# Mood Swings and Money:

# The Role of Financial Technology in Household Credit Demand

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## Abstract

Fintech lending allows borrowers to apply for loans anytime and from anywhere, complete their applications within minutes, and obtain immediate credit decisions. As such, transient mood swings that would be mitigated in a traditional loan setting can play an important role in modern household credit demand. Using hourly fluctuations in local sunshine as an instrument for sentiment, we find that positive sentiment leads to higher loan demand both at the extensive margin (more loan applications) and the intensive margin (higher loan amounts and loan-to-income ratios). The effects lead to higher default rates, especially for lower-income and inexperienced borrowers. We also find evidence consistent with self-corrective actions where individuals later withdraw their applications, suggesting that "cooling-off" periods can be an effective consumer protection mechanism. Overall, we provide some of the cleanest estimates to date that sentiment affects the demand for consumer credit.

**Key Words**: FinTech, Consumer Credit Demand, Sentiment, Marketplace Lending, Default

**JEL Classifications**: D12, D14, G4, G21, G23, O33

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## 1. Introduction

The advent of financial technology has fundamentally changed the landscape of households' financial decision-making. Borrowers on online marketplace platforms can apply for loans from the comfort of their homes, day or night, complete their loan applications within minutes using their smartphone or computer, and never speak to a banker or a loan officer. Such developments, in turn, can have a material effect on overall financial decision-making. At the extensive margin, lower transaction costs can increase the consumption of credit. The unsecured consumer loan market has grown dramatically in the last decade, from $57.7 billion in 2009 to $156 billion in 2019, with marketplace lenders responsible for roughly 40% of the market.[1] At the intensive margin, they can affect the quality of credit decisions and subject them to influences that more traditional settings would mitigate.

In this paper, we use micro-level data from an online marketplace lending platform to study the role of sentiment and financial technology in households' credit demand. The analyses utilize 1.4 million timestamped loan applications from 2007-2021 to study the effects of transitory emotional states on households' borrowing decisions, the real consequences of those decisions, and the efficacy of features such as "cooling-off" periods in mitigating the emotional effects.

As a source of exogenous variation in consumers' sentiment that matches the high frequency of loan applications, we exploit hourly variation in local sunshine across 2,482 counties during the period 2007-2021. This approach 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).

[1] Based on TransUnion data – see: https://www.supermoney.com/studies/personal-loans-industry-study/

A key empirical challenge is to separate the effect of sentiment on households' borrowing decisions, or credit demand, from its effect on credit supply and local economic conditions. Indeed, prior studies have shown that sunshine affects both credit supply (Cortès et al., 2016) and economic expectations (Chhaochharia et al., 2019). Our empirical setting has several features that allow us to overcome this challenge. First, the data contain loan applications irrespective of their eventual origination or funding status, thus capturing households' credit demand rather than credit supply. Second, the test specifications match each application's granular time stamp with *hourly* variation in sunshine within a *county-week*, thus holding constant local economic conditions and removing seasonal variation in sunshine for a given county. Third, by design, all credit decisions on the online marketplace lending platform are based on an algorithmic credit model, and the investors are nonlocal and institutional. As such, the supply of credit on the platform is unrelated to variation in local sunshine.

We confirm that hourly variation in sunshine does not affect credit supply by studying loan pricing, risk assessment, and funding. Consistent with our identifying assumption, we find that sunshine is uncorrelated with loan interest rates, the platform's estimated loss rate, or the proportion of the application that is funded. These results suggest that variation in local sentiment does not affect loan origination or loan terms, nor is it accounted for by the platform or investors.

Our main findings can be summarized as follows. First, positive sentiment, attributable to hourly variation in local sunshine, corresponds to higher credit demand both at the extensive and intensive margins. At the extensive margin, we find that the number of applications is 2% higher during sunny hours compared to cloudy hours. At the intensive margin, we find that requested loan amounts, loan-to-income ratios, and monthly payment-to-income ratios increase by 1.3%, 1.3%, and 1.1%, respectively, during sunny hours. Combined, these results suggest that sentiment operates through both the extensive and intensive margins.

The above findings hold after the inclusion of county-by-week fixed effects, which absorb weekly variation in economic conditions specific to each county, as well as credit rating, loan purpose, hour, and day-of-week fixed effects, which absorb variation across borrower credit quality, loan type, time-of-day, and weekday, respectively. The analyses also control for a wide range of borrowers' characteristics, such as employment duration, income level, prior platform experience, and participation on the platform as a lender.

As such, we provide novel causal estimates of a behavioral credit demand channel, augmenting recent studies that have mostly focused on the implications of behavioral factors for credit supply, including personal connections (Engelberg, Parsons, and Yao, 2012), the perception of borrower trustworthiness (Duarte, Siegel, and Young, 2012), and most related to our study, sunshine-induced sentiment (Cortès et al., 2016).[2] In contrast, we focus on credit demand in a setting that holds constant credit supply and economic conditions. Our finding, that sentiment has considerable implications for credit demand in the FinTech consumer loan marketplace, differs from prior evidence that sentiment does *not* affect credit demand in more traditional credit markets (e.g., Cortès et al., 2016). These findings highlight the role of traditional loan market features, such as live interactions with loan officers, in mitigating the impact of sentiment on credit demand.

Second, we find that loan applications initiated on sunny hours are significantly more likely to be charged-off compared to those initiated on overcast hours during the same week in the same county. In particular, loan applications initiated during sunny hours are 0.39 percentage points more likely to be charged-off, or 1.49% relative to the sample standard deviation, compared to those initiated during cloudy hours. These findings show that sentiment has real effects on households' financial outcomes.

[2] A related literature examines the effect of sunshine-induced sentiment on other consumer decisions such as car choice (Busse et al., 2015) housing prices (Hu and Lee, 2020), and credit card spending (Agarwal et al., 2020).

Third, we find considerable demographic differences in the effects of sentiment on credit outcomes across income groups. Specifically, we find that loans initiated by low-income individuals during sunny hours are roughly 1.4 percentage points more likely to be charged-off, or about 5.3% relative to the sample standard deviation, compared to those initiated during cloudy hours. In contrast, we do not find strong sentiment effects for high-income borrowers. The results suggest that low-income borrowers are less capable of bearing the financial burden of sentiment-driven loans, and subsequently experience negative economic consequences.[3]

Fourth, we investigate the role of previous experience and cooling-off periods in mitigating the effect of sentiment on credit demand. Consumer protection advocates point to behavioral research to justify regulations in financial markets. One such regulation is a "cooling-off period", which allows borrowers to withdraw from financial contracts within a certain time window. Thaler and Sunstein (2008) note that cooling-off periods "make best sense, and tend to be imposed, when two conditions are met: (a) people make the relevant decisions infrequently and therefore lack a great deal of experience and (b) emotions are likely to be running high."

Consistent with the Thaler and Sunstein (2008) view, we find that the effect of sunlight on requested loan amounts, loan-to-income ratios, and charge-offs is concentrated in first-time borrowers, and disappears for borrowers with prior platform experience. In particular, loan applications initiated during sunny hours by first-time borrowers are 1.3% larger and have 1.12-1.4% higher loan-to-income ratios compared to applications initiated during cloudy hours. We also find substantial negative outcomes for inexperienced borrowers, who experience a 0.62 percentage points, or 2.4%, increase in charge-off rate when they begin their application during sunny hours. In contrast, sunny-hour applications initiated by experienced borrowers are indistinguishable from cloudy-hour applications.

[3] These individuals may also be the least financially literate and hence most susceptible to sentiment (see, i.e., Campbell, 2006; Thaler and Sunstein, 2008; Lusardi and Mitchell, 2014; Ru and Schoar, 2016).

We also find that experienced applicants are considerably more likely than first-time applicants to withdraw a sunny-hour loan listing before accessing the funds. While experienced borrowers are 1.78% more likely to withdraw a sunny-hour loan application compared to a cloudy-hour loan application, first-time borrowers are not economically or statistically significantly more likely to withdraw such applications. Further, experienced applicants whose previous application was initiated during a sunny hour are more likely to withdraw a current loan listing compared to those whose previous application was initiated during a cloudy hour. As such, our results suggest that individuals learn from previous experience, and that mandating a cooling-off period provides benefits in the consumer credit market by potentially protecting households from irrational, sentiment-based decisions.

Lastly, we find that sentiment influences the composition of loans. Local sunshine increases the demand for discretionary loans such as those for large purchases, vacations, or home improvement by 1.1%. In contrast, it does not affect business loan applications and reduces the demand for debt consolidation by 1.63%. These results are consistent with a shift toward "impulse" credit expansion for households when sentiment is high. This effect, however, does not spill over to business credit demand. These findings complement research in experimental economics that studies consumption composition in consumer markets (see, e.g., Busse et al., 2015).

Our paper contributes to the growing literature on the real effects of FinTech. On the positive side, technology may improve financial education (Breza, Kanz, and Klapper, 2020), enhance consumption-smoothing and risk sharing (Jack and Suri, 2014; Suri, 2017), increase financial attention (Stango and Zinman, 2014; Karlan, Morten, and Zinman, 2017; Bursztyn, 2019; Medina, 2021), or relieve information frictions (Carlin, Olafsson, and Pagel, 2023). Several studies specifically examine future outcomes of FinTech borrowers and find mixed results. Balyuk (2023) finds that FinTech borrowing provides information spillovers that facilitate future credit access from banks. Conversely, Chava et al. (2021) and Di Maggio and Yao (2021) find negative long-term consequences of FinTech borrowing in terms of lower credit scores, higher costs of credit, and higher default rates. Wang and Overby (2022) find that FinTech borrowers overconsume loans from marketplace lenders, leading to bankruptcy. Our results suggest that the ease of accessing consumer credit heightens the effect of transitory sentiment on financial decisions, potentially leading to overconsumption of credit and negative future outcomes.

Our paper also contributes to the literature on household participation in debt markets. Prior studies rely primarily on surveys, and provide evidence on socio-demographic variables, economic variables, and deviations from optimal choice (e.g., Cox and Jappelli, 1993; Duca and Rosenthal, 1993; Gropp, Scholz, and White, 1997; Lea and Webley, 1995; Leece, 2000; Graham and Isaac, 2002; Karlsson, Dellgran, Klingander, and Garlin, 2004; Brown, Taylor, and Wheatley Price, 2005; Easterlin, 2005; Magri, 2007; Siemens, 2007; Del Rio and Young, 2006, 2008; Ranyard et al., 2006; Meier and Sprenger, 2007, 2010; Rohde, 2009; Etzioni, 2010.). We add to this literature by providing evidence from micro-level observational data on high frequency credit demand decisions of households. As such, our work is related to Ben-David and Bos (2021), who use observational Swedish data, and find that an increase in the availability of liquor increases credit demand, default, welfare dependence, and crime.

Lastly, we also add to the growing literature on the role of sentiment in financial markets. Early work in this field examines the effect of sunshine-induced mood on the stock market and on trading behavior (Suanders, 1993; Kamstra, Kramer, and Levi, 2003; Hirshleifer and Shumway, 2003; Goetzmann et al., 2015). We add to this literature by studying household credit demand.

## 2. Institutional Details and Data

This section describes the institutional details of the loan application process of the marketplace lender (Prosper Marketplace), as well as the theoretical motivation for sunshine as a mood primer. Additionally, this section details the data sources and variables we use in this study.

### *2.1. Prosper Marketplace*

The empirical analyses focus on FinTech consumer loan applications from the universe of listings provided by Prosper Marketplace, the second largest online consumer lender in the United States.[4] To initiate a loan application, individuals state their desired loan amount (up to $40,000) and the purpose of the loan.[5] The applicant must then provide her name, address, and date of birth, along with her occupation, income, homeownership status, employment status, and other general credit history terms. The platform then performs a soft credit inquiry, and generates a set of potential loan packages with either a 3- or 5-year term from which the borrower chooses. Once the applicant accepts the desired loan terms, the platform conducts a hard credit inquiry, and uses a proprietary credit-scoring model to evaluate the riskiness of each loan. The platform may also request additional documentation to verify certain items on the borrower's credit profile and provided information. The listing then goes public on the Prosper platform and is available to be funded by investors. The entire application process takes only minutes, and the platform approves most loans and provides funding within 1 day.

Upon going public, a listing has two weeks to be funded, and may be funded by individuals or institutional investors. In practice, the loans are overwhelming funded by institutional investors

[4] Prosper has issued over $21 billion in loans to over 1.2 million people since 2005.
[5] Loan purpose is separated into 10 main categories. The most common loan purpose is debt consolidation, which makes up roughly 70% of the applications in our data.

using passive means based on observable quantitative variables from the credit bureau (Balyuk and Davydenko, 2019). At any time prior to funding, a borrower may withdraw her application at no cost. Investors observe the requested amount, loan purpose, and the borrower's credit characteristics, but not the personal characteristics of the borrower, such as the borrowers' precise location. Investors then decide whether to fund the loan partially or completely. Once funding is complete, contingent on the borrower's approval, the loan is originated, and the funds are deposited in the account of the borrower. Borrowers incur fees and notifications of past due accounts on their credit reports if they are unable to make the necessary loan payments. If the borrower misses five consecutive monthly payments, the loan is considered "charged-off," and the entire loan balance is due immediately (including fees, interest, and principal).

Prosper loan applications are ideal for examining the effect of sentiment on consumer credit demand for three reasons. First, we can observe the precise location and timestamp when a potential borrower begins an application, allowing us to map the exact weather in the area on a granular level. Second, the platform itself is fully automated, and is therefore unaffected by sentiment. Finally, investors are primarily non-local and unable to observe the precise location of the applicant, making it unlikely that they are affected by similar sentiment or are able to incorporate local weather into their investment strategy.[6]

Prosper provides anonymized data on all loan applications to its platform. It contains detailed information on both the loan application and borrower credit characteristics. In terms of loan applications, the platform provides information on the requested loan amount, (*Amount Requested*), the amount the loan is funded (*Amount Funded*), the proportion the loan is funded (*Percent Funded*), whether the borrow would accept only partial funding of the loan (*Partial*

[6] In Section 4.4, we test these assumptions by examining both the pricing of the loans and the probability of funding.

*Funding Indicator*), and whether the borrower withdraws the application (*Withdrawn*). We construct additional variables relating the size of the requested loan and the size of the monthly payment to applicant's monthly income (in thousands), which we call *LTI* and *Monthly LTI*, respectively. The platform also provides pricing characteristics, such as the estimated loss rate (*Estimated Loss Rate*), or the historical default rate on loans with similar characteristics, and interest rate (*Loan APR*).

To examine loan outcomes, we match listing details to loan outcomes by merging the Prosper listing and loan datasets. These datasets lack a unique identifier for matching, so we leverage the granularity of the data to match unique observations between datasets based on borrower and loan application characteristics. Most loan applications are unique and thus successfully merged, and any loan outcome which cannot be verifiably matched is removed. We define *Charged-Off* as an indicator equal to 1 if a borrower misses five consecutive monthly payments, in which the loan is written off as a loss by the platform and sent to collections.[7] Approximately 7% of loans are charged-off.

The platform also provides detailed information on applicant quality. Specifically, we observe employment duration in months (*Months Employed*), stated monthly income (*Monthly Inc.*, in thousands), an indicator variable for whether the applicant can validate her income (*Inc. Verifiable)*, an indicator variable for whether the applicant is also an investor on the platform (*Prosper Lender*), and the number of prior Prosper loan applications (*Prior Loans*). Most importantly, we observe the proprietary, platform-calculated metric of borrower quality integrating all observable credit components (*Prosper Rating*).[8] We report the summary statistics associated with these variables in Table 1, and variable definitions and in Appendix A.

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[7] See https://help.prosper.com/hc/en-us/articles/210013713-What-does-it-mean-for-a-loan-to-be-charged-off-
[8] There are 7 rating categories, ranging from HR (high risk) to AA.

Panels A and B of Internet Appendix Table IA1 also show the breakdown of applicants by income range, and applications by loan purpose, respectively. Panel B shows that applicants are fairly evenly distributed across the income distribution, with 27.6% reporting annual income between $25,000-$49,999, 28.4% between $50,000-$74,999, 17.3% between $75,000-$99,999, and 21.8% above $100,000. We define *Low Income* as an indicator equal to 1 if an applicant has annual income of less than $50,000. On the application side, the majority of loans are intended for Debt Consolidation (66.2%), with Home Improvement (9.3%), and Other (6.9%) making up the next largest categories. For later analyses, we define Debt Consolidation and Business applications as *Non-Discretionary*, and all other loans as *Discretionary*.

### *2.2. Hourly Sunshine*

We use hourly variation in sunshine at the county level as a primer for an individual's mood. Our use of sunshine as a mood primer is motivated by extensive research in social psychology, experimental economics, and neurobiology. Howarth and Hoffman (1984) find that sunshine is related to optimism scores. Bassi, Colacito, and Fulghieri (2013) perform experiments in which subjects are randomly assigned to sessions held on sunny or overcast days, finding sunshine leads to a higher self-reported mood. Persinger and Levesque (1983) demonstrates weather conditions, including sunshine, can explain about 40% of daily variation in mood. These mood changes are attributable to the effect of sunshine on aspects of brain chemistry. Lambert et al. (2002), Praschak-Rieder et al. (2008), and Spindelegger et al. (2012) all provide evidence that sunlight increase the rate of serotonin release, the monoamine neurotransmitter associated with an elevated mood. Taken together, this evidence suggests the efficacy of hourly sunshine as a high-frequency instrument for mood.

The role of sunshine and mood has also been examined in various settings in financial economics. Saunders (1993) finds that sunshine impacts stock markets after considering several alternative environmental factors. Hirschleifer and Shumway (2003) show that sunshine during the morning hours is correlated with higher stock returns, while Goetzmann et al. (2015) find that weather-induced mood impacts individual stock returns via the locations of institutional investors who are holding the stock. Cortes, Duchin, and Sosyura (2016) also use daily fluctuations in sunshine as an instrument for mood, finding that mood is associated with higher risk aversion in loan officers. Additionally, Chhaochharia, Kim, Korniotis, and Kumar (2019) find that monthly sunshine positively affects the economic expectations of small business managers, and thus the aggregate state-level economy. Overall, the evidence supports the interpretation of sunshine as an important driver of sentiment, with significant implications for a wide range of economic outcomes.

Hourly variation in sunshine has a number of useful properties for our empirical analyses. First, sunshine serves as a plausibly exogenous driver of sentiment at a local (county) level. Second, the weather data matches the high-frequency variation in FinTech loan demand, allowing us to identify the prevailing weather at the exact hour that a borrower begins her loan application. Finally, wide variation in sunlight even within a particular county and week allows us to identify the effect of sentiment controlling for local economic conditions at the granular (weekly) level.

Following prior studies, we collect hourly cloud cover data from the Integrated Surface Database of the National Oceanic and Atmospheric Administration (NOAA) (Cortes, Duchin, and Sosyura, 2016; Chhaochharia, Kim, Korniotis, and Kumar, 2019). Hourly cloud cover values are sorted into 5 bins from perfectly sunny (cloud cover equal to 0) to perfectly cloudy (cloud cover equal to 4). We map sunshine to individual borrowers by utilizing the geographic coordinates of the weather stations and the coordinates of the geographic centroid of the county of the borrower. In the cases where there are multiple weather stations within 50 miles of the county centroid, we take the average cloud cover value.[9] To ensure the data capture actual weather patterns in the county, we exclude counties located more than 50 miles from the nearest weather station (Cortes, Duchin, and Sosyura, 2016).

We define several variables to capture the effect of sunshine on mood. The main variable of interest is *Hourly Sun*, which is a continuous variable ranging from 0 to 4 identifying the amount of sunlight at the hour when an individual begins a loan application.[10] We assign a value of zero to *Hourly Sun* for the nighttime hours between 8 pm and 6 am.[11] In addition, we define several alternative measures to capture the effect of the mood instrument. We also define the dummy variables *Sunny Hour*, which is equal to 1 if *Hourly Sun* is greater than 2, and *Cloudy Hour*, which is equal to 1 if *Hourly Sun* is less than 2. We report the summary statistics of the weather-related variables in Table 1. Average *Hourly Sun* during application hours is 2.09. In the sample, about 54% of loan applications are filled out while it is sunny (*Sunny Hour)*, although this measure has exhibits considerable variation with a standard deviation of 50%. In contrast, only 44% of applications are initiated during cloudy hours.

Figure 1 shows the breakdown of average hourly application volume by sunlight over the whole sample. This figure accounts for any possible differences in the number of sunny and cloudy hours by taking the average of application counts or dollar volume conditional on the weather

[9] Weather observations are taken at different times within the hour. To ensure that we are not capturing weather following the loan application, we use *Hourly Sun* in the hour before the application as our main independent variable. The results are similar if we instead use the contemporaneous *Hourly Sun*, or the average *Hourly Sun* between the contemporaneous and previous hour (See Internet Appendix Table IA2).
[10] The inclusion of county-week fixed effects in our empirical analyses effectively removes seasonal variation in weather specific to a given county.
[11] Over 80% of loan applications occur between 6 am and 8 pm. The results are robust to other definitions of nighttime. See Internet Appendix Table IA3.

during that hour. Consistent with the summary statistics above, the average number and dollar amount of loans requested during sunny hours is significantly higher than that of cloudy hours.

## 3. Empirical Design

We estimate the effect of sentiment on consumer FinTech loan demand using exogenous variation in hourly sunlight within county-weeks. The unit of observation for our analysis is the loan application, for which we have detailed time and location data. To examine this effect, we primarily employ the following regression model:[12]

$$Y_{i,b,c,h,w} = \alpha + \beta_1 Hourly\ Sun_{c,h,w} + \beta_2 X_{i,b} + \gamma_{c,w} + \phi_h + \omega_d + \tau_r + \eta_p + \epsilon \qquad (1)$$

where $Y_{i,b,c,h,w}$ is the outcome variable of interest for application $i$, borrower $b$, county $c$, hour $h$, and week-year $w$. $Hourly\ Sun$ is defined as in Section 2.2 above. $X_{i,b}$ includes a wide range of loan and borrower characteristics, such as the duration of employment, monthly income, an indicator for whether the applicant also participates on the platform as an investor, the number of prior Prosper loans, and a partial funding indicator. We also include county-week fixed effects ($\gamma_{c,w}$), day-of-week fixed effects ($\omega_d$), hour fixed effects ($\phi_h$), Prosper credit rating fixed effects ($\tau_r$), and loan purpose fixed effects ($\eta_p$). These fixed effects allow us to identify the effect of sunlight within a given county and week, controlling for variation across time of day, day of the week, credit ratings, and loan types. Standard errors are clustered at the county level.

Importantly, this specification effectively isolates the impact of sentiment on credit demand by comparing loans applied for in the same county in the same week, but with differing levels of sunshine when the application was initiated. Previous studies have shown that sunlight can affect

[12] For tests of application counts, we aggregate the number of applications to the county-hour level and estimate PPML regressions including county-week, hour, and day-of-week fixed effects.

both local economic conditions (Chhaochharia et al., 2019) as well as credit supply (Cortès et al., 2016). The inclusion of county-week fixed effects holds constant local economic conditions, while the institutional details of the FinTech lending process preclude any incorporation of local weather into loan pricing or funding decisions. We explicitly test for credit supply effects in Section 4.4.

## 4. Results

In this section we examine how variation in sunlight affects household demand for FinTech credit. We first examine the effect of sunlight on the number of applications in a given county. We then analyze the size of requested loans, and the size relative to the applicant's income. We then examine the economic consequences of sentiment-induced borrowing in the form of loan charge-offs and whether these effects are accounted for by the platform or by investors.

### *4.1. Extensive Margin – Application Counts*

This subsection examines the extensive margin of credit demand, or whether sentiment leads individuals to begin new loan applications. For this test, we include all hours within the relevant county-weeks, and count the number of applications in each hour. We then estimate fixed-effect PPML regressions following Cohn, Liu, and Wardlaw (2022), including county-week, hour, and day-of-week fixed effects. The unit of observation for this analysis is a county-hour.

Column 1 of Table 2 displays the results of this analysis. The estimates show the relation between total loan applications and sunshine in a given county-hour, controlling for time-of-day and day-of-week effects. Consistent with the interpretation that sunshine acts as a positive mood primer that consequently increases the demand for personal credit, the point estimate indicates that moving from perfect cloudiness to perfect sunshine increases the overall number of hourly loan applications by 2%.

*4.2. Intensive Margin – Loan Amounts and Loan-to-Income Ratios*

We next examine the effect of sunshine on the size of the loans requested by applicants and the loan size relative to the applicant's income. Since sunlight acts as a positive mood primer, borrowers may respond to sunlight by taking out larger loans than they otherwise would have.

In column 2 of Table 2, we first investigate the effect of sentiment on the size of the requested loan using the specification in Equation 1. This empirical design compares the size of applications begun during sunnier hours to other applications in the same county and week, holding constant a full set of applicant credit characteristics and fixed effects. The key variable of interest is again *Hourly Sun*, which ranges from 0 (cloudiest) to 4 (sunniest) for a given county and hour.[13] The estimates in column 1 show that moving from perfect cloudiness to perfect sunniness increases the size of the requested loan by an average of $94. The estimate is statistically significant at the 1% level, and represents an increase of 1.13% relative to the sample standard deviation.

The economic magnitude of the average effect is relatively modest, but could mask important heterogeneity in the size of requested loans relative to the income of the applicant. We therefore examine the size of the listing and the size of the monthly payment scaled by the applicant's monthly income. Columns 3 and 4 of Table 2 show the results of these analyses. The estimates suggest that moving from perfect cloudiness to perfect sunniness increases the ratio of listing amount to monthly income by 1.29% (column 3), and monthly payment to monthly income by 1.14% (column 4), both relative to their respective standard deviations. Both estimates are significant at the 1% level. The results indicate that applicants not only request larger loans, but also loans that are significantly larger relative to income.

[13] In Internet Appendix Table IA4, we separately examine the effect of sun and clouds using indicator variables.

Taken together, the results provide novel evidence of the impact of sentiment on consumer credit demand. During sunnier hours, individuals are more likely to begin a FinTech loan application. The applicants are also more likely to request larger loans, especially relative to their income, compared to their local neighbors during the same week. The results suggest that the relative ease and convenience of accessing credit via FinTech lenders allows for transitory sentiment to affect financial decision-making.

### *4.3. Loan Outcomes*

We next examine the implications of sentiment for loan outcomes. The consequences of sentiment-induced increases in credit demand depend on both the size of the increase and the borrower's ability to repay the loan. To examine loan outcomes, we narrow our focus to funded loans and define the variable *Charged-Off* as a dummy variable equal to 1 if the borrower misses 5 consecutive monthly payments, and 0 otherwise. We then multiply *Charged-Off* by 100 for ease of interpretation. The matching of loan applications to loan outcomes reduces the sample size from just under 1.4 million observations to just under 500,000.

Figure 2 Panel A shows the univariate relationship between the amount of sunshine and eventual loan charge-off. For this figure, we take the average number of charge-offs for all hours during the sample, conditional on whether the hour is exceptionally sunny ($HourlySun \geq 3$) or exceptionally cloudy ($HourlySun \leq 1$). This figure accounts for the fact that there could be different probabilities of sunshine or cloudiness that would mechanically lead to a greater number of charge-offs. The figure shows that loans initiated during sunny hours have a noticeably higher average charge-off rate than those initiated during cloudy hours. To test this relation more formally, we next re-estimate the baseline regression with *Charged-Off* as the dependent variable, both in the whole sample and subsamples related to borrower income level.

Table 3 shows the results of this analysis. In column 1, we examine the charge-off rate for the whole sample, including the full set of controls and fixed effects in Equation 1. We find that the amount of sunshine at the time of the loan application positively predicts eventual loan charge-off. The coefficient estimate indicates that moving from overcast to sunny increases the probability of default by 0.39 pp, or 1.49% relative to the sample standard deviation.

We next examine whether more constrained borrowers, who are less able to bear the financial burden of FinTech loans, experience a disproportionate increase in the probability of charge-off when they begin their application during sunnier hours. Figure 2 Panel B shows preliminary univariate evidence that this may be the case. The figure shows a significant jump in the average charge-off rate for low-income borrowers if they initiate their application during a sunny hour. To formally test this conjecture, we focus first on the subsample of loans of low-income borrowers in column 2 and regress *Charged-Off* on *Hourly Sun* and the full set of controls. Consistent with the intuition that these borrowers are more constrained, we find that moving from overcast to sunny increases the probability of loan charge-off by low-income borrowers by 1.38 pp, or 5.3% relative to the sample standard deviation.[14]

Turning next to high-income borrowers in column 3, we find that these borrowers experience no change in the probability of loan charge-off when they begin their applications during sunnier hours. The difference between the point estimates for low and high-income

[14] We also test for differences in application counts, loan amounts, and LTI ratios by applicant income (Internet Appendix Tables IA5 and IA6). Low-income individuals are more likely to apply for a loan during a sunny hour, but the requested loans are similar in size to those of high-income applicants.

borrowers is also economically and statistically significant.[15] Taken together with the results in Table 2, these results suggest that the sentiment-induced increase in credit demand has negative consequences for borrowers' financial outcomes, primarily for low-income individuals.

Overall, the results suggest that positive sentiment leads to mistakes in financial decision-making, with real effects for borrowers' financial well-being. Our results are consistent with Chava et al. (2021) and Wang and Overby (2022), who find negative consequences of FinTech borrowing. Our results suggest that the ease of accessing consumer credit heightens the effect of transitory sentiment on financial decisions, potentially leading to overconsumption of credit and negative future outcomes.

### *4.4. Loan pricing and funding success*

A key empirical challenge is separating the effect of sentiment on credit demand from its effect on credit supply and local economic conditions. We argue above that the fully automated platform is unlikely to account for high-frequency variation in local weather, and that investors are largely nonlocal (and thus unaffected by the same sentiment) and unable to observe the precise location of the applicants. In this section, we explicitly test whether the platform incorporates weather into its algorithm, and whether investors account for the impact of sentiment when choosing which loans to fund. In the first set of analyses, we examine potential platform effects via the interest rate on the loan and the estimated loss rate. Then, we make use of the granular application data and analyze the proportion of each loan application that is eventually funded by investors.

Table 4 shows the results of this analysis. In column 1, we examine the effect of *Hourly Sun* on the loan interest rate. The coefficient estimate indicates that hourly sunshine is statistically

[15] The t-statistic of 2.13 shows that the estimate for the low-income sample is significantly larger than that of the high-income sample (significant at the 5% level).

unrelated to loan pricing and very close to zero. We next examine the effect of sunshine on the estimated loss rate, which is calculated by the platform as the historical default rate on loans with similar characteristics (column 2). Like the estimate in column 1, the coefficient on *Hourly Sun* is statistically insignificant and close to zero. Both results suggest that the platform does not incorporate the effect of sunshine into its algorithm.

We next test for potential investor effects by examining the proportion of the loan that is eventually funded. If investors are able to incorporate the effect of sunshine into their funding decisions, we would expect the coefficient on *Hourly Sun* to be negative. However, the results in column 3 show that *Hourly Sun* is also unrelated to the proportion of the loan that is eventually funded. These results suggest that investors do not consider the effects of hourly sun on the applicants, despite its significant impact on loan default.

Overall, the results show that the actions of both the platform and investors are unrelated to sunshine-induced sentiment. Taken together with the county-week fixed effects that control for local economic conditions on a granular level, these results help to rule out confounding effects related to credit supply or local economic conditions.

## 5. Borrower Learning and Policy Implications

In this section we explore the implications of previous platform experience for sentiment-induced borrowing. First, we examine how the effect of sentiment differs for first-time vs. experienced applicants in terms of loan size, loan-to-income ratios, and charge-off rates. Then, we examine whether experienced borrowers exhibit self-corrective action (i.e., loan withdrawal before funding) if they begin an application during a sunnier hour. Finally, we discuss the implications of the findings for consumer protection policy.

*5.1. First-time vs. experienced borrowers*

In this subsection we examine whether the effects of sentiment are concentrated in individuals who have less experience with the platform. Thaler and Sunstein (2008) note that behavioral biases are more likely to be prevalent in decision-making when "people make the relevant decisions infrequently and therefore lack a great deal of experience." Therefore, we split our sample into first-time and experienced applicants, and estimate the baseline regression.

Panel A of Table 5 explores the relation between hourly sun and requested loan amounts and LTI ratios based on applicant experience. Column 1 shows that first-time applicants who begin their application during sunnier hours request $110 more (1.3% relative to the sample standard deviation) than other first-time applicants in the same county and week. These applicants are also more likely to apply for larger loans relative to income (1.4%, column 3), and have larger monthly payments relative to income (1.12%, column 5). Conversely, sunshine has no impact on any of these outcomes for experienced borrowers (columns 2, 4, and 6).

Finally, we examine differences in loan charge-off rates by borrower experience. Figure 2 Panel B shows preliminary univariate evidence that first-time applicants have higher charge-off rates when the loan is initiated during sunny hours compared to cloudy hours. The regression analysis in Table 5 Panel B formally tests this univariate relation. Column 1 shows that first-time borrowers experience worse outcomes when they apply during a sunny hour. Specifically, the estimate suggests that moving from perfectly cloudy to perfectly sunny increases the charge-off rate for first-time borrowers by 0.62 pp, or 2.4% relative to the sample standard deviation. For experienced borrowers, the effect of sunshine on loan charge-off is insignificant and close to zero (column 2).

Taken together, the results provide suggestive evidence that experienced borrowers are less likely to be negatively impacted by sentiment when applying for a FinTech loan. First-time borrowers are significantly more likely to take out larger loans and subsequently default if they began the application during a sunnier hour, whereas experienced borrowers are not. As such, our results suggest that the effect of sentiment is transitory, and individuals learn from previous experience. In the next subsection, we explore a potential avenue through which experienced borrowers may mitigate the effect of sentiment on financial decision-making.

### *5.2. Loan withdrawals and previous experience*

In this subsection, we examine another element of borrower learning related to self-corrective action: application withdrawal. Prosper allows applicants to withdraw their listing any time before it is funded, allowing us to examine whether applicants experience a "change of heart" in the aftermath of sunlight-induced sentiment. We therefore examine whether the individual's previous platform experience affects the propensity to withdraw an application begun during a sunnier hour.

Panel A of Table 6 shows the results of this analysis. Column 1 reports results for the whole sample, column 2 reports results for the subsample of applicants without previous a loan application, and column 3 reports results for the subsample of applicants with at least one prior listing on the platform. Column 1 shows that on average applicants are significantly more likely to withdraw their loan listings that were begun during sunnier hours. Moving from perfectly overcast to perfectly sunny increases the chance of withdrawing the listing by 0.76% relative to the sample standard deviation.[16] The results are consistent with the presence of transitory sentiment in the initial application, and a subsequent change of heart once the effects wear off.

[16] Internet Appendix Table IA7 shows that experienced applicants are slightly more likely to apply for a loan during a sunny hour. However, this extensive margin effect is later counterbalanced by significantly higher withdrawal rates.

We next examine the relation between hourly sun and loan withdrawal based on the experience of the applicant. Column 2 shows that first-time applicants are no more likely to subsequently withdraw the application if it was made during a sunnier hour. Conversely, column 3 shows that applicants with prior platform experience, who are presumably more experienced and may therefore be more cognizant of sentiment effects when applying for a new loan, are significantly more likely to withdraw their applications if they are begun during a sunny hour. The magnitude of the effect is nontrivial, corresponding to a 1.78% increase in the probability of withdrawal relative to the sample standard deviation. The results are consistent with the presence of learning, where individuals recognize and self-correct for the effects of transitory sentiment.

Panel B of Table 6 explores heterogeneity in the prior experience of borrowers. Since we also observe the weather conditions at the time of the applicant's previous listing, we can test for the presence of learning more directly. Intuitively, applicants are more likely to be aware of the effects of sunshine-induced sentiment if their previous platform experience also involved sunshine. Therefore, we split experienced applicants into 2 subsamples– those whose *previous* listing was begun during sunny hours (*Hourly Sun>2*) and those whose *previous* listing was begun during cloudy hours (*Hourly Sun<2*). If learning about sentiment depends on direct experience with sunlight, then we would expect individuals with previous sunshine experience to exhibit stronger self-corrective effects. Consistent with this intuition, we find that applicants with previous sunshine experience are significantly more likely to withdraw an application made during a sunny hour (column 1), while applicants with no previous sunshine experience are significantly *less* likely to withdraw (column 2). The results suggest that more salient experience, in this case regarding the mood priming effect of sunshine, has a greater impact on borrower learning and subsequent self-corrective action.

The results of this section have important implications for consumer protection policies such as “cooling-off periods”, which allow borrowers to withdraw from financial contracts within a certain time window if they have a change of heart. We find that the effect of sunshine is transitory, and that borrowers learn from prior experience and exhibit self-corrective action based on this experience. Although experienced applicants are more likely to begin new listings during sunny hours, they are also significantly more likely to withdraw their applications than first-time borrowers, especially if their previous experience involved sunshine. Taken together, our results suggest that mandating a cooling-off period in markets potentially protects borrowers from irrational, sentiment-induced borrowing.

## 6. Additional Tests and Economic Mechanisms

In this section we exploit the granularity of the listing data and explore additional effects related to the composition of loans.

### *6.1.Discretionary vs. Non-Discretionary Loans*

In this subsection we examine another element of credit demand: the stated purpose of the loan application. Presumably, loan applications with a discretionary purpose are more likely to be susceptible to sentiment, since the applicant has some freedom regarding whether to initiate these loans. We therefore examine whether local sunshine affects the probability of discretionary loan application, which we define as any of the following loan categories: Home Improvement, Business, Personal loan, Student use, Auto / Motorcycle / RV / Boat, Other, Baby & Adoption, Boat, Cosmetic Procedures, Engagement Ring Financing, Green Loans, Household Expenses, Large Purchase, Medical / Dental, Motorcycle, RV, Taxes, Vacation, Wedding Loans, Special

Occasion.[17] We then estimate a linear probability model using this indicator variable, which we multiply by 100 to ease interpretation of the coefficients.

Table 7 reports the results of this analysis. Column 1 shows the results for discretionary loans, as defined above. The coefficient on *Hourly Sun* indicates that local sunshine is positively and significantly related to the probability of a discretionary loan application. Moving from perfectly cloudy to perfectly sunny in the hour of application increases the likelihood of a discretionary loan application by 0.5 pp, or 1.1% relative to the sample standard deviation. Columns 2 and 3 show the results for the individual non-discretionary categories, Debt Consolidation and Business, respectively. While individuals are more likely to apply for a discretionary loan during a sunnier hour, they are proportionately less likely to apply for a debt consolidation loan (column 2), and no more/less likely to apply for a business loan.

The baseline results show a positive association between sunlight and requested loan amounts, especially relative to borrower income. The results of this section explore an additional element of credit demand– the composition of loans by purpose. We show that individuals are significantly more likely to request discretionary loans during sunnier hours, which is consistent with the ability of sentiment to influence decisions over which the applicants exert some control. These results provide additional depth to the analysis and suggest that sentiment affects credit demand along a number of dimensions.

[17] It may also be argued that Medical/Dental is not a discretionary loan type. In Internet Appendix Table IA8, we show that the results are robust to excluding this category from the definition of discretionary. Internet Appendix Table IA1 Panel B shows a breakdown of applications by loan purpose.