In the Mood to Consume:
Effect of Sunshine on Credit Card Spending*

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Abstract

Using a large, representative sample of high-frequency credit card transactions in the United States, this paper examines the causal effect of sunshine-induced mood on contemporaneous household credit card spending. We document a 0.3 percent increase in credit card spending in response to a one-unit increase in the same-day local abnormal sunshine. The spending response is stronger for consumers with higher credit card debt, lower FICO score, and shorter tenure with the bank. The effect manifests in long-term, durable goods spending, and is not driven by other weather conditions, complementarity between sunshine and consumption, or intentional choice of consumption time. We document similar responses of spending on seasonal and non-seasonal goods and during times with high and low sunshine levels. Finally, the sunshine effect occurs among consumers with various characteristics.

Keywords: Credit Cards, Mood, Sunshine, Household Finance, Consumption

JEL Classification: D12, D14, E21, H31

1. Introduction

Consumption accounts for over 50 percent of GDP in many countries, and this number has risen to almost 70 percent in the United States since the 2000s (*World Bank*, 2019). Given the large stake, investigating the factors that influence household consumption is an economic question of first-order importance. Besides the income shocks that typically occur at relatively low frequency, an often ignored factor is the mood.

On the one hand, mood shocks can be highly volatile and frequent, and have a substantial aggregate impact. Therefore, studying the mood effect on consumption offers a more comprehensive understanding of individual consumption decisions. As Loewenstein (2000) writes, "Understanding the emotions people experience at the time of consuming, or deferring consumption, is critical for understanding and predicting the intertemporal trade-offs they make." On the other hand, consumption fluctuations caused by mood, especially overconsumption, could contribute to household indebtedness. The growth of revolving debt is a major contributor to the rapid accumulation of household debt in recent decades. The fraction of US revolving debt was approximately 40% in 1999, and has remained around 30% in recent years (*Federal Reserve*, 2019). Given the generally high interest rate for revolving debt (for example, credit card debt), households with large amounts of revolving debt typically bear this burden for a lengthy period. In this sense, understanding the mood effect on household consumption has important implications for policies that target the household over-consumption and debt accumulation.

Despite its importance, it is empirically challenging to identify the causal relationship between mood and consumption. Reverse causality and omitted variable concerns both add difficulty to the identification. Specifically, individuals may change their consumption behavior in response to mood fluctuations or, conversely, the consumption of goods may effectively change the consumer's mood, leading to the reverse causality problem. On the other hand, omitted variables, such as income or economic trends, can potentially affect the individual's mood and consumption at the same time. In this sense, a valid identification calls for high-frequency exogenous mood shocks, together with the corresponding consumption records at the individual level. This paper attempts to study the causal effect of mood on individual consumption using a proprietary dataset that combines the daily individual-level credit card spending and the exogenous variations in local sunshine.

Exploiting the mood changes induced by exogenous local sunshine shocks can largely mitigate the reverse causality problem. Psychological studies have documented the effect of sunshine on inducing positive mood, which in turn affects the individual's judgment and behavior in various respects.[1] Moreover, the literature has also shown that individuals in a good mood tend to be more optimistic and think in a heuristic way. This, in turn, leads to more optimistic choices and higher evaluations in many perspectives, including life satisfaction, past experience, and consumer products.[2] Consistent with those findings, financial studies have documented that investors tend to be more optimistic during high-sunshine times and depressed and more conservative during low-sunshine times, which gives rise to a significant positive relation between stock returns and local sunshine (Saunders, 1993; Hirshleifer and Shumway, 2003; Kamstra, Kramer, and Levi, 2003). Applying similar logic to the consumption, we expect that positive local sunshine shocks shall induce individuals' good mood, leading to an over-optimistic evaluation of the goods value while consuming; and negative sunshine shocks work oppositely. Therefore, we expect a positive relation between abnormal local sunshine and individual consumption.

Using a proprietary credit card transaction dataset from a large US bank that issues credit cards nationwide, we are able to measure individual real-time consumption at the daily frequency. The high-frequency nature of both sunshine and credit card spending variations allows us to study consumption responses to mood shocks on the same day, alleviating the omitted variables concern from relatively low-frequency common factors such as income or economic trends. In addition to credit card spending information (including spending amount, time, and goods category), the data also provide a rich array of consumer financial and demographic characteristics, including the residential zipcode, credit card debt, credit line, and credit score, etc., which allow us to further disentangle the economic mechanisms and explore heterogeneous effects from different consumer groups. As a representative consumer spending instrument, credit cards play an important role in studies of household consumption behavior (Japelli, Pischke and Souleles, 1998; Gross and Souleles, 2002).

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[1] See studies by Cunningham (1979), Howarth and Hoffman (1984), and Kämpfer and Mutz (2013) for the sunshine as positive mood inducer. Positive mood induced by sunshine is shown to trigger more helping behaviors (Guéguen and Lamy, 2013) and romantic relationships (Guéguen, 2013), and even affects school enrollment choice (Simonsohn, 2010). On the other hand, a lack of sunshine is associated with depression (Eagles, 1994) and suicide (Tietjen and Kripke, 1994).

[2] See, e.g., Schwarz and Clore (1983); Schwarz (1990); Petty, Gleicher, and Baker (1991); Bless, Clore, Scjwarz, Golisano, Rabe, and Wölk (1996); Bless, Schwarz, and Kemmelmeier (1996); Wright and Bower (1992); Sinclair and Mark (1995); Bagozzi, Gopinath, and Nyer (1999).

The final merged sample covers over 2 million credit card transactions from more than 125,000 consumers in 19,000 zipcodes of the United States, during the sample period from 1st March to 31st October in 2003. For each zipcode in the sample, we construct the time series of sunshine proxy—the *sky cover*—using available *sky cover* information from the closest weather station of the top 10 closest weather stations within a 1,000 km radius for each day. To remove seasonal patterns, we construct an *abnormal sky cover* measure for each zip-day in the sample as the deviation of *sky cover* on that day from the weekly average *sky cover* during the same week of 1998-2008, with the same day of the year being the week center. This *abnormal sky cover* measure captures exogenous sunshine variations in each zipcode at the daily level; and a lower *abnormal sky cover* is associated with a higher abnormal sunshine.

We first document that local abnormal sunshine significantly positively affects the individual's credit card spending on the same day. Specifically, a one-unit increase in abnormal sunshine (proxied by a one *okta* decrease in *abnormal sky cover*) leads to around 0.3 percent increase in the same-day total credit card spending, controlling for individual time-varying characteristics and individual and calendar-day fixed effects. This effect is statistically significant and economically large: a one-unit increase in abnormal sunshine is estimated to increase daily spending by around $0.41 for an average individual or, equivalently, around $51,000 in total for the over 125,000 consumers in our sample. This can translate to a $6.8 billion of additional spending and a $3 billion of extra credit card debt from all US credit card holders during the 30 days with the highest abnormal sunshine. We also document a more pronounced sunshine effect for individuals with lower self-control over consumption (proxied by higher credit card debt, lower *FICO score*, and shorter tenure with the bank), whose spending is more likely to be affected by mood.

We conduct several tests to investigate possible alternative explanations for the sunshine effect. First, as sunshine can be correlated with other weather conditions—for example, high-temperature days or non-rainy days usually have higher levels of sunshine—the sunshine effect we document could be attributed to the effect of other weather conditions. To dispel this concern, we residualize the *abnormal sky cover* regarding three other abnormal weather variables that might affect spending: *abnormal temperature*, *abnormal wind speed*, and *abnormal precipitation*. We find the effect of *residualized abnormal sky cover*, which is orthogonal to the effects of the other three abnormal weather variables, remains strong and robust, whereas the effects of the other three abnormal weather variables are statistically insignificant and economically small. This suggests that the sunshine effect is unlikely to be a recapture of other weather conditions' effects. The sunshine effect is also unlikely to be driven by extreme weather conditions that impede the consumer's ability to travel to shops, as the impact of abnormal sunshine remains strong after we exclude days with extremely low temperature, high wind speed, or high precipitation.

Another possible alternative explanation for the positive relation between abnormal sunshine and consumption is that sunshine and consumption are complements. Specifically, people will consume more entertainment goods on sunny days, the utility from which is higher when consumed on sunny days. This explanation predicts that the sunshine effect should be the strongest for entertainment goods, which are direct complements for good sunshine weather. However, we find inconsistent evidence. When we decompose total spending into spending on non-discretionary goods (including local transportation and supermarket goods), entertainment goods (including entertainment and dining), and long-term goods (including travel, service, durable, and apparel), we find that the sunshine effect is driven by spending on long-term and durable goods. In contrast, the effect of abnormal sunshine on entertainment goods spending is close to zero.

As the sunshine effect is mainly driven by spending on durable goods, which on average have a higher value than other types of goods, individuals could intentionally plan the date for durable goods purchases. For example, one can check the weather forecast and intentionally shift the consumption of durable goods to the upcoming good-weather days, leading to higher spending on sunny days. To test this possibility, we investigate the distributed lag effect of *abnormal sky cover* during the 3 weeks before the consumption date, which is presumably the longest period for which one can obtain a relatively accurate weather forecast. We find that durable goods spending only exhibits a large and negative response to *abnormal sky cover* on the same day, whereas the responses to *abnormal sky cover* in 3 weeks before the consumption date fluctuate around zero and are mostly statistically insignificant. This suggests that the sunshine effect cannot be fully explained by the intertemporal shifting of durable goods consumption.

Next, we discuss and disentangle two possible economic mechanisms for the sunshine effect. On the one hand, an abnormally high sunshine level may induce a good mood in consumers, which gives rise to an over-optimistic evaluation of the value of goods and overconsumption in general (Hirshleifer and Shumway, 2003). On the other hand, it is also possible that individuals overvalue the salient sunshine-relevant features on sunny days, thus their purchase of (long-term) goods is overly affected by the preference on the consumption date, leading to a projection bias/salience effect (Loewenstein, O'Donoghue, and Rabin, 2003).

The projection bias/salience mechanism directly predicts that the positive sunshine effect should be driven by the "seasonal goods" during the summertime, which are more likely to have sunshine-relevant features; whereas the over-optimism mechanism predicts a significant response for both seasonal goods and non-seasonal goods during both summer and non-summer times. Moreover, the projection bias/salience mechanism would predict that the positive relation between abnormal sunshine and consumption is concentrated during times with high sunshine levels, when sunshine-relevant features are more salient and valuable. In contrast, the over-optimism mechanism predicts that the sunshine effect shall present in both high-sunshine and low-sunshine times, as long as the abnormally good sunshine can induce a good mood and over-optimism. The documented evidence is more consistent with the over-optimism mechanism. Specifically, we find that the spending response for non-seasonal goods is two times of that for seasonal goods, and the positive sunshine effects during summer and non-summer times are similar for both types of goods; we also document a similar (larger) response for total spending (long-term spending) during low-sunshine times for each zipcode.

We document a significant sunshine effect on consumers with various demographic characteristics. Specifically, the sunshine effect is larger for consumers residing in zipcodes with lower average sunshine levels, where the marginal impact on mood from the same amount of abnormal sunshine is higher. Males and females exhibit similar sunshine effects, but the spending response to abnormal sunshine is larger for older and married consumers. This potentially suggests that consumers with lower financial constraints (and hence higher discretion over consumption) are more affected by the mood. We also document a significant positive relation between abnormal sunshine and the number of credit card transactions, but with a much smaller magnitude.

Finally, we show that our findings are robust to alternative specifications regarding the standard error clustering unit and the construction of daily *sky cover*. We also show that the documented sunshine effect is unlikely to be driven by spurious relations at the zipcode level.

This paper directly contributes to the literature on the influence of mood on economic and financial decisions. Events associated with sentiment fluctuations, such as sunshine and sporting events, are shown to affect local stock index returns through the impact on investors' mood (Saunders, 1993; Hirshleifer and Shumway, 2003; Edmans, Garcia, and Norli, 2007; Kamstra, Kramer, and Levi, 2003). Agarwal, Duchin, Evanoff, and Sosyura (2013) records a significant impact of sentimental events on the local loan approval rate, and Carroll, Fuhrer, and Wilcox (1994) document a significant positive relationship between consumer sentiment index and consumer spending growth at the macro level. However, the unavailability of granular-level individual behavior information potentially generates higher noise in the match between the shock (i.e., sunshine) and the outcome (i.e., investment or consumption), making the causal identification difficult. We contribute to this literature by directly linking exogenous local sunshine shocks to same-day credit card spending at the individual level. Confirmed credit card spending measures granular consumer spending with a higher signal-to-noise ratio, and high-frequency analysis using both the time-series and cross-sectional variations largely facilitates the causal relationship identification.

We also contribute to the growing literature on the effect of environmental factors on consumption. Earlier marketing and psychology studies conduct small-scale laboratory or field experiments, and find that environmental factors, including sunlight, rainfall, temperature, and store environment, significantly affect consumers' purchasing behavior by modifying their mood (Donovan, Rossiter, Marcoolyn, and Nesdale, 1994; Spangenberg, Crowley, and Henderson, 1996; Sherman, Mathur, and Smith, 1997; Parsons, 2001; Murray, Muro, Finn, and Leszczyc, 2010). Recently, the availability of high-frequency spending data has allowed researchers to investigate this question among a larger scale of consumers. Studies document that weather factors, including temperature, sunshine, and rainfall, have a significant impact on the purchase of specific types of goods, including cars, clothes, movie tickets, and mobile-push promotions (Conlin, O'Donoghue, and Vogelsang, 2007; Busse, Pope, and Silva-Risso, 2015; Buchheim and Kolaska, 2016; and Li, Luo, Zhang, and Wang, 2017).

We provide new insights for this literature in three respects. First, instead of focusing on one particular type of goods, our comprehensive credit card spending data allow us to estimate the overall spending response in a large sample of consumers across the US. This directly generalizes the sunshine effect to the overall (disposable) consumption of households. Moreover, based on detailed goods-type information, we are able to disentangle the projection bias/salience and over-optimism mechanisms, which cannot be addressed by only investigating a specific type of goods. Lastly, the rich consumer characteristics information further enables us to investigate the heterogeneous effects on different consumer groups, which are seldom explored in previous studies.

More broadly, this paper is linked to the household consumption and indebtedness literatures. A large literature documents consumption responses to income shocks at the individual level.[3] On the flipside, overconsumption could result in the accumulation of household debt, which has been shown to hamper the economic growth of a country (Glick and Lansing, 2010; Georgarakos, Haliassos, and Pasini, 2014; Mian and Sufi, 2015; Mian, Sufi, and Verner, 2017; Lee and Mori, 2019). This paper shows that abnormally high sunshine significantly increases the individual's credit card spending, which could contribute to the household debt accumulation, especially the high-interest credit card debt.

The rest of the paper is organized as follows. Section 2 describes our data and methodology; Sections 3 and 4 report the main results and additional analysis respectively; and Section 5 concludes.

2. Data and Methodology

2.1. Raw data

2.1.1. Consumption data

We use a proprietary credit card transaction dataset obtained from a leading US financial institution that issues credit cards nationwide to measure daily individual consumption. By the end of 2016, this financial institution took more than 10 percent of all bank deposits in the US, and has a retail consumer base of around 46 million; its customer base is representative of the US consumer population (see also the description in Agarwal, Liu, and Souleles, 2007). This dataset covers more than 3 million credit card transactions from 1st March to 31st October in 2003, from over 127,000 random, representative accounts in the institution's customer base.

This dataset provides transaction-level credit card spending information during the 8-month sample period, including transaction amount, transaction date, and goods type.[4] In addition, we

[3] See, for example, Shapiro and Slemrod (1995, 2003), Souleles (1999), Hsieh (2003), Stephens (2003, 2006. 2008), Johnson, Parker and Souleles (2006), Agarwal, Liu and Souleles (2007), Parker, Souleles, Johnson, and McClelland (2013), Gelman, Kariv, Shapiro, Silverman, and Tadelis, (2014), Agarwal and Qian (2014, 2017), Di Maggio, Kermani, Keys, Piskorski, Ramcharan, Seru, and Yao (2017), Olafsson and Pagel (2018), Agarwal, Qian, and Zou (2020). For a complete review of the literature, please refer to Browning and Collado (2001) and Jappelli and Pistaferri (2010).

[4] We can observe the merchant category code (i.e., MCC code) information for each transaction. The MCC code is a standard four-digit number assigned to the merchant to classify the type of goods or services it provides, hence we are able to know the category of goods bought in each transaction for an individual.

observe monthly-level individual financial information, including credit line, credit card debt, *FICO score*, and tenure with the institution. We can also observe a rich array of demographic information, including the account holder's residential zipcode, age, gender, and marital status. This wide range of consumer characteristics allows us to disentangle the underlying economic channels and further explore the rich heterogeneity of the sunshine effect.[5]

Credit cards, and in particular bank cards (e.g., Visa, MasterCard, Discover, and Optima cards), represent the leading source of unsecured consumer credit in the US (Japelli, Pischke, and Souleles, 1998). According to the 2004 Survey of Consumer Finances, more than 70 percent of US households had at least one credit card, and the median (mean) household credit card balance was $2,200 ($5,100). Around 50 percent of bank card holders still concentrate at least 90 percent of their total general-purpose balances on a single card. As one of the largest consumer credit markets, total revolving credit balances in the US have exceeded $925 billion, and spending via general-purpose credit card accounts for 15 percent of GDP in 2014 (*Consumer Financial Protection Bureau*, 2015). Additionally, studies have shown that compared with cash/check spending, households typically use cards to adjust their disposable consumption in response to shocks (Gelman, Kariv, Shapiro, Silverman, and Tadelis, 2014). In this paper, we aim to investigate the individual's consumption response to same-day sunshine shocks; hence, individual-level credit card spending serves as an important source to capture the consumption decisions.

This dataset offers several advantages compared with previous studies based on survey data (e.g., Carroll, Fuhrer, and Wilcox, 1994) or specific types of purchases (e.g., Busse, Pope, and Silva-Risso 2015; Buchheim and Kolaska, 2016; Li, et al., 2017). First, relative to traditional survey-based datasets such as the Survey of Consumer Finances (SCF) or Consumer Expenditure Survey (CEX), our administrative dataset captures consumption with little measurement error. The real-time confirmed customer spending largely mitigates the selection bias or response bias that can arise from survey data. Moreover, relative to spending on a particular type of goods, credit

[5] Similar as in Agarwal, Qian, and Zou (2020), while our data only capture consumer spending through credit cards from one major financial institution, it is important to note that our identification strategy does not require a complete account of all spending by the individual. To the extent that the choice of consumer spending instrument is exogenous to abnormal sunshine (i.e., consumers do not systematically choose to use cards from different institutions under different sunshine conditions), the credit card spending in our dataset is an unbiased indicator of consumers' overall consumption. Since only 2 percent accounts in the whole dataset correspond to individuals with multiple credit card accounts with the institution, we will use "individual," "consumer," "customer," and "account" interchangeably. We verify that the findings are robust when we drop individuals with multiple accounts, or aggregate the spending at the individual level.

card spending that covers various types of goods allows for a more comprehensive estimation of the sunshine effect, and also enables us to disentangle the economic mechanisms. Additionally, the combined high-frequency credit card spending and local sunshine shocks for a large, representative consumer group is crucial for the causal effect identification. Lastly, the dataset's rich information on consumer characteristics empowers us to further investigate the heterogeneity of different consumer groups.

To serve our purposes, we aggregate credit card spending for each individual at the daily level. To capture "real" spending on goods, we exclude obvious bank-fee items such as late payment fees, cash advance fees, over-limit fees, and financial charges. The dataset covers 127,239 consumers from 20,179 zipcodes. To mitigate the possible influence of outliers, we winsorize the credit card spending at 1st and 99th percentiles.

2.1.2. Weather data

We collect weather information from the Integrated Surface Data (ISD) on the National Climate Data Center's website.[6] The raw weather data files report intra-day records for eight weather variables from weather stations nationwide: air temperature, dew point, sea-level pressure, wind direction, wind speed, sky cover, one-hour accumulated liquid precipitation, and six-hour accumulated liquid precipitation. Following the previous studies (Saunders, 1993; Hirshleifer and Shumway, 2003), we use *sky cover* as a proxy for sunshine. *Sky cover* ranges from 0 *okta* (clear) to 8 *oktas* (overcast), and could be recorded several times within a day.[7] We use 6 a.m. to 10 p.m. as the relevant time period, during which individual consumption can be affected by exposure to sunshine. In the main analysis, therefore, we use the average *sky cover* during this period to construct the daily *sky cover* for each weather station, and a lower *sky cover* is associated with a higher sunshine level.

2.2. Sample construction and summary statistics

We construct the time series of *sky cover* at the zipcode level. Specifically, for each zipcode in the credit card spending dataset, we identify the 10 closest weather stations within a 1,000 km

[6] http://www.ncdc.noaa.gov/oa/climate/isd/.

[7] Different weather stations have different recording times and frequencies for the weather variables.

radius for each year during the period 1998-2008 (i.e., from 5 years before to 5 years after 2003).[8] For each zip-day, we use the *sky cover* from the closest weather station as the local sunshine proxy; if the *sky cover* from the closest weather station is missing, we employ the *sky cover* from the second closest weather station, etc. We repeat this process until we have found non-missing *sky cover* for a zip-day, or the *sky cover* information from all of the 10 closest weather stations within 1,000 km have been exploited. Based on this strategy, the *sky cover* value for each zip-day comes from the record of the closest possible weather station, and the time-series of *sky cover* for a zipcode can be a combination of *sky cover* information from several nearby weather stations. We are able to construct *sky cover* time series for 18,829 zipcodes from the credit card spending dataset, which covers 125,608 consumers.

To remove seasonal patterns, we construct the *abnormal sky cover* measure to capture exogenous sunshine shocks for each zip-day. Specifically, we define the *abnormal sky cover* in zip *z* on day *t* of 2003 as the deviation of *sky cover* on day *t* from the weekly average *sky cover* of the same week during 1998-2008, with the same day of the year being the week center:

$$abnormal\ sky\ cover_{zt} = sky\ cover_{zt} - weekly\ mean\ sky\ cover_{\mathrm{zt}}$$

where $sky\ cover_{zt}$ is the *sky cover* level at zipcode *z* on day *t*; and $weekly\ mean\ sky\ cover_{\mathrm{zt}}$ is the mean of *sky cover* at *z* in the [-3,+3] day window around day *t* from the year 1998 to 2008.[9] Please refer to the Appendix for detailed variable definitions.

We present summary statistics for daily credit card spending and monthly consumer characteristics for individuals in the final sample in Panel A of Table 1. Mean daily total credit card spending for the 125,608 consumers in the sample is around $135, which can be decomposed into $13 of non-discretionary spending (including spending on transportation and supermarket goods); $3 of entertainment spending (including spending on dining and entertainment goods); and $109 of long-term spending (including spending on travel, service, durable, and apparel goods). An average consumer in the sample carries monthly credit card debt of $2,147, and has a credit line of around $9,000; the average *FICO score* is 710, and the average tenure with the bank

[8] To avoid losing too much credit card spending information, and at the same time, accurately measure the local weather, we choose the 1,000 km radius. The average distance between the 10 closest weather stations and zipcodes in the sample is 63 km. Please refer to Figure IA1 in the Internet Appendix for the geographic distribution of zipcodes and the corresponding 10 closest weather stations within 1,000 km in the continental US in the final sample.

[9] For example, the *abnormal sky cover* of zip *z* on June 4th, 2003, is the deviation of the *sky cover* of zip *z* on June 4th, 2003, from the mean *sky cover* between June 1st and June 7th in 1998-2008 for zip *z*.

is 4 years. Around 47 percent of consumers are female, and around 30% are married. The average age of consumers in the sample is 47 years old.

Panel B of Table 1 reports the cross-sectional distribution of *sky cover* and *abnormal sky cover* for the zipcodes in the final sample. The average *sky cover* level for zipcodes in the sample is 3.5 *oktas* (i.e., median sky coverage); the mean *abnormal sky cover* is 0.1 *okta,* which is very close to zero. The time-series distribution of average *sky cover* (Panel A, Figure 1) and *abnormal sky cover* (Panel B, Figure 1) during our sample period shows that although the raw sunshine level is on average higher in the summertime and lower in the wintertime, there are no systematic seasonal patterns for *abnormal sky cover*. The randomness in both the cross-section and time-series suggests that *abnormal sky cover* serves as a good proxy for the random, exogenous local sunshine shocks.

[Insert Figure 1 about Here]

2.3. Empirical strategy

We examine the response of individuals' credit card spending to same-day abnormal sunshine using the following regression model:

$$Log\ (1 + total\ spending)_{izt} \times 100\% = \alpha + \beta Abnormal\ sky\ cover_{\mathrm{zt}} + \phi \mathrm{X}_{\mathrm{izt}} + \delta_i + f_{\mathrm{t}} + \epsilon_{izt} \tag{1}$$

where $total\ spending_{izt}$ is the daily total credit card spending amount of individual *i* in zipcode *z* on day *t*, and $abnormal\ sky\ cover_{\mathrm{zt}}$ is the same-day local *abnormal sky cover*.[10] $\mathrm{X}_{\mathrm{izt}}$ is a vector of individual time-varying characteristics that are potentially associated with the consumption decision: the *FICO score*, which captures one's credit quality; and the *credit room*, defined as the fraction of the remaining credit line in the current month after excluding outstanding credit card debt, which captures available credit. We also include individual fixed effect δ_i and calendar day fixed effect f_{t} to control for the effects of time-invariant unobservable variables and common time trends. As the *abnormal sky cover* from one weather station can be matched with more than one zipcodes, we cluster standard errors for our estimates at the weather station level.

[10] We calculate log of spending as log (spending+1) to include 0 spending cases.

We are particularly interested in the coefficient for *abnormal sky cover* (β). A significant negative β indicates that positive shocks in local sunshine lead to higher credit card spending on the same day, after controlling for relevant individual characteristics and fixed effects.

3. Main Results

3.1. Credit card spending response to abnormal sunshine

We begin by examining consumers' average credit card spending response to the same-day abnormal sunshine (measured by *abnormal sky cover*). We add control variables step by step and report the results in Panel A of Table 2. In column (1), we conduct a univariate test on the relation between the log of total credit card spending and the same-day *abnormal sky cover*, without controlling for any characteristics or fixed effects. We find a significant negative effect of *abnormal sky cover* on consumption, with an estimated coefficient of -0.289 (p value<0.001). In column (2), we add individual and calendar day fixed effects to the regression, and the estimated coefficient for *abnormal sky cover* remains similar (coefficient=-0.304; p value<0.001). In column (3), we further control for the individual's time-varying credit quality and available credit (i.e., *FICO score* and *credit room*). The effect of *abnormal sky cover* remains strong and robust, despite the significant positive impact of credit quality and credit room on the spending. The magnitude of -0.295 (p value<0.001) suggests that a one-unit increase in abnormal sunshine (proxied by a one *okta* decrease in *abnormal sky cover*) leads to around 0.3 percent increase in the same-day total credit card spending.

[Insert Table 2 about Here]

As we propose that the sunshine effect is caused by an abnormal sunshine-induced mood, we expect the spending response to be larger among customers with lower self-control ability, especially those lacking control over consumption. We employ three proxies for the self-control ability. First, a high level of outstanding credit card debt probably indicates the individual's low ability in controlling overspending (Angeletos, Liabson, Repetto, Tobacman, and Weinberg, 2001). In column (1) of Panel B, we find that the sunshine effect is stronger for customers with average monthly credit card debt higher than the sample average (coefficient=-0.216, p value=0.001 for individuals with *low credit card debt*; coefficient=-0.458, p value<0.001 for individuals with *high credit card debt*), and the difference of -0.24 percent is statistically significant (p value=0.027). Similarly, consumers with higher credit quality are more likely to have smoother consumption patterns and better self-control (Agarwal and Qian, 2014). Consistently, column (2) shows that the magnitude of the sunshine effect for *low-FICO* consumers is 0.14 percent larger than that for *high-FICO* consumers. Lastly, consumers with higher financial sophistication should have stronger self-control ability, and hence a smaller sunshine effect. In column (3), we find that the sunshine effect for consumers with longer *tenure with the bank* (i.e., those who are more experienced and sophisticated) is 0.11 percent smaller than that for shorter-tenure consumers.

Back-of-the-envelope calculations suggest a sizable economic magnitude of the sunshine effect. Specifically, the average 0.3 percent increase in total credit card spending in response to a one-unit increase of abnormal sunshine is equivalent to a daily spending increase of $0.41 per individual, or around $51,000 in total for the over 125,000 consumers in the sample. Given that there are 164 million credit card holders in 2003 in the US, and the average *abnormal sky cover* for the 30 days with the highest abnormal sunshine (i.e., lowest *abnormal sky cover*) in each zipcode in the sample is -3.39 *okta*, the additional credit card spending on those days aggregates to $6.8 billion. According to the statistics that the total outstanding credit card debt is equivalent to 45.3 percent of the total credit card spending in 2003 (*US Census Bureau*, 2006), the $6.8 billion in additional spending could translate into $3 billion of extra credit card debt. Since we document that the sunshine effect is stronger for consumers with lower self-control, especially those with higher credit card debt, fluctuations in abnormal sunshine could lead to an even larger debt accumulation by the already indebted consumers.

3.2. Alternative explanations

3.2.1. The effects of other weather conditions

We propose that the significant positive relation between abnormal sunshine and individual spending on the same day is caused by the mood induced by local sunshine shocks. However, given that sunshine is usually correlated with other weather factors, it is possible that the sunshine effect we document simply captures the effects of other weather conditions. For example, high sunshine usually accompanies high temperatures or low rainfall, which have been shown to impact individual spending (Conlin, O'Donoghue, and Vogelsang, 2007; Busse, Pope, and Silva-Risso 2015; Buchheim and Kolaska, 2016; and Li, et al., 2017).

To address this concern, we control for the effect of three other abnormal weather variables that might affect consumption: *abnormal temperature*, *abnormal wind speed*, and *abnormal* *precipitation*. To avoid the multicollinearity problem, we residualize the *abnormal sky cover* regarding the three weather variables, and replace *abnormal sky cover* with *residualized abnormal sky cover* in the regression.[11] Specifically, at the zip-day level, we regress *abnormal sky cover* on the other three abnormal weather variables (and control for the zipcode fixed effects), and take the regression residual as the *residualized abnormal sky cover*, which captures the part of variation from *abnormal sky cover* that is orthogonal to the other three abnormal weather variables.

Column (1) of Panel A, Table 3 shows that the estimated coefficient for the *residualized abnormal sky cover* is -0.34, which is similar to our main finding. In column (2), we further add the other three abnormal weather variables into the regression. The effect of *residualized abnormal sky cover* remains strong and robust; however, estimated coefficients for the other three abnormal weather variables are statistically insignificant and economically small. These results suggest that the effect of abnormal sunshine is unlikely a recapture of the effect of other weather variables.

[Insert Table 3 about Here]

It is also possible that extreme weather conditions, such as snowstorms and heavy rain, impede consumers from going out to consume. And the probability for cloudy days to have extreme weather conditions is higher, which could lead to the positive relation between abnormal sunshine and consumer spending. To test this possibility, we directly examine the effect of *abnormal sky cover* after excluding the 10 percent of days with extreme weather conditions during our sample period.[12]

In column (1) of Panel B, Table 3, we drop the 10 percent of days with the lowest temperature in each zipcode, and the regression coefficient for *abnormal sky cover* remains similar to the full sample effect (coefficient= -0.283; p value<0.001). In columns (2) and (3), we exclude the 10 percent of days with the highest wind speed or highest precipitation from the regression respectively, and still find a strong and robust sunshine effect. In column (4), we exclude a day from the regression if that day has any of the extreme weather condition(s) in columns (1)-(3), and we still find a significant negative coefficient of -0.35 for the *abnormal sky cover* (p value<0.001). Again, this evidence suggests that the positive relation between abnormal sunshine and individual spending is unlikely to be driven by the effect of other weather conditions.

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[11] Time-series for the other three weather variables and the corresponding abnormal weather variables are constructed in the same way as for *sky cover*. Please refer to the Appendix for detailed variable definitions.

[12] We verify that the results are robust when we exclude the 5 percent or 20 percent of days with extreme weather conditions.

3.2.2. Sunshine and consumption as complements

Another possible explanation for a higher consumption on sunny days is that sunshine and consumption are complements. Specifically, the marginal utility of consuming entertainment goods, such as drinking outside or going to a theme park, is higher during sunny times, which leads to higher spending on sunny days. This explanation predicts that the sunshine effect should be strongest for spending on entertainment goods, which can be consumed immediately within a day, and are direct complements for the good sunshine.

To investigate this possibility, we exploit the heterogeneity of the sunshine effect by product type purchased. Base on the merchant type code from credit card transactions, we classify the goods purchased by consumers into eight categories: transportation, supermarket, travel, entertainment, apparel, dining, durable, and service. We then decompose total credit card spending into spending on three types of goods: non-discretionary goods (including transportation and supermarket goods); entertainment goods (including entertainment and dining goods); and long-term goods (including travel, service, durable, and apparel goods). Non-discretionary goods are likely to be necessities; entertainment goods are direct complements for good sunshine weather and can be consumed immediately; and the value of long-term goods is going to be depreciated into the future. A large response driven by entertainment goods spending will be consistent with the complementary sunshine-consumption explanation.

However, Table 4 documents inconsistent results. Panel A of Table 4 shows that the sunshine effect is largely driven by long-term goods spending (coefficient=-0.370; p value<0.001), whereas the response of entertainment goods is statistically insignificant and close to zero (coefficient=0.050; p value=0.142).[13] Non-discretionary spending is also not significantly affected by the abnormal sunshine (coefficient= -0.070; p value=0.200). Further decomposition of long-term goods spending in Panel B shows that durable goods spending shows the most significant sunshine effect (coefficient= -0.336; p value<0.001).

[Insert Table 4 about Here]

3.2.3. Intertemporal shift of durable spending

[13] The effect on long-term goods spending implies that a one unit increase in abnormal sunshine will lead to $0.33 increase in daily long-term goods spending, which is equivalent to $40,923 in total for the over 125,000 consumers in the sample.

As the sunshine effect is mainly driven by the response of durable goods spending, which costs relatively higher than other types of goods, consumers could rationally shift their durable goods purchases to days when the sunshine is (expected to be) pleasant. In this sense, higher durable spending on sunny days can be intentionally planned—for example, by checking the weather forecast—and hence is not triggered by mood shocks on the consumption day. If this explanation prevails, we expect to see the spending change on the consumption date to be "reimbursed" by significant spending changes on prior days in the opposite direction, rendering an unchanged total spending.

We test the intertemporal shift explanation using a distributed lag model that includes the *abnormal sky cover* in 3 weeks before the consumption day, which is potentially the longest time period one can obtain relatively accurate weather forecasts and plan ahead. Specifically, we follow Busse, Pope, and Silva-Risso (2015) and Buchheim and Kolaska (2016) and investigate the effect of *abnormal sky cover* on the consumption day (day 0) and for 3 weeks before the consumption day (day -1 to day -21 relative to the consumption day) using the following regression:

$$Log\ (1 + durable\ spending)_{izt} \times 100\% = \alpha + \beta Abnormal\ sky\ cover_{izt} + \sum_{j=1}^{21} \beta_j Abnormal\ sky\ cover_{izt-j} + \phi \mathrm{X}_{\mathrm{izt}} + \delta_i + f_{\mathrm{t}} + \epsilon_{izt} \quad (2)$$

where the $Abnormal\ sky\ cover_{izt-j}$ is the *abnormal sky cover* on *j* days before the consumption date *t*.

As plotted in Figure 2, the response of durable spending is only large and negative to *abnormal sky cover* on the consumption day (coefficient=-0.359, *p* value<0.001), while it is statistically insignificant and economically small to the *abnormal sky cover* from the previous 3 weeks. This pattern is contrary to the prediction of the intertemporal shift explanation. We also follow Busse, et al. (2015) and extend the time range to 60 days before the consumption day. Figure IA2 in the Internet Appendix shows a similar pattern, whereby durable goods spending only significantly responds to *abnormal sky cover* on the consumption day.

[Insert Figure 2 about Here]

3.3. Economic mechanisms

Since we document that the sunshine effect is mainly driven by spending on long-term and durable goods, there are two possible economic mechanisms for this effect. One possibility is that abnormal sunshine induces a good mood among consumers, which gives rise to an over-optimistic evaluation of the goods' value in general, leading to more consumption on days with high abnormal sunshine (Hirshleifer and Shumway, 2003). Another possible channel is the projection bias/salience, whereby individuals overvalue the salient sunshine-relevant features for certain goods on sunny days, and underestimate the change in their preference in the future; hence the consumption decision for long-term (durable) goods is overly affected by the preference in the current status, leading to higher consumption on sunny days (Loewenstein, O'Donoghue, and Rabin, 2003).

We conduct two sets of tests to disentangle the two possible mechanisms. First, given that the merchant category code allows us to identify the goods type purchased, we are able to classify them into seasonal goods—the goods that are suitable for the relevant season, and non-seasonal goods. The projection bias/salience mechanism suggests that individuals will over-estimate the goods feature that is suitable for the weather conditions on the purchase date. Therefore individuals shall over-buy the seasonal goods on sunny days in the summer (eg., swimming suits), as they are suitable for the sunny weather; while shall buy less seasonal goods on sunny days in other seasons (eg., boots), since the seasonal goods for other seasons are not suitable for the sunny weather. And the purchase of non-seasonal goods is not expected to be affected by the abnormal sunshine, as they don't have specific sunshine-relevant features. On the other hand, the over-optimism mechanism simply predicts a higher purchase for all long-term goods on sunny days in all seasons, due to the individuals' good mood and over-optimism induced by the sunny weather.

Base on this logic, we further divide long-term goods into seasonal goods and non-seasonal goods. Specifically, seasonal goods include travel, clothes, department store goods, and lawn and gardening equipment, which are more likely to have seasonal features; other long-term goods are classified as non-seasonal goods.[14] As reported in columns (1)-(2) of Panel A Table 5, we find that although a one-unit increase in abnormal sunshine does increase seasonal goods spending by 0.13 percent, the effect is more than doubled for non-seasonal goods spending (i.e., 0.262 percent). Moreover in columns (3)-(4), we classify June to September as the summertime, and other months in the sample as non-summer time. We document significant and similar positive sunshine effects during summer and non-summer times for both seasonal goods and non-seasonal goods spending (p value for the difference of sunshine effect during summer and non-summer for seasonal goods=0.660; p value for the difference for non-seasonal goods=0.950). Therefore the evidence is

[14] The results are similar if we classify department store goods as non-seasonal goods instead of seasonal goods.

more consistent with the over-optimism mechanism, whereby individuals overvalue long-term goods in general on days with abnormally high sunshine.

[Insert Table 5 about Here]

Second, the projection bias/salience mechanism predicts that the response to abnormal sunshine is driven by spending during the period with high sunshine levels, when sunshine-relevant features are more salient and valuable. While during low-sunshine times, when sunshine-relevant features are not suitable for the current weather status, the sunshine effect should be muted or even reversed. In contrast, the over-optimism mechanism predicts that the sunshine effect will be present in both high-sunshine times and low-sunshine times: as long as the sunshine on a given day is better than normal, the individual will overestimate the goods' value due to the induced better mood, leading to a higher consumption. In fact, the sunshine effect could be even stronger in low-sunshine times, during which the marginal effect of abnormally good sunshine on inducing positive mood is larger.

In column (1) of Panel B, we find that compared with the 4 months with a higher average sunshine level, the total spending response to *abnormal sky cover* is similar during the 4 months with a lower average sunshine level. Column (2) shows that the long-term spending response to abnormal sunshine is larger during low-sunshine times. Again, this finding is more consistent with the over-optimism channel prediction.[15]

4. Additional Analyses

4.1. Heterogeneity by consumer characteristics

We further investigate the heterogeneous sunshine effect by consumer demographic characteristics. Specifically, we compare the sunshine effect on consumer groups divided by average sunshine level in residential zipcodes, gender, age, or marital status, respectively. Column (1) of Table 6 documents a stronger sunshine effect for consumers residing in zipcodes with a lower average sunshine level in 2003. This, together with the finding that the sunshine effect is stronger during low sunshine times, suggests that the sunshine effect will be stronger when (where) the marginal effect of abnormal sunshine on mood is higher.

[Insert Table 6 about Here]

[15] Since the sunshine is usually positively correlated with temperature, we also test the sunshine effect in low-temperature versus high-temperature times, and obtain similar results.

The sunshine effect is equally strong for male and female consumers (column (2)). We also document stronger sunshine effects for relatively older consumers and married consumers (columns (3)-(4)). We conjecture that this could be due to lower financial constraints and higher discretion regarding consumption among these consumers.

4.2. Response of number of purchases

We also examine the effect of abnormal sunshine on the number of credit card purchases. Table 7 shows that the number of credit card transactions also significantly positively responds to same-day abnormal sunshine, but with a much smaller magnitude. Specifically, a one-unit increase in abnormal sunshine is associated with a 0.02 percent increase in total credit card transactions, a 0.03 percent increase in long-term goods transactions, and a 0.07 percent increase in durable goods transactions. Combined with the response of credit card spending amount, the results suggest that both the spending amount per purchase and the number of purchases are significantly positively associated with abnormal sunshine, with the main driver of the sunshine effect being the higher spending amount per purchase.

[Insert Table 7 about Here]

In addition to affecting credit card spending at the intensive margin (i.e., conditional on having used the credit card, what is the response of the credit card spending amount), abnormal sunshine may also influence the individual's extensive margin decision—i.e., the decision to consume or not on a particular day. We investigate the extensive margin effect in Table IA1 of the Internet Appendix. For each individual in the sample, we consider all days without credit card transaction record between the first and last spending days during the sample period to be non-spending days. Panel A shows that in response to a one-unit increase of abnormal sunshine, the probability to consume is 0.03 percent higher for any credit card spending, 0.02 percent for long-term spending, and 0.01 percent for durable goods spending respectively. In Panel B, we investigate the intensive margin and extensive margin effects together, by treating the total spending amount on non-spending days as 0. We show that for active consumers who have at least one credit card transaction in every month of their tenure in the 8-month sample period, the total spending response is -0.25 percent, which is similar to the effect in the main finding.

We also find that the online spending is not significantly affected by same-day abnormal sunshine, suggesting that the presence of a sunshine effect probably requires the individual's exposure to actual sunshine variations.

4.3. Robustness tests

Our results are robust to alternative regression and variable specifications. Panel A of Table 8 shows that the estimated coefficient of *abnormal sky cover* remains statistically significant when we alter the clustering unit of standard errors to the state level, zipcode level, or individual level. In Panel B, we alternate the time range used to construct the daily *sky cover*. We use the average *sky cover* between 6 a.m. and10 p.m. each day in the main analysis, as this is the time range that sunshine and consumption overlap. But one might be concerned that *sky cover* (or the sunshine) could be an invalid proxy for mood after the sunset. To ensure the robustness, we use the average *sky cover* between 6 a.m. and 4 p.m. following Hirshleifer and Shumway (2003) (column (1)), or only use the average *sky cover* in the morning between 6 a.m. and 12 noon (column (2)). The sunshine effect remains strong and robust.

[Insert Table 8 about Here]

Additionally, we show that the sunshine effect is unlikely a spurious relation at the zipcode level. We conduct two sets of permutation tests following the method in Chetty, Looney, and Kroft (2009) to address this concern. First, within each zipcode, we assign *abnormal sky cover* from a zip-day in the sample to an arbitrary day in the same zip, and rerun the main regression. We iterate the random match 4,000 times. As shown in Panel A of Figure 3, the mean of the 4,000 estimated coefficients from the random match is statistically indistinguishable from 0, whereas the main effect estimation (i.e., -0.295) is much smaller than the 5th percentile of the coefficients from random assignments. Second, we assign the time-series of *abnormal sky cover* for a zipcode to an arbitrary zipcode in the sample and rerun the main regression, and also iterate the random assignment 4,000 times. The results in Panel B still suggest that the main finding of the paper is unlikely to be driven by spurious relation.

[Insert Figure 3 about Here]

We also verify that the sunshine effect is unlikely to be driven by state-specific holiday patterns. After controlling for a state-specific public holiday dummy, the estimated coefficient for *abnormal sky cover* remains unchanged.

Finally, we investigate the linearity of the sunshine effect. The insignificant and small coefficient for the squared *abnormal sky cover* in Panel A of Table IA2 suggests that the sunshine effect is likely to be linear. Panel B shows that the effects of *abnormal sky cover* on credit card spending in higher *abnormal sky cover* quintiles are larger compared with that in the bottom quintile, suggesting that the sunshine effect is relatively monotonic.

5. Conclusion

This paper investigates the causal effect of sunshine-induced mood on individuals' contemporaneous consumption. We identify a significant positive relation between abnormal sunshine and the same-day credit card spending, after controlling for time-varying individual characteristics and individual and calendar-day fixed effects. A one-unit increase in abnormal sunshine (proxied by a one *okta* decrease in *abnormal sky cover*) is associated with around 0.3 percent increase in total credit card spending. The response is larger for high-debt, low credit quality, and less experienced individuals, who presumably have lower self-control ability regarding consumption.

We provide a collection of evidence to show that the relationship is unlikely to be driven by alternative explanations, including the effect of other weather conditions, sunshine and consumption as complements, and intertemporal shift of durable goods consumption. We document a strong response of long-term goods and durable goods spending. We also document a significant positive sunshine effect for spending on seasonal goods and non-seasonal goods during both summertime and non-summer times, and for spending during high-sunshine and low-sunshine times. These results are more consistent with the over-optimism channel, whereby individuals overvalue goods in general on days with abnormally high sunshine.

Overall, our findings highlight the causal effect of sunshine-induced mood on household consumption decisions, especially the purchase of long-term, durable goods. Policies that remind consumers of the true value of goods can be beneficial for reducing over-consumption and household indebtedness, and in particular for the accumulation of high-interest credit card debt by consumers with low self-control ability.

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Appendix. Variable Definitions

1. Credit card spending

Total spending is the total credit card spending amount for an individual within a day, measured in US dollars.

Non-discretionary spending is the amount of credit card spending on non-discretionary goods (including goods in the transportation and supermarket categories), measured in US dollars.

Entertainment spending is the amount of credit card spending on entertainment goods (including goods in entertainment and dining categories), measured in US dollars.

Long-term spending is the amount of credit card spending on long-term goods (including goods in travel, service, durable, and apparel categories), measured in US dollars.

Seasonal goods spending is the amount of long-term spending on goods likely to have seasonal patterns, including travel, clothes, department store goods, and lawn and gardening equipment, measured in US dollars. Spending on other long-term goods is ***non-seasonal goods spending***.

Summer is a dummy variable for June to September. Other times within the sample period are classified as ***non-summer*** times.

2. Weather-related variables

Sky cover is the average sky cover level from 6 a.m. to 10 p.m. for a zipcode area within a day, measured in *oktas*. Lower *sky cover* corresponds to less cloudiness and more sunshine. We define the 4 months during our sample period (i.e., 2003:03-2003:10) with lower monthly average *sky cover* as ***high-sunshine times*** for each zipcode area, and the other 4 months as ***low-sunshine times***. We define the zipcodes in the sample with average *sky cover* in 2003 lower than the sample mean as ***high average sunshine zipcodes***, and the other zipcodes as ***low average sunshine zipcodes***.

Abnormal sky cover is the deviation of *sky cover* on day *t* of 2003 from the weekly average *sky cover* of the same week during 1998-2008 (i.e., from 5 years before to 5 years after 2003), with the same day of the year being the week center. Specifically, the abnormal sky cover for zipcode *z* on day *t* of 2003 is:

$$abnormal\ sky\ cover_{zt} = sky\ cover_{zt} - weekly\ mean\ sky\ cover_{zt}$$

where the $weekly\ mean\ sky\ cover_{zt}$ is the mean of *sky cover* at *z* in the [-3,+3] day window around day *t* from the year 1998 to 2008. For example, the *abnormal sky cover* of zip *z* on June 4th, 2003, is the deviation of the *sky cover* of zip *z* on June 4th, 2003, from the mean *sky cover* between June 1st and June 7th in 1998-2008 for zip *z*.

Temperature is the average temperature from 6 a.m. to 10 p.m. for a zipcode within a day, measured in *centigrade*. ***Abnormal temperature*** is the deviation of *temperature* on day *t* of 2003 from the weekly average *temperature*, with the same day of the year being the week center during 1998-2008 (i.e., from 5 years before to 5 years after 2003).

Wind speed is the average temperature from 6 a.m. to 10 p.m. for a zipcode within a day, measured in *meters per second (m/s)*. ***Abnormal wind speed*** is the deviation of *wind speed* on day *t* of 2003 from the weekly average *wind speed*, with the same day of the year being the week center during 1998-2008 (i.e., from 5 years before to 5 years after 2003).

Precipitation is the average 6-hour accumulated precipitation from 6 a.m. to 10 p.m. for a zipcode within a day measured in *millimeters*. ***Abnormal precipitation*** is the deviation of *precipitation* on day *t* of 2003, from the weekly average *precipitation,* with the same day of the year being the week center during 1998-2008 (i.e., from 5 years before to 5 years after 2003).

Residualized abnormal sky cover is the *abnormal sky cover* after residualizing regarding the *abnormal temperature, abnormal wind speed*, and *abnormal precipitation*. Specifically, we use the following regression to estimate the *residualized abnormal sky cover* for zipcode *z* on day *t*:

$$\begin{aligned} abnormal\ sky\ cover_{zt} \\ &= \theta_1 abnormal\ temperature_{zt} + \theta_2 abnormal\ wind\ speed_{zt} \\ &+ \theta_3 abnormal\ precipitation_{zt} + \delta_z + residualized\ abnormal\ sky\ cover_{zt} \end{aligned}$$

3. Individual characteristics

Monthly credit card debt is the amount of credit card debt outstanding for an individual within a month, measured in US dollars. We classify individuals with average monthly *credit card debt* higher than the sample mean as having ***high credit card debt***, and the rest individuals as having ***low credit card debt***.

FICO score is the FICO score for the individual in a month. We classify individuals with average *FICO score* lower than the sample mean as having ***low FICO score***, and the rest individuals as having ***high FICO score***.

Tenure with the bank is the accumulated length of the credit card account's life in a month, measured in months. We classify individuals with average *tenure with the bank* shorter than the sample mean as having ***short tenure***, and the rest individuals as having ***long tenure***.

Credit line is the credit limit provided by the bank for an account, measured in US dollars.

Credit room is the percentage of the credit line available for an individual in a month. The credit room for individual *i* in month *m* is: $Credit\ room_{im} = (credit\ line_{im} - monthly\ credit\ card\ debt_{im})/credit\ line_{im}$.

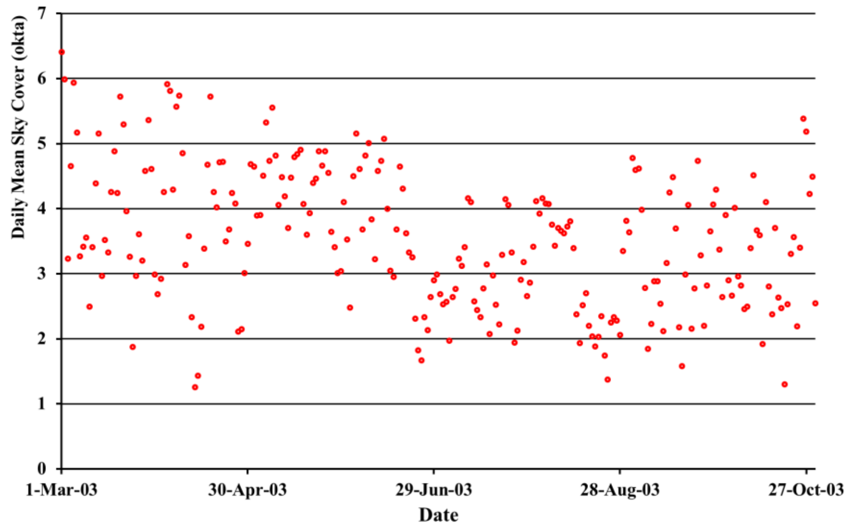
Female is a dummy variable equal to one if an individual is female.

Age is the age of an individual in 2003, measured in years. We classify individuals with *age* higher than the sample mean as ***old*** consumers.

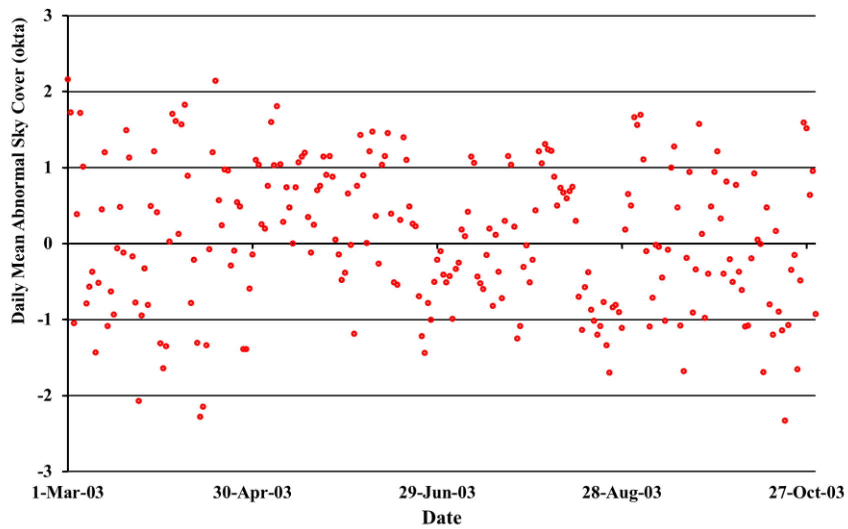
Married is a dummy variable equal to one if an individual has reported his/her spouse's name to the bank.

Figure 1. Time-series Distribution of Sky Cover in Sample

Panel A: Daily mean sky cover

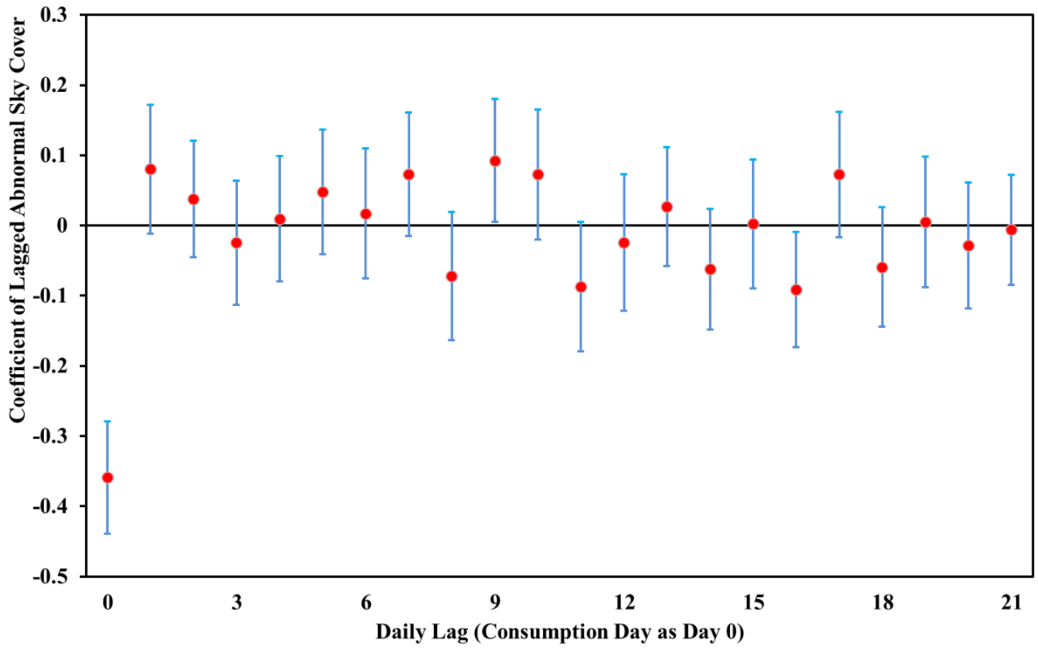


Panel B: Daily mean abnormal sky cover



Note. This figure plots the time-series distribution of daily mean *sky cover* (Panel A) and daily mean *abnormal sky cover* (Panel B) for zipcodes in our final merged sample during the period 2003:01:01 to 2003:10:31. Each dot represents the cross-sectional mean value of *sky cover* or *abnormal sky cover* on the corresponding calendar day.

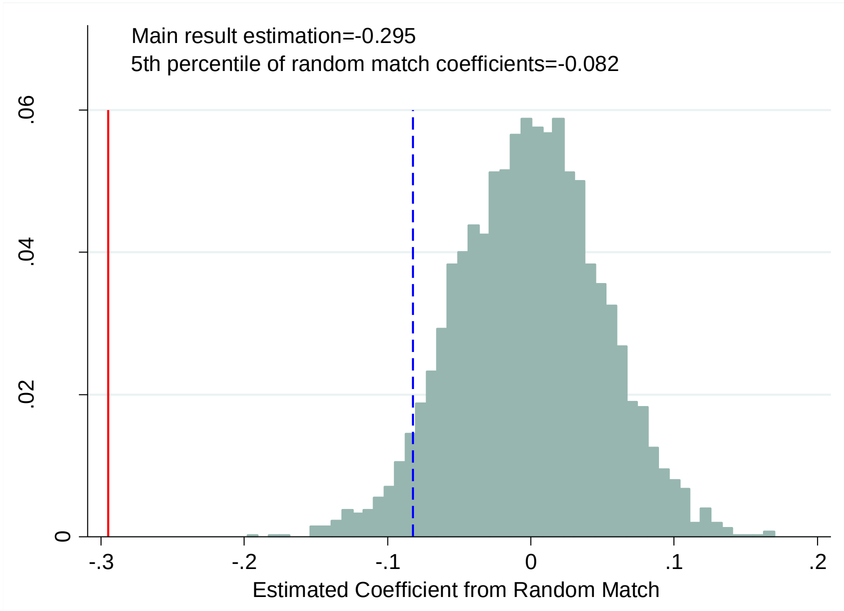
Figure 2. Distributed Lag Analysis of Abnormal Sky Cover



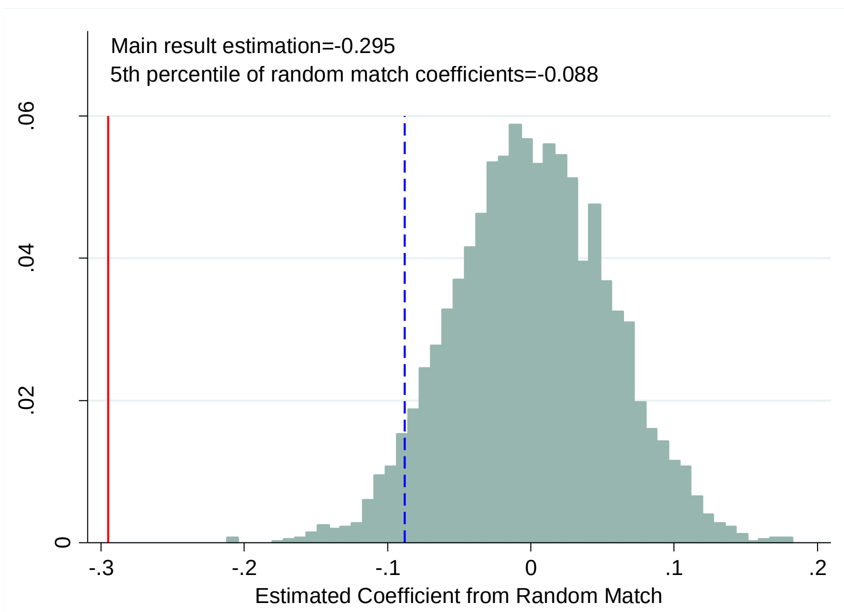
Note. This figure plots the estimated coefficients and 95% confidence intervals for *abnormal sky cover* on day 0 to day -21 relative to the consumption day from the regression model (2). The horizontal axis displays the daily lag relative to the consumption day, and the vertical axis displays the magnitude of the regression coefficient.

Figure 3. Distribution of Estimated Coefficients from Random Match

Panel A: Randomized time of abnormal sky cover received within each zipcode



Panel B: Randomized abnormal sky cover among zipcodes



Note. This figure plots the distribution of estimated coefficients for *abnormal sky cover* from regression equation (1), when the time of *abnormal sky cover* received being randomly assigned within each zip (Panel A), and when the *abnormal sky cover*s from one zipcode are assigned to a random zipcode (Panel B). Each of the random matches is replicated 4000 times. The horizontal axis is the estimated coefficient, and the vertical axis is the fraction of estimated coefficients in each bin. The estimated coefficient from the main regression in Table 2 is represented by the solid red line (i.e., -0.295), and the 5th percentile of the random match coefficients is represented by the dashed blue line.

Table 1. Summary Statistics

Panel A: Consumer spending and consumer characteristics

	Mean (1)	Std. Dev. (2)	25th percentile (3)	Median (4)	75th percentile (5)
Daily credit card spending					
Total spending ($)	135.2	277.1	7.6	51.6	131.7
Non-discretionary spending ($)	13.0	19.4	0.0	4.4	20.9
Entertainment spending ($)	3.0	13.0	0.0	0.0	2.1
Long-term spending ($)	108.6	269.5	0.0	23.1	85.2
Financial and demographic characteristics					
Monthly credit card debt ($)	2,147.3	2,923.4	54.1	908.2	3,235.0
FICO score	710.8	81.1	683.5	723.0	759.0
Tenure with the bank (months)	46.8	56.7	11.5	26.5	60.5
Credit line ($)	8,962.5	4,833.1	5,000.0	9,000.0	13,000.0
Age	46.5	15.4	35.0	45.0	56.0
Female (%)	47.2	49.9	0.0	0.0	100.0
Married (%)	30.3	45.9	0.0	0.0	100.0
Number of individuals	125,608				

Panel B: Sky cover

	Mean (1)	Std. Dev. (2)	25th percentile (3)	Median (4)	75th percentile (5)
Sky cover (okta)	3.5	1.2	2.7	3.4	4.3
Abnormal sky cover (okta)	0.1	0.4	-0.2	0.0	0.3
Number of zipcodes	18,829				

Note. This table provides summary statistics for consumer credit card spending, individual characteristics, and sky cover for individuals and zipcodes in the final sample. Panel A reports the distribution of credit card spending and consumer characteristics. Spending variables are measured at the daily level, and financial and demographic characteristics are measured at the monthly level. All consumer spending and characteristics are averaged and reported at the individual level. Panel B reports the distribution of sky cover. Sky cover variables are measured daily during our sample period (i.e., March 1, 2003, to October 31, 2003), and reported at the zipcode level. Please refer to the Appendix for detailed variable definitions.

Table 2. Consumer Spending Response to Abnormal Sunshine

Panel A: Average effect

	Log (1+total spending)×100%		
	(1)	(2)	(3)
Abnormal sky cover	-0.289***	-0.304***	-0.295***
	(-2.71)	(-5.21)	(-5.11)
FICO score			0.037***
			(6.22)
Credit room			109.870***
			(38.15)
Constant	280.803***	281.308***	169.723***
	(252.93)	(9,651.48)	(34.44)
Individual FE	N	Y	Y
Calendar day FE	N	Y	Y
Observations	2,133,516	2,125,991	2,125,991
R-squared	0.00	0.32	0.33

Panel B: Heterogeneity by self-control ability over consumption

	Log (1+total spending)×100%		
	Credit card debt	FICO score	Tenure with the bank
	(1)	(2)	(3)
Abnormal sky cover: low credit card debt	-0.216***		
	(-3.28)		
Abnormal sky cover: high credit card debt	-0.458***		
	(-4.72)		
Abnormal sky cover: low FICO score		-0.253***	
		(-3.73)	
Abnormal sky cover: high FICO score		-0.388***	
		(-4.24)	
Abnormal sky cover: long tenure			-0.227**
			(-2.56)
Abnormal sky cover: short tenure			-0.334***
			(-4.85)
Constant	169.733***	169.715***	169.721***
	(34.44)	(34.42)	(34.44)
Individual character controls	Y	Y	Y
Individual FE	Y	Y	Y
Calendar day FE	Y	Y	Y
Observations	2,125,991	2,125,991	2,125,991
R-squared	0.33	0.33	0.33

Note. This table presents the response of individual credit card spending to same-day *abnormal sky cover*. Panel A reports the average effect on total spending. Column (1) presents the univariate regression of the log of total credit card spending on same-day *abnormal sky cover*. Column (2) adds individual and calendar-day fixed effects. Column (3) further adds the individual characteristic controls (*FICO score* and *credit room*). Panel B reports heterogeneous effects by the individual's self-control ability over consumption. Column (1) compares the effect of individuals with high and low credit card debt. Column (2) compares the effect of individuals with high and low *FICO scores*. Column (3) compares the effect for individuals with short and long tenure with the bank. Please refer to the Appendix for detailed variable definitions. Individual and calendar day fixed effects are included, and standard errors are clustered at the weather station level. T-statistics are reported in parentheses. *** indicates significance at the 1 percent, ** at the 5 percent, and * at the 10 percent level, respectively.

Table 3. Effect of Other Weather Conditions

Panel A: Controlling for abnormal temperature, wind speed, and precipitation

	Log (1+total spending)×100%	
	(1)	(2)
Residualized abnormal sky cover	-0.335***	-0.334***
	(-5.41)	(-5.39)
Abnormal temperature		-0.056
		(-1.13)
Abnormal wind speed		0.048
		(0.45)
Abnormal precipitation		-0.006
		(-0.54)
Constant	170.036***	170.013***
	(33.11)	(33.12)
Individual character controls	Y	Y
Individual FE	Y	Y
Calendar day FE	Y	Y
Observations	2,026,256	2,026,256
R-squared	0.33	0.33

Panel B: Excluding days with extreme weather conditions

	Log (1+total spending)×100%			
	Exclude the 10% of days during 2003:03-2003:10 with			Exclude the days under any condition in (1)-(3)
	Lowest temperature	Highest wind speed	Highest precipitation	
	(1)	(2)	(3)	(4)
Abnormal sky cover	-0.283***	-0.324***	-0.378***	-0.349***
	(-4.82)	(-5.44)	(-5.45)	(-4.79)
Constant	175.393***	171.702***	170.734***	176.672***
	(34.35)	(32.45)	(31.62)	(31.12)
Individual character controls	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y
Calendar day FE	Y	Y	Y	Y
Observations	1,885,497	1,905,397	1,670,378	1,363,694
R-squared	0.33	0.33	0.33	0.34

Note. This table reports the effect of other weather conditions. Panel A residualize the *abnormal sky cover* regarding three other abnormal weather variables: *abnormal temperature, abnormal wind speed*, and *abnormal precipitation*, and investigates the response of total spending to *residualized abnormal sky cover*. Panel B excludes days with extreme weather conditions and conducts subsample analysis. Columns (1)-(3) exclude the 10 percent of days with the lowest temperature, highest wind speed, or highest precipitation during the sample period from the regression, respectively. Column (4) excludes the days under any condition in columns (1)-(3). Coefficients for individual characteristics control variables are omitted. Please refer to the Appendix for detailed variable definitions. Individual and calendar day fixed effects are included, and standard errors are clustered at the weather station level. T-statistics are reported in parentheses. *** indicates significance at the 1 percent, ** at the 5 percent, and * at the 10 percent level, respectively.

Table 4. Consumer Spending Response by Type of Goods

Panel A: Response of non-discretionary, entertainment, and long-term goods

	Log (1+non-discretionary spending)×100% (1)	Log (1+entertainment spending)×100% (2)	Log (1+long-term spending)×100% (3)
Abnormal sky cover	-0.070	0.050	-0.370***
	(-1.32)	(1.51)	(-5.74)
Constant	116.171***	31.238***	44.038***
	(30.33)	(11.80)	(8.83)
Individual character controls	Y	Y	Y
Individual FE	Y	Y	Y
Calendar day FE	Y	Y	Y
Observations	2,125,991	2,125,991	2,125,991
R-squared	0.24	0.19	0.16

Panel B: Response of subcategories of long-term goods

	Log (1+travel spending)×100% (1)	Log (1+service spending)×100% (2)	Log (1+durable spending)×100% (3)	Log (1+apparel spending)×100% (4)
Abnormal sky cover	-0.027	-0.028	-0.336***	-0.004
	(-1.03)	(-0.64)	(-8.60)	(-0.11)
Constant	6.587***	0.431	22.668***	15.944***
	(3.68)	(0.11)	(7.48)	(6.61)
Individual character controls	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y
Calendar day FE	Y	Y	Y	Y
Observations	2,125,991	2,125,991	2,125,991	2,125,991
R-squared	0.11	0.15	0.16	0.11

Note. This table reports the response of consumers' credit card spending to *abnormal sky cover* by goods type. Panel A decomposes total credit card spending into non-discretionary spending (including goods in transportation and supermarket categories); entertainment spending (including goods in entertainment and dining categories); and long-term spending (including goods in travel, service, durable, and apparel categories). Panel B investigates the response of the four subcategories of long-term goods spending. Coefficients for individual characteristics control variables are omitted. Please refer to the Appendix for detailed variable definitions. Individual and calendar day fixed effects are included, and standard errors are clustered at the weather station level. T-statistics are reported in parentheses. *** indicates significance at the 1 percent, ** at the 5 percent, and * at the 10 percent level, respectively.

Table 5. The Economic Mechanism

Panel A: Response of seasonal goods vs. non-seasonal goods

	Log (1+seasonal goods spending)×100% (1)	Log (1+non-seasonal goods spending)×100% (2)	Log (1+seasonal goods spending)×100% (3)	Log (1+non-seasonal goods spending)×100% (4)
Abnormal sky cover	-0.130***	-0.262***		
	(-2.98)	(-4.65)		
Abnormal sky cover: non-summer			-0.112*	-0.265***
			(-1.94)	(-3.35)
Abnormal sky cover: summer			-0.150**	-0.258***
			(-2.35)	(-3.05)
Constant	22.152***	22.797***	22.147***	22.798***
	(8.03)	(4.81)	(8.03)	(4.81)
Individual character controls	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y
Calendar day FE	Y	Y	Y	Y
Observations	2,125,991	2,125,991	2,125,991	2,125,991
R-squared	0.12	0.16	0.12	0.16

Panel B: Response during high sunshine vs. low sunshine times

	Log (1+total spending)×100% (1)	Log (1+long-term spending)×100% (2)
Abnormal sky cover: high sunshine times	-0.293***	-0.263***
	(-3.45)	(-3.06)
Abnormal sky cover: low-sunshine times	-0.297***	-0.448***
	(-4.16)	(-5.30)
Constant	169.724***	44.074***
	(34.44)	(8.83)
Individual character controls	Y	Y
Individual FE	Y	Y
Calendar day FE	Y	Y
Observations	2,125,991	2,125,991
R-squared	0.33	0.16

Note. This table investigates the economic mechanism of the sunshine effect. Panel A reports the response of seasonal goods spending and non-seasonal goods spending to *abnormal sky cover*. Columns (1)-(2) report the effect of abnormal sunshine on seasonal and non-seasonal goods spending. Seasonal goods are more likely to have seasonal features, including travel, clothes, department store goods, and lawn and gardening equipment. Other long-term goods are classified as non-seasonal goods. Columns (3)-(4) compares the effect of abnormal sunshine on seasonal and non-seasonal goods spending during summer and non-summer times. June to September is classified as the summertime, and other months in the sample are classified as non-summer time. Panel B compares the response of credit card spending during low-sunshine times versus high-sunshine times. Column (1) reports the effect on total spending, and column (2) reports the effect on long-term goods spending. The 4 months in the sample with lower average monthly sunshine levels (i.e., higher average monthly *sky cover* levels) are defined as low-sunshine times. Coefficients for individual characteristics control variables are omitted. Please refer to the Appendix for detailed variable definitions. Individual and calendar day fixed effects are included, and standard errors are clustered at the weather station level. T-statistics are reported in parentheses. *** indicates significance at the 1 percent, ** at the 5 percent, and * at the 10 percent level, respectively.

Table 6. Heterogeneity by Demographic Characteristics

	Log (1+total spending)×100%			
	Average sunshine level	Gender	Age	Marital status
	(1)	(2)	(3)	(4)
Abnormal sky cover: high average sunshine zipcodes	-0.173**			
	(-2.31)			
Abnormal sky cover: low average sunshine zipcodes	-0.442***			
	(-5.43)			
Abnormal sky cover: male		-0.432***		
		(-3.17)		
Abnormal sky cover: female		-0.497***		
		(-3.48)		
Abnormal sky cover: young			-0.193***	
			(-2.73)	
Abnormal sky cover: old			-0.428***	
			(-5.30)	
Abnormal sky cover: unmarried				-0.254***
				(-3.61)
Abnormal sky cover: married				-0.367***
				(-4.24)
Constant	169.759***	140.276***	169.809***	169.724***
	(34.44)	(11.70)	(34.53)	(34.44)
Individual character controls	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y
Calendar day FE	Y	Y	Y	Y
Observations	2,125,991	725,798	2,110,264	2,125,991
R-squared	0.33	0.32	0.33	0.33

Note. This table reports heterogeneous sunshine effects by consumer demographic characteristics. Column (1) compares total spending responses in zipcodes with high average sunshine levels versus low average sunshine levels during 2003. Column (2) compares the total spending responses of male versus female consumers. Column (3) compares the total spending responses of young versus old customers. Column (4) compares the total spending responses of married versus unmarried customers. Coefficients for individual characteristics control variables are omitted. Please refer to the Appendix for detailed variable definitions. Individual and calendar day fixed effects are included, and standard errors are clustered at the weather station level. T-statistics are reported in parentheses. *** indicates significance at the 1 percent, ** at the 5 percent, and * at the 10 percent level, respectively.

Table 7. Response of Number of Purchases

	Log (1+total number of credit card transactions)×100% (1)	Log (1+number of long-term goods transactions)×100% (2)	Log (1+number of durable goods transactions)×100% (3)
Abnormal sky cover	-0.024***	-0.032***	-0.070***
	(-3.25)	(-2.64)	(-9.38)
Constant	77.556***	47.239***	5.806***
	(144.06)	(57.22)	(8.56)
Individual character controls	Y	Y	Y
Individual FE	Y	Y	Y
Calendar day FE	Y	Y	Y
Observations	2,125,991	2,125,991	2,125,991
R-squared	0.21	0.18	0.18

Note. This table reports the response of the number of credit card transactions to same-day *abnormal sky cover*. Columns (1)-(3) investigate the response of the total number of credit card transactions, the number of long-term goods transactions, and the number of durable goods transactions, respectively. Coefficients for individual characteristics control variables are omitted. Please refer to the Appendix for detailed variable definitions. Individual and calendar day fixed effects are included, and standard errors are clustered at the weather station level. T-statistics are reported in parentheses. *** indicates significance at the 1 percent, ** at the 5 percent, and * at the 10 percent level, respectively.

Table 8. Robustness Tests

Panel A: Changing the clustering unit of standard errors

	Log (1+total spending)×100%		
	Cluster SE by state	Cluster SE by zip	Cluster SE by individual
	(1)	(2)	(3)
Abnormal sky cover	-0.295***	-0.295***	-0.295***
	(-4.57)	(-5.15)	(-5.28)
Constant	169.723***	169.723***	169.723***
	(23.73)	(38.72)	(40.32)
Individual character controls	Y	Y	Y
Individual FE	Y	Y	Y
Calendar day FE	Y	Y	Y
Observations	2,125,991	2,125,991	2,125,991
R-squared	0.33	0.33	0.33

Panel B: Alternative time ranges for daily sky cover

	Log (1+total spending)×100% Daily sky cover as the average sky cover during	
	6 a.m. to 4 p.m.	Morning (6 a.m. to 12 noon)
	(1)	(2)
Abnormal sky cover	-0.270***	-0.211***
	(-5.21)	(-4.24)
Constant	169.689***	169.468***
	(34.40)	(34.20)
Individual character controls	Y	Y
Individual FE	Y	Y
Calendar day FE	Y	Y
Observations	2,125,991	2,125,991
R-squared	0.33	0.33

Note. This table reports two sets of robustness tests. Panel A changes the clustering unit of standard errors in the main regression. Column (1) clusters standard errors at the state level, column (2) clusters standard errors at the zipcode level, and column (3) clusters standard errors at the individual level. Panel B alters the time range for calculating the daily average *sky cover*. Column (1) uses the mean of sky cover value(s) between 6 a.m. and 4 p.m. as the daily *sky cover* value. Column (2) uses the mean of sky cover value(s) in the morning (i.e., between 6 a.m. and 12 noon) as the daily *sky cover* value. Coefficients for individual characteristics control variables are omitted. Please refer to the Appendix for detailed variable definitions. Individual and calendar day fixed effects are included, and standard errors are clustered at the weather station level for Panel B. T-statistics are reported in parentheses. *** indicates significance at the 1 percent, ** at the 5 percent, and * at the 10 percent level, respectively.

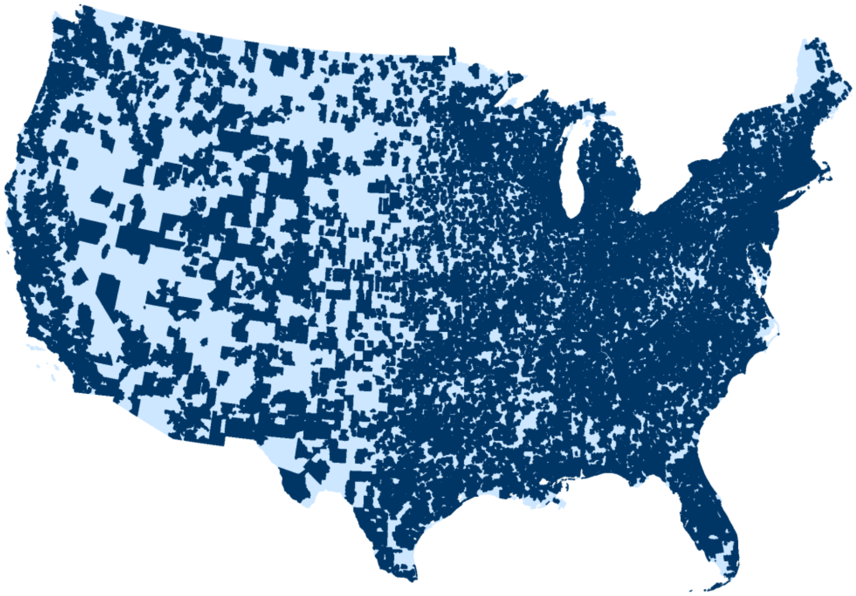
INTERNET APPENDIX
for

In the Mood to Consume: Effect of Sunshine on Credit Card Spending

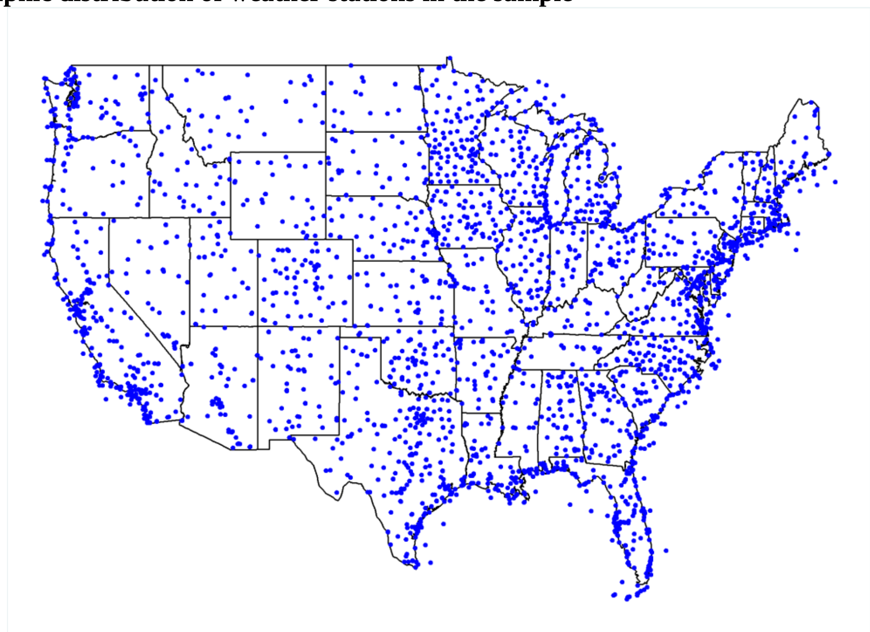
(Not Intended for Publication)

Figure IA1. Geographic Distribution of Zipcodes and Weather Stations in Sample

Panel A: Geographic distribution of zipcodes in the sample

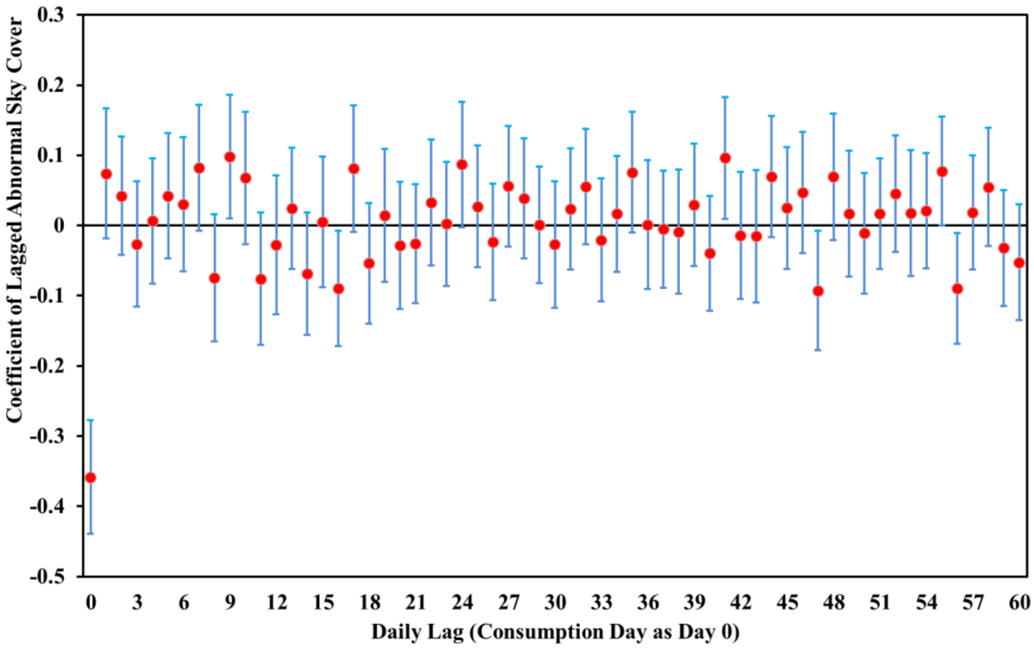


Panel B: Geographic distribution of weather stations in the sample



Note. This figure plots the geographic distribution of zipcodes (Panel A) and weather stations used (Panel B) in the final sample in the continental US.

Figure IA2. Distributed Lag Analysis of Abnormal Sky Cover (60-day Lags)



Note. This figure plots the estimated coefficients and 95% confidence intervals for *abnormal sky cover* on day 0 to day -60 relative to the consumption day from the regression model (2). The horizontal axis displays the daily lag relative to the consumption day, and the vertical axis displays the magnitude of the regression coefficient.

Table IA1. The Extensive Margin Effect

Panel A: The decision to consume

	Positive total spending×100%	Positive long-term spending×100%	Positive durable spending×100%
	(1)	(2)	(3)
Abnormal sky cover	-0.026***	-0.020***	-0.014***
	(-8.78)	(-9.16)	(-10.47)
Constant	2.999***	0.482**	0.323**
	(7.22)	(2.04)	(2.38)
Individual character controls	Y	Y	Y
Individual FE	Y	Y	Y
Calendar day FE	Y	Y	Y
Observations	17,687,386	17,687,386	17,687,386
R-squared	0.21	0.10	0.08

Panel B: Non-spending days as have 0 spending

	Log (1+total spending)×100%			
		Consumers have at least 1 positive spending during card holding life in sample for		
	All consumers	≥50% of the months	≥2/3 of the months	All months
	(1)	(2)	(3)	
Abnormal sky cover	-0.100***	-0.172***	-0.204***	-0.248***
	(-8.18)	(-7.89)	(-7.72)	(-6.29)
Constant	7.417***	18.948***	28.836***	51.767***
	(4.59)	(7.22)	(9.25)	(11.41)
Individual character controls	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y
Calendar day FE	Y	Y	Y	Y
Observations	17,687,386	9,923,335	7,575,378	4,377,946
R-squared	0.19	0.15	0.15	0.16

Note. This table investigates the extensive margin effect of *abnormal sky cover*. For each individual in the sample, we consider all days without credit card transaction record between the first and last spending days during the sample period to be non-spending days. Panel A investigates the effect of *abnormal sky cover* on the individual's decision to consume any goods, long-term goods, and durable goods in columns (1)-(3) respectively. Panel B treats non-spending days as having 0 total spending for each individual, and investigates the responses of log total spending. Column (1) investigates the response of all consumers in the sample. Columns (2)-(4) investigate the responses of active consumers that have at least 1 positive spending during the card holding life in sample for 50%, 2/3, and all months respectively. Coefficients for individual characteristics control variables are omitted. Please refer to the Appendix for detailed variable definitions. Individual and calendar day fixed effects are included, and standard errors are clustered at the weather station level. T-statistics are reported in parentheses. *** indicates significance at the 1 percent, ** at the 5 percent, and * at the 10 percent level, respectively.

Table IA2. Linearity of Sunshine Effect

Panel A: Control for the square of abnormal sky cover

	Log (1+total spending)×100%	Log (1+long-term spending)×100%	Log (1+durable spending)×100%
	(1)	(2)	(3)
Abnormal sky cover	-0.309***	-0.358***	-0.329***
	(-5.32)	(-5.49)	(-8.19)
Abnormal sky cover^2	0.026	-0.023	-0.014
	(1.06)	(-0.91)	(-0.90)
Constant	169.580***	44.162***	22.744***
	(34.44)	(8.83)	(7.47)
Individual character controls	Y	Y	Y
Individual FE	Y	Y	Y
Calendar day FE	Y	Y	Y
Observations	2,125,991	2,125,991	2,125,991
R-squared	0.33	0.16	0.16

Panel B: Effect in each quintile of abnormal sky cover

	Log (1+total spending)×100%	Log (1+long-term spending)×100%	Log (1+durable spending)×100%
	(1)	(2)	(3)
Abnormal sky cover: Q2	-0.508	-0.130	-0.493*
	(-1.06)	(-0.28)	(-1.74)
Abnormal sky cover: Q3	-1.464***	-1.031**	-0.870***
	(-3.01)	(-2.18)	(-2.95)
Abnormal sky cover: Q4	-2.374***	-1.789***	-1.562***
	(-5.39)	(-3.63)	(-5.40)
Abnormal sky cover: Q5	-1.831***	-2.491***	-2.295***
	(-3.74)	(-5.16)	(-7.70)
Constant	170.957***	45.083***	23.678***
	(34.76)	(9.07)	(7.83)
Individual character controls	Y	Y	Y
Individual FE	Y	Y	Y
Calendar day FE	Y	Y	Y
Observations	2,125,991	2,125,991	2,125,991
R-squared	0.33	0.16	0.16

Note. This table investigates the linearity of the sunshine effect. Panel A investigates the response of total spending, long-term spending, and durable spending to level and the square of *abnormal sky cover*, respectively. Panel B sorts the *abnormal sky cover* in each zipcode area into five quintiles and estimates the responses of total spending, long-term spending, and durable goods spending in higher quintiles of *abnormal sky cover*, compared to that in the lowest quintile of *abnormal sky cover*. Coefficients for individual characteristics control variables are omitted. Please refer to the Appendix for detailed variable definitions. Individual and calendar day fixed effects are included, and standard errors are clustered at the weather station level. T-statistics are reported in parentheses. *** indicates significance at the 1 percent, ** at the 5 percent, and * at the 10 percent level, respectively.