
Overcast		−0.873***		
		(0.072)		
Housing boom × Overcast		−1.044***		
		(0.138)		
Sunny			0.523***	
			(0.076)	
Housing boom × Sunny			−0.016	
			(0.155)	
Deseasoned cloud cover				−0.117***
				(0.011)
Housing boom × Deseasoned cloud cover				−0.159***
				(0.022)
County∗month fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	3,223,181	3,223,181	3,223,181	2,924,420
R-squared	0.192	0.192	0.191	0.191

including private information from the bank's own records, to ensure an accurate compensation for loan risk. As a result, the analysis of loan interest rates provides a useful experiment to separate the effect of daily variation in hard loan data from the effect of daily variation in managerial discretion, which is largely muted in this setting.

Table 6 studies the relation between daily variation in sunshine and loan interest rates. The dependent variable is the average interest rate of loans approved on a given county-day (stated as an annual percentage rate (APR) and expressed in percent). The main independent variables of interest are the measures of cloud cover on the same county-day. Control variables include the average FICO score, the average loan-to-value (LTV) ratio, and the fraction of low-documentation loans approved on a given county-day. As discussed earlier, these characteristics are available only for originated loans. The unit of observation is a county-day, and the number of observations declines to 1.3 million due to data availability in LPS Applied Analytics. All regressions include county∗month fixed effects and use standard errors clustered by county.

The evidence in Table 6 shows no relation between daily sunshine and loan interest rates across all specifications. The coefficients on all measures of cloud cover are statistically insignificant across all specifications and have near-zero point estimates. The coefficients on other borrower and loan characteristics highlight the main drivers of loan interest rates. As expected, interest rates are negatively related to FICO scores and positively related to loan-to-value ratios. The positive coefficient on the low-documentation variable shows that borrowers without full documentation pay higher interest rates. These relations are significant at the 1% level and economically meaningful. For example, based on point estimates in column 1, a one standard deviation increase in the fraction of low-documentation applicants ($\sigma = 17.7\%$) corresponds to a 165 bps increase in the interest rates of originated loans.

In summary, we find no significant relation between daily sunshine and loan interest rates. These results indicate that higher approval rates on applications reviewed on sunny days are not offset by higher interest rates on these loans.

4.4. Loan performance and real effects

This subsection studies the economic consequences of financial decisions made on days with positive and negative mood primers. In particular, we compare the ex post performance of loans originated on sunny and cloudy days and estimate their economic effects.

Table 7 provides evidence on loan defaults. The dependent variable is the average default rate (stated in percent) on loans approved on a given county-day. The average default rate is defined as the fraction of loans that become 90-day delinquent or enter foreclosure during the first two years of a loan's life. As in Rajan, Seru, and Vig (2015), we focus on the early years of a loan's life to ensure that borrower characteristics closely resemble the information

Table 5
Variation by application quality.

This table studies how the relation between local weather and loan approvals varies with application quality, proxied by annual borrower income. Panels A, B, and C correspond to three groups of applications sorted on borrower income: low income (below \$30,000), medium income (\$30,000–100,000), and high income (over \$100,000), respectively. The dependent variable is the loan approval rate, defined as the ratio of the number of loan applications approved to the number of loan applications reviewed on a given county-day and expressed in percent. The main variable of interest is one of the measures of local cloud cover. Control variables include the average debt-to-income ratio of applications reviewed, the average borrower income, and the fraction of applications from minority borrowers, which are defined in Appendix A. The unit of observation is a county-day. All regressions include county∗month fixed effects. Standard errors (in parentheses) are clustered by county. Significance levels are indicated as follows: *=10%, **=5%, ***=1%. See Table 1 for sample descriptive characteristics.

Model	(1)	(2)	(3)	(4)
Panel A: Low-income applications				
Cloud cover	−0.029**			
	(0.012)			
Overcast		−0.167**		
		(0.079)		
Sunny			0.449***	
			(0.082)	
Deseasoned cloud cover				−0.028**
				(0.013)
County∗month fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	2,378,241	2,378,241	2,378,241	2,158,363
R-squared	0.140	0.140	0.140	0.139
Panel B: Medium-income applications				
Cloud cover	−0.127***			
	(0.025)			
Overcast		−1.105***		
		(0.171)		
Sunny			0.520***	
			(0.067)	
Deseasoned cloud cover				−0.174***
				(0.026)
County∗month fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	3,223,181	3,223,181	3,223,181	2,924,420
R-squared	0.157	0.157	0.157	0.157
Panel C: High-income applications				
Cloud cover	−0.037			
	(0.038)			
Overcast		−0.429		
		(0.274)		
Sunny			0.262	
			(0.249)	
Deseasoned cloud cover				−0.013
				(0.045)
County∗month fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	1,886,906	1,886,906	1,886,906	1,712,937
R-squared	0.158	0.158	0.158	0.160

available to the loan officer at the time of application review. The main independent variable of interest is one of the four measures of cloud cover on the county-day when the loan was approved. Control variables are the same as in Table 6 and include borrower and loan characteristics that predict performance outcomes, such as FICO scores, LTV ratios, and the fraction of low-documentation borrowers. As before, each observation is a county-day, and all regressions include county∗month fixed effects.

The evidence shows that loans originated on sunnier days have higher defaults. This outcome persists across all four measures of cloud cover, with coefficient estimates significant at the 1% level. Based on the point estimates in column 1, a one standard deviation reduction in *Cloud cover* ($\sigma = 3.14$) corresponds to a 7.2 bps (or 2.8%) increase in defaults relative to loans with similar characteristics approved in the same county during the same calendar month. Column 4 shows that after removing seasonal

Table 6
Loan interest rates.
This table studies the relation between local weather and loan interest rates. The dependent variable is the average interest rate (stated as an APR and expressed in percent) on loans approved on a given county-day. The main independent variable is one of the measures of local cloud cover on the county-day when a loan is approved. Control variables include the average FICO score, the loan-to-value ratio (stated in percent), and the fraction of low-documentation mortgage applicants (stated in percent) for loans approved on a given county-day. Variable definitions appear in Appendix A. The unit of observation is a county-day. All regressions include county∗month fixed effects. Standard errors (in parentheses) are clustered by county. Significance levels are indicated as follows: *=10%, **=5%, ***=1%.

Model	(1)	(2)	(3)	(4)
Cloud cover	<0.001			
	(<0.001)			
Overcast		<0.001		
		(0.002)		
Sunny			<0.001	
			(0.002)	
Deseasoned cloud cover				<0.001
				(<0.001)
FICO score	−0.002***	−0.002***	−0.002***	−0.002***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Loan-to-value ratio	0.004***	0.004***	0.004***	0.004***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Fraction of low-doc applicants	0.093***	0.093***	0.093***	0.096***
	(0.010)	(0.010)	(0.010)	(0.011)
County∗month fixed effects	Yes	Yes	Yes	Yes
Observations	1,269,070	1,269,070	1,269,070	1,153,327
R-squared	0.743	0.743	0.743	0.743

variation in cloud cover, a one standard deviation reduction in *DCC* ($\sigma = 3.08$) corresponds to a similar effect: a 7 bps increase in defaults (0.023∗3.08), indicating a 2.7% increase in the average default rate over the two-year horizon. These estimates suggest that financial decisions made on days with positive and negative mood primers lead to economically different ex post outcomes. These estimates already account for changes in the observable measures of loan risk, such as FICO, LTV, and loan documentation, and can be viewed as incremental changes in the quality of the firm's assets over and above the variation attributable to common risk characteristics.

To assess the economic importance of the difference in default rates, we provide a crude quantitative estimate based on several simplifying assumptions. Using the discussed estimates of the average daily volume of mortgage originations nationwide and the average recovery rate of 55% (Federal Housing Administration, 2010), a 7 bps difference in loan defaults corresponds to an extra $5.4 million in defaults per day nationwide and an extra $2.4 million in losses from default.

The analysis of control variables yields expected conclusions. In particular, loan defaults increase when borrowers have higher credit risk, make smaller down-payments, and provide less documentation. Based on column 1, a one standard deviation decrease in the average FICO score ($\sigma = 54$ points) corresponds to an increase in the default rate of 162 bps.

In summary, financial decisions made on days with positive and negative mood primers have economically different outcomes and real effects. Our estimates of these real effects are likely conservative because they capture only a fraction of the daily variation in an agent's mood linked to just one environmental factor and shared across agents. In the next section, we explore several potential explanations for the observed changes in loan officers' financial decisions.

5. Economic channels

This section studies three non-mutually exclusive mechanisms through which daily variation in sunshine may affect loan officers' decisions: (1) risk tolerance, (2) mood attribution, and (3) allocation of effort.

5.1. Risk tolerance

This channel conjectures that positive mood, induced by sunshine, increases a loan officer's risk tolerance. Because the incentives of loan officers are tied to the number of originated loans and their subsequent performance, an increase in risk tolerance corresponds to a higher approval rate of risky loans. Conversely, a decrease in risk tolerance corresponds to a higher rejection rate.

This channel is motivated by theoretical frameworks that model an agent's emotional state as an important determinant of risk-taking behavior (Loewenstein, Weber, Hsee, and Welch, 2001; Slovic, Finucane, Peters, and MacGregor, 2002) and experimental studies that support this conjecture. In psychology, Isen and Patrick (1983) and Isen (2000) show that the inducement of a positive mood increases risk-taking. In experimental economics, Kuhnen and Knutson (2011) find that subjects in positive emotional states take on more risk, and Bassi, Colacito, and Fulghieri (2013) provide evidence that weather-induced

Table 7
Loan performance.
This table studies the relation between local weather and loan performance. The dependent variable is the default rate (in percent) for loans approved on a given county-day, defined as the fraction of loans that become 90-days delinquent or enter foreclosure within 24 months since origination. The main independent variable is one of the measures of local cloud cover on the county-day when a loan is approved. Control variables include the average FICO score, the loan-to-value ratio (stated in percent), and the fraction of low-documentation applicants (stated in percent) for loans approved on a given county-day. Variable definitions appear in Appendix A. The unit of observation is a county-day. All regressions include county∗month fixed effects. Standard errors (in parentheses) are clustered by county. Significance levels are indicated as follows: *=10%, **=5%, ***=1%.

Model	(1)	(2)	(3)	(4)
Cloud cover	−0.023***			
	(0.006)			
Overcast		−0.106***		
		(0.039)		
Sunny			0.200***	
			(0.040)	
Deseasoned cloud cover				−0.023***
				(0.006)
FICO score	−0.030***	−0.030***	−0.030***	−0.030***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Loan-to-value ratio	0.025***	0.025**	0.025***	0.026***
	(0.002)	(0.002)	(0.002)	(0.002)
Fraction of low-doc applicants	0.012***	0.012***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
County∗month fixed effects	Yes	Yes	Yes	Yes
Observations	1,279,030	1,279,030	1,279,030	1,162,423
R-squared	0.396	0.396	0.396	0.397

positive mood increases agents' risk tolerance in a choice of lottery payoffs.

To explore this channel, we study whether variation in sunshine is associated with riskier lending, as measured by ex-ante risk characteristics available to the officer at the time of loan approval. Table 8 tests whether loans approved on sunny days are observably riskier than loans approved on cloudy days. The dependent variable is one of the salient measures of loan risk: FICO score (Panel A) and LTV (Panel B), and the independent variable of interest is one of the measures of local sunshine on the day of the loan approval. All regressions include county∗month fixed effects and use standard errors clustered by county.

Table 8 shows that an increase in sunshine is associated with riskier lending. This conclusion holds across all measures of sunshine, with coefficient estimates significant at the 1% level throughout both panels. The economic effects are nontrivial. For example, in Panel A, a reduction in the deseasoned measure of cloud cover from the score of 8 to 0 on the day of the loan approval is associated with a 3.44 point reduction in the average FICO scores of originated loans. This estimate reflects a meaningful increase in ex ante credit risk, equivalent to 6.4% of the sample-wide standard deviation ($\sigma = 54$ points). In Panel B, the said reduction in the deseasoned measure of cloud cover is associated with an increase in LTV of 108 bps, an effect equal to 9% of the sample-wide standard deviation ($\sigma = 12\%$). These estimates reflect a significant increase in credit risk over and above the daily variation in the approval rate.

In summary, the relation between local sunshine and loan approvals is likely linked to temporal variation in loan officers' risk tolerance in response to mood primers. Loans originated on sunny days are riskier based on ex ante characteristics, consistent with the theories that link mood and risk aversion.

5.2. Mood attribution

This channel posits that loan officers in a good mood make more optimistic assessments about loan prospects than officers in a bad mood. This conjecture is grounded in a large body of work in psychology which demonstrates that agents project their moods onto unrelated economic tasks. For example, subjects in a good mood report higher probabilities for positive events and lower probabilities for negative events (Wright and Bower, 1992), and this effect is stronger when such assessments are more subjective and rely on incomplete information (Clore, Schwarz, and Conway, 1994; Forgas, 1995).

In contrast to the risk tolerance channel, which focuses on the officers' willingness to take on risk, the mood attribution channel predicts that holding risk constant, loan officers in a good mood overestimate the borrower's ability to service the loan. If this channel is operative, loan officers in a good mood may approve some of the marginal loan applications that would not be approved otherwise. Conversely, loan officers in a bad mood may show a downward bias in their assessments of loan prospects, thus rejecting loans for subjective reasons.

To test the role of such subjective assessments in loan officers' decisions, we investigate the decision criteria reported for denied applications. We focus on denied

Table 8
Credit risk of approved loans.
This table studies the relation between local weather and loan risk. In Panel A, the dependent variable is the average FICO score for loans approved on a given county-day. In Panel B, the dependent variable is the average loan-to-value ratio for loans approved on a given county-day, stated in percent. The main independent variable is one of the measures of local cloud cover on the county-day when a loan is approved. The unit of observation is a county-day. All regressions include county∗month fixed effects and controls for the loan approval rate. Variable definitions appear in Appendix A. Standard errors (in parentheses) are clustered by county. Significance levels are indicated as follows: *=10%, **=5%, ***=1%. See Table 1 for sample descriptive characteristics.

Model	(1)	(2)	(3)	(4)
Panel A: FICO scores				
Cloud cover	0.378***			
	(0.097)			
Overcast		1.854***		
		(0.649)		
Sunny			−2.198***	
			(0.735)	
Deseasoned cloud cover				0.430***
				(0.104)
County∗month fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Observations	1,651,256	1,651,256	1,651,256	1,493,810
R-squared	0.254	0.254	0.254	0.254
Panel B: Loan-to-value ratios (in percent)				
Cloud cover	−0.126***			
	(0.012)			
Overcast		−0.739***		
		(0.086)		
Sunny			0.678***	
			(0.096)	
Deseasoned cloud cover				−0.135***
				(0.013)
County∗month fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Observations	1,651,256	1,651,256	1,651,256	1,493,810
R-squared	0.155	0.155	0.155	0.155

applications because throughout our sample, loan officers are requested to report their reasons for loan denials, while the reasons for loan approvals are unobservable. While the statement of denial reasons is not mandatory, it is reported for 85% of rejected loans. The list of reasons for denial (shown in Appendix B) includes a number of well-specified risk characteristics, such as the applicant's debt-to-income ratio, credit history, and denied mortgage insurance, as a well as a separate category for decisions based on other, less tangible factors, collectively labeled as "other" reasons. Using this classification, we introduce a variable *Subjective rejection*, which denotes rejections for "other" reasons, which do not correspond to the common risk characteristics or logistical factors. According to this definition, 10% of loan rejections with available data are subjective.

Table 9 examines whether an increase in cloud cover is associated with a higher fraction of subjective loan rejections. The dependent variable is the percent of *Subjective rejections* in the total volume of loan rejections on a given county-day. Because this definition exploits variation in decision criteria (already adjusted for total rejections on a given county-day), it is not mechanically related to the variation in loan approval rates between sunny and cloudy days. The main variables of interest are the four measures of cloud cover. All regressions include county∗month fixed effects and use the same controls as in the baseline loan approval regressions.

Table 9 shows that the fraction of subjective rejections increases on cloudy days and declines on sunny days, controlling for observable borrower and loan characteristics. These effects are statistically significant at conventional levels and economically nontrivial. For example, based on column 1, an increase in the average cloud cover from the score of 0 (clear skies) to the score of 8 (overcast) corresponds to a 34 bps or 3.4% increase in the share of subjective rejections. A similar increase in the deseasoned cloud cover is associated with a 3.0% increase in the share of subjective rejections. This evidence suggests that when loan officers are primed with negative mood stimuli, they are more likely to reject observationally similar loans for subjective reasons.

Overall, the mood attribution channel likely contributes to daily variation in loan officers' financial decisions. This interpretation is supported by evidence from other mood primers, such as sporting events and holidays. For example, Agarwal, Duchin, Evanoff, and Sosyura (2013) show that victories of local sports teams in title games produce a short-lived spike in credit approvals in their home

Table 9
Loan decision criteria.
This table studies the relation between local weather and subjective loan denials. The dependent variable is the percentage of loan denials for subjective reasons among all loan denials on a given county-day. Subjective reasons are defined as 'other' reasons, which do not correspond to common risk characteristics or logistical factors. The classification of reasons for loan denials appears in Appendix B. The main independent variable is one of the measures of local cloud cover on the day when a loan application is denied. Control variables correspond to the characteristics of loan applications denied on a given county-day. They include the average debt-to-income ratio, the average borrower income, and the fraction of applications from minority borrowers, which are defined in Appendix A. The unit of observation is a county-day. All regressions include county∗month fixed effects. Standard errors (in parentheses) are clustered by county. Significance levels are indicated as follows: *=10%, **=5%, ***=1%. See Table 1 for sample descriptive characteristics.

Model	(1)	(2)	(3)	(4)
Cloud cover	0.043***			
	(0.014)			
Overcast		0.153*		
		(0.089)		
Sunny			−0.431***	
			(0.115)	
Deseasoned cloud cover				0.037**
				(0.015)
County∗month fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	928,559	928,559	928,559	843,824
R-squared	0.281	0.281	0.281	0.281

counties.[11] The authors also find a similar effect around major national holidays, a period associated with elevated mood. These results support the sentiment interpretation of our evidence and suggest that our conclusions extend to other sentiment proxies and empirical settings.

5.3. Allocation of effort

The effort allocation channel posits that variation in the mood of loan officers affects the pool of applications they choose to review. According to this hypothesis, loan officers prefer to exert less effort on sunny days and to review easy-to-approve applications. For example, loan officers may wish to leave work early on sunny days or prefer to avoid reporting bad news to borrowers while being in a good mood. In contrast to the risk tolerance and mood attribution channels, this channel implies that application approvals and denials are merely reshuffled across days without a material impact on credit origination.

To explore this channel, we investigate whether the volume and quality of applications reviewed on a given county-day vary with local sunshine. In Table 10, we estimate regressions explaining the daily volume of reviewed applications (column 1), the daily average debt-to-income ratio of reviewed applications (column 2), and the daily average household income of reviewed applicants (column 3). For brevity, we report the results for the deseasoned measure, *DCC*. Other measures yield similar conclusions.

Columns 1–3 show that the volume and quality of reviewed applications do not vary significantly with local sunshine. The coefficients on *DCC* have near-zero point estimates, flip signs, and are never statistically significant (p-values of 0.32–0.97). Thus, to the extent that application quality can be inferred from these observable characteristics, we do not find that changes in sunshine lead to a selective review of strong or weak applications.

Columns 4–6 examine whether the loan officer's decision is affected by the incoming pool of applications received on a given day, which might vary with sunshine. Using the same measures of volume and quality for applications received on a given county-day, we do not find strong evidence in support of this explanation. Columns 4–6 show that the volume and quality of applications received on a given county-day do not vary significantly with local sunshine, as evident from the small and insignificant coefficients on *DCC*. However, this evidence should not be viewed as a test of the influence of sunshine on a borrower's decision to obtain a mortgage. In our empirical setting, the timing of the home purchase decision, the preparation of a loan application, and the assembly of the accompanying documentation for its submission is unobservable, and these processes are scattered in time. Because these decisions are unlikely to be made on a single day, their timing cannot be inferred from the date when the bank receives an application.

As another test of the effort allocation channel, we examine how loan approval rates change *after* sunny and cloudy days. If managers selectively review stronger applications on sunny days, they will create a backlog of denials that would have to be cleared later. Conversely, if managers selectively review weaker applications on cloudy days, they will accumulate a backlog of extra approvals that would be cleared over the next few days.

[11] This research project has been discontinued.

Table 10
Characteristics of applications reviewed and new applications received.

This table studies the relation between local weather and the characteristics of loan applications reviewed and new loan applications received. In columns 1–3, the dependent variable is one of the characteristics of applications reviewed by loan officers on a given county-day. In columns 4–6, the dependent variable is one of the characteristics of new applications received by the bank on a given county-day. The characteristics include the number of applications (columns 1 and 4), the average debt-to-income ratio (columns 2 and 5), and the average borrower income (columns 3 and 6). The main independent variable is *Deceasoned cloud cover*, defined as the average cloud cover between 8 a.m. and 4 p.m. on a given county-day minus the average cloud cover observed in the same county over the trailing three years during the same week of the year. In columns 1–3, weather conditions are recorded for the county-day on which a decision on the loan application is made. In columns 4–6, weather conditions are recorded for the county-day on which a new application is received by the bank. Variable definitions appear in Appendix A. The unit of observation is a county-day. All regressions include county∗month fixed effects. Standard errors (in parentheses) are clustered by county. Significance levels are indicated as follows: *=10%, **=5%, ***=1%. See Table 1 for sample descriptive characteristics.

	Characteristics of applications reviewed			Characteristics of new applications received		
Dependent variable Model	Number of apps (1)	Debt-to-income (2)	Income (3)	Number of apps (4)	Debt-to-income (5)	Income (6)
Deseasoned cloud cover	0.0605 (1.893)	−0.001 (0.001)	−0.007 (0.013)	−0.447 (0.532)	<0.001 (0.001)	0.025 (0.021)
County∗month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,146,532	2,146,532	2,146,532	2,146,532	2,146,532	2,146,532
R-squared	0.802	0.229	0.332	0.848	0.225	0.233

Table 11, Panel A, examines loan approval rates using lagged measures of sunshine. The dependent variable in these regressions is the average loan approval rate (in percent) over the next five workdays relative to the day when local weather is observed. We use a conservative five-day window to allow for the possibility that a backlog of extra approvals or denials is cleared gradually or with a delay, at any time over the next workweek. Our conclusions are similar if we use a narrower, three-day window.

If loan officers are handling backlogs of approvals or denials on subsequent days, lagged measures of sunshine should have significant coefficients with signs opposite of those in the baseline tests, indicating short-term reversals. In contrast to this prediction, Panel A shows that the coefficients on lagged sunshine are economically small and statistically indistinguishable from zero across all columns. This evidence indicates that the relation between sunshine and loan approvals is observed only on the day when the application decision is made. The effect of sunshine on loan approvals is not reversed over subsequent days, a pattern that does not support the effort allocation channel.

One caveat with the analysis of application volume and application quality is that these measures do not capture unobservable application characteristics and soft information that might be available to a loan officer. Therefore, it is possible that the effort allocation channel manifests in a selective review of applications whose quality varies on important unobservable dimensions. For example, if a loan officer selects loans with negative soft information on overcast days, this practice will create a backlog of loans with positive soft information that would be approved over subsequent days. To the extent that these unobservable characteristics are important for loan performance, they should be ultimately reflected in loan defaults. Therefore, under the above scenario, loans approved over the next few days following an overcast day should be unobservably better and less likely to default.

Table 11, Panel B, tests for selection on unobservable measures of loan quality by studying whether local sunshine predicts the default rate of loans approved over subsequent days. The dependent variable is the average default rate on loans approved in the same county over the next five workdays relative to the day when local weather is reported. The results are similar if we focus on the next three days.

Panel B shows that lagged measures of sunshine are unrelated to loan defaults. The coefficients on the lagged measures of cloud cover across all columns are statistically insignificant and close to zero. Combined with prior evidence on defaults, these results suggest that the relation between sunshine and the outcomes of financial decisions is contemporaneous. When the true loan quality is revealed in its subsequent performance, we find no strong evidence that variation in sunshine is followed by backlogs of applications with abnormal defaults, as would be expected under the effort allocation channel.

In summary, the mechanism underlying the effect of mood on loan approvals is likely linked to variation in risk tolerance and subjective judgment. In contrast, we do not detect a reliable effect of mood on the choice of applications to review. While our study seeks to provide one of the first pieces of evidence on the channels through which an agent's mood may affect corporate decisions, this list of channels is not exhaustive, and other mechanisms may play a role.

6. Conclusion

We study how daily fluctuations in the mood of corporate officers affect their professional decisions. Using variation in local sunshine as a primer for managerial mood, we find that managers increase loan approval rates on sunny days and reduce approval rates on cloudy days. These effects are stronger when managers have more discretion. We explore several channels through which the variation in sunshine may affect financial decisions and find evidence consistent with mood attribution and time-varying risk aversion. These factors affect the subsequent

Table 11
A test of reversals: lagged sunshine and loan outcomes. This table studies whether the effect of sunshine on loan outcomes is followed by reversals.

This table examines the relation between loan approvals (Panel A) and loan defaults (Panel B) and both lagged and contemporaneous measures of sunshine. In Panel A, the dependent variable is the average loan approval rate (in percent) over the next five business days following the day when weather conditions are observed (these weather conditions are denoted by the subscript *lagged*). In Panel B, the dependent variable is the average default rate (in percent) for loans approved over the next five business days following the day when weather conditions are observed. All regressions include controls for the average weather conditions over the five-day period that matches the dependent variables (these weather conditions are denoted by the subscript *contemporaneous*). Other controls include the same independent variables as in the regressions of loan approvals and loan defaults, respectively. Variable definitions appear in Appendix A. Standard errors (in parentheses) are clustered by county. Significance levels are indicated as follows: *=10%, **=5%, ***=1%. See Table 1 for sample descriptive characteristics.

Model	(1)	(2)	(3)	(4)
Panel A: Approval rates				
Cloud cover$_{lagged}$	−0.001			
	(0.001)			
Cloud cover$_{contemporaneous}$	−0.002***			
	(0.001)			
Overcast$_{lagged}$		−0.004		
		(0.004)		
Overcast$_{contemporaneous}$		−0.007**		
		(0.003)		
Sunny$_{lagged}$			0.001	
			(0.003)	
Sunny$_{contemporaneous}$			0.009***	
			(0.003)	
DCC$_{lagged}$				−0.001
				(<0.001)
DCC$_{contemporaneous}$				−0.001
				(0.001)
County∗month fixed effects & Controls	Yes	Yes	Yes	Yes
Observations	2,388,437	2,388,437	2,388,437	2,155,933
R-squared	0.619	0.589	0.589	0.589
Panel B: Default rates				
Cloud cover$_{lagged}$	0.006			
	(0.006)			
Cloud cover$_{contemporaneous}$	−0.022***			
	(0.006)			
Overcast$_{lagged}$		0.041		
		(0.041)		
Overcast$_{contemporaneous}$		−0.122***		
		(0.039)		
Sunny$_{lagged}$			−0.017	
			(0.043)	
Sunny$_{contemporaneous}$			0.149***	
			(0.042)	
DCC$_{lagged}$				0.008
				(0.006)
DCC$_{contemporaneous}$				−0.019***
				(0.006)
County∗month fixed effects & Controls	Yes	Yes	Yes	Yes
Observations	1,228,746	1,228,746	1,228,746	1,104,596
R-squared	0.420	0.420	0.420	0.423

performance of approved loans and generate large real effects that extend beyond the boundaries of the firm.

While most research on corporate financial decisions has focused on the upper management, our evidence shows that the decisions of lower-level officers responsible for day-to-day operations have an important effect on the composition of a firm's assets and their subsequent performance. Our findings suggest that further analysis of this group of non-executive employees can improve our understanding of the inner functioning of the firm and its relation to corporate outcomes.

Our findings have important implications because the majority of financial decisions rely on managerial judgment. While we focus on repeated, well-understood decisions of trained financial intermediaries, sentiment could also influence many other economic agents who face ambiguity and have significant discretion, such as stock analysts, executives, directors, and economic forecasters.

Our empirical design can be extended to test for the effect of sentiment on the behavior of these other economic agents. For example, using daily variation in sunshine in a stock analyst's location, combined with temporal stamps of analysts' actions, one could test whether this mood primer affects analysts' recommendations, earnings forecasts, and growth estimates and compare their subsequent performance with realized outcomes. A similar approach could be applied to test for the effect of daily sunshine on professional macroeconomic forecasters located across the nation, such as those in the Survey of Professional Forecasters, the oldest quarterly U.S. survey of macroeconomic forecasts. Finally, other possible experiments might exploit geospatial variation in sunshine during a firm's conference call or board meeting to investigate whether it affects managerial optimism or the voting behavior of directors, respectively. We hope that some of these experiments will provide avenues for future research.

Appendix A. Variable definitions

Weather variables

Cloud cover = the average hourly cloud cover between the hours of 8 a.m. and 4 p.m. (local time) reported for each county-day, which ranges from the score of 0 (clear skies) to 8 (fully overcast).

Overcast = an indicator that equals one on fully overcast days (*Cloud cover* = 8) and zero on all other days.

Sunny = an indicator that equals one on perfectly sunny days (*Cloud cover* = 0) and zero on all other days.

Deseasoned cloud cover (DCC) = *Cloud cover* minus the average cloud cover observed in the same county during the same workweek of the year over the trailing three years.

HMDA variables

Loan approval rate = the number of approved applications divided by the total number of applications reviewed on a given county-day, stated in percent.

Debt-to-income (DTI) = the average ratio of the requested loan amount in a mortgage application to the applicant's annual income for applications reviewed on each county-day, stated in percent.

Income = the average borrower income for applications reviewed on each county-day, stated in thousands of dollars per year.

Low income, Medium income, and *High income* = terciles formed on the annual income of mortgage applicants. The low-income tercile includes applicants with an annual income of less than $30,000. The medium-income tercile includes applicants with an annual income between $30,000 and $99,999. The high-income tercile corresponds to an annual income of at least $100,000.

Fraction of minority applicants = the ratio of the number of applications from minority applicants to the total number of applications reviewed for each county-day, stated in percent. Minority applicants include all applicants whose reported race is other than white.

Number of applications = the total number of applications reviewed or received on a given county-day.

Housing boom = an indicator that equals one in 2002–2004 and zero in all other years.

National bank = a bank with total book assets of at least $80 billion.

Community bank = a bank with total book assets of less than $2 billion.

Subjective loan rejection = an indicator that equals one if the stated rejection reason for a mortgage application is reported as "other."

LPS variables

Default rate = the percentage of loans that become 90-days delinquent or enter foreclosure within two years of origination in the total number of originated loans for each county-day.

FICO score = the average FICO score across approved mortgage applicants for each county-day.

Interest rate = the average interest rate, in percent, charged on originated loans for each county-day.

Loan-to-value (LTV) = the average ratio of loan amount to property value for originated loans for each county-day, stated in percent.

Fraction of low-doc applicants = the percentage of borrowers with less than full documentation of household financials within the total number of loans originated on a given county-day.

Appendix B. Reasons for loan denials

See Table B1.

Table B1
Reasons for loan denials.

This table shows the classification of reasons for loan denials used in the Home Mortgage Disclosure Act loan application registry. The sample period is 1998–2010. The table reports the fraction of loan denials with available data that fall into each classification category. The reason for denial is reported for approximately 85% of rejected loan applications.

Denial reason	% of obs.
Debt-to-income ratio	23.6
Employment history	1.7
Credit history	18.1
Collateral	24.5
Insufficient cash (down-payment and closing costs)	3.8
Unverifiable information	5.1
Credit application incomplete	13.0
Mortgage insurance denied	0.2
Other	10.0

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