Insufficient Sleep and Intra-Day Financial Decision-Making: Evidence from Online Lending*

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Abstract

Using online lending microdata, I show that sleep has important consequences for household financial outcomes. I find that insufficient sleep has a significant impact on credit risk, particularly for loans that are applied for in the early morning. This effect diminishes as the day progresses, with applications submitted later in the afternoon and evening being unaffected. For identification, I apply a spatial regression discontinuity design leveraging exogenous discontinuities in sunset time across time zone boundaries, supplemented by additional identification strategies, including daylight savings time shifts. The results also suggest that the psychological mechanism behind this effect is increased levels of heuristic thinking resulting from the cognitive deficits commonly associated with sleep loss. Overall, the evidence indicates sleep has important implications for household financial behavior and welfare.

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1. Introduction

Sleep plays a highly important role in governing human behavior and cognition over the course of the day. Sleep deficiency is associated with significant cognitive deficits that can have wide-ranging impacts (Killgore and Weber, 2014). In this study, I explore the effect of sleep loss on financial decision-making in an online lending market using multiple identification strategies with a wide set of validating robustness tests. Importantly, by exploiting the granularity of the main dataset, I examine the times of day in which sleep loss may have the greatest effect as predicted by the medical literature on sleep (Tassi and Muzet, 2000; Wertz, Ronda, and Czeisler, 2006). Additionally, I explore the mechanisms that relate insufficient sleep to higher loan risk. In these ways, I can not only explore whether sleep loss impacts financial decision-making, but when and how it does so.

This study joins an international public health conversion on “social jetlag”, or the general misalignment of sleep and social schedules (Cespedes Feliciano et al., 2019). For example, a contemporary and well-studied topic surrounding social jetlag is on school start times. Adolescents are more likely to stay up later in the evening, decreasing their total hours of sleep due to rigid school start times, leading to worse academic performance (Itzek-Greulich, Randler, and Vollmer, 2016). Evidence suggests these declines concentrate in the morning, with less clear effects in the afternoon (Goldstein et al., 2007). This study asks very similar questions related to adult financial behavior: I apply an instrument that prompts individuals to delay their bedtimes, leading to declines in sleep, and then I examine the subsequent effects on financial behavior at different times of the day given the cognitive limitations induced by sleep loss.

This is the first study to examine the impact of sleep deficiencies on household financial decision-making and welfare. While there are many laboratory studies that indicate a relationship between sleep loss and lower risk aversion, which carries natural implications for financial decision-making, the tangible household financial outcomes in real-world settings are unclear and untested (Killgore, 2010; Killgore, Balkin, and Wesenten, 2006; Xu, Liu, and Wang, 2021). Additionally, chronic sleep restriction (getting less than six hours of sleep) is regular for about 30% of U.S. adults, making the topic of sleep loss a public health issue (Schoenborn and Adams, 2010).

I examine my hypotheses in the market for online (peer-to-peer) loans, testing the effects of sleep deficiency on loan outcomes.[2] Online lending, and online financial settings in general, provide a beneficial setting to examine such effects. Online loan marketplaces are open 24 hours a day, 365 days a year, allowing me to examine individual behavior over a 24-hour period. Additionally, the location and the time of the day (down to the millisecond) the individual fills out their application is also directly observable in the data. The setting also allows me to track the same individual over time and in different locations which allows me to exploit individual-specific fixed effects across different identification strategies. This is crucial for measuring the effect of sleep loss, given individuals vary dramatically in sleep needs and their associated cognitive requirements. The inclusion of individual fixed effects also makes it unlikely that selection effects can explain the main results.[3] Additionally, the setting allows me to rule out possible confounding factors related to the behavior of the *investors*, rather than the behavior of the borrowers.[4]

It is a unique empirical challenge to identify the effect of insufficient sleep on financial decision-making and household financial outcomes. Sleep duration is voluntarily chosen based on the individual's specific needs, which presents a threat to identification if borrowers who choose

[2] The online lender I use is Prosper.com.
[3] I apply individual fixed effects for both the analysis using the spatial RDD (see Table 8) and daylight savings time shifts (see Table 9).
[4] I address this possible confounding factor in Section 6.7.

to sleep less also make riskier lending choices (Porkka-Heiskanen, Zitting, and Wigren, 2013).

To mitigate these empirical challenges, I apply a spatial regression discontinuity design (RDD) leveraging US time zone boundaries, which exogenously disrupt sunset times, resulting in later bedtimes and shorter sleep durations. In this way, I can measure the discontinuity in sleep times using US Census American Time Use Survey (ATUS) data and estimate the associated effects of this first-stage discontinuity in the online lending market. Furthermore, as the exact times in which individuals fill out their applications is observable, I can leverage time of day effects to ascertain the times of day individuals are most likely to be impacted by sleep. In other words, not only am I able to measure discontinuities across time zone boundaries, but I am also able to examine the times of the day in which those discontinuities are at their greatest extent. I apply a secondary test using daylight savings time shifts with individual fixed effects to validate the primary empirical design and provide additional robustness. Finally, given I observe all aspects of the individual's loan application, I apply behavioral proxies from the finance literature to measure the degree of heuristic thinking and ascertain a cognitive channel by which sleep is impacting loan risk (Pursiainen, 2022, Hu et al., 2023).

First, using the spatial RDD and a wide range of geographic and demographic fixed effects, I estimate the primary discontinuity in sleep. The results show that living on the late sunset side of a time zone border is associated with several discontinuities in sleep related variables. I find that being on the late sunset side of the time zone boundary is associated with a 8.7-percentage point increase in going to sleep after 10 p.m., with no effect on the individual's time of waking. This is consistent with solar cues impacting bedtimes but not waking times (Walch, Cochran, and Forger, 2016). As a result of this discontinuity, being on the late sunset side of a time zone boundary is also associated with about a 35.8-minute decrease in average sleep time and a 11.9 percentage point increase in the probability of getting less than six hours of sleep.

Upon establishing the discontinuity in sleep duration, I proceed by estimating the effects on loan outcomes. I find a distinct discontinuity across time zone boundaries in loan default. Being on the late sunset side of the time zone boundary is associated with a 2.97 percentage point increase in default, equivalent to a 10.5% increase in default risk relative to its standard deviation.[5] Additionally, this effect is concentrated in the early morning hours following waking, dissipating by afternoon. This follows the hypothesis that the effects of sleep loss occur most strongly in the morning, consistent with insufficient sleep extending and exacerbating the period of grogginess and cognitive deficit following waking (Balkin and Bedia,1998; Tassi and Muzet, 2000; Tassi et al., 2006). The results are robust to a wide set of bandwidths and an alternative regression discontinuity polynomial design.[6]

To mitigate concerns related to selection and endogeneity, I apply a barrage of alternative specifications and robustness checks. I test for observable differences in borrower characteristics and find no significant discontinuities across the threshold. I proceed and analyze discontinuities in pricing and find no significant discontinuity, providing evidence that the economically and statistically significant effects of sleep on loan default is not priced into the financial market. As an additional test to mitigate concerns related to unobserved discontinuities in other confounding factors across time zone boundaries, I examine a unique setting for a natural experiment between the states of California, Nevada, and Arizona. California and Nevada follow daylight savings time (DST), while Arizona does not, which means that as California advances ahead an hour in spring and moves back an hour in autumn, the treatment (late sunset) in the spatial RDD turns off and on. The analysis illustrates that there is a significant effect *only* when Arizona has a later sunset time,

[5] This is also equivalent to about 33.5% of the mean.
[6] I report these results in Table 5.

which supports the validity of the instrument and mitigates concerns related to confounding factors.

Finally, as another test to validate the main spatial RDD, I restrict the sample to individuals who relocate around time zone boundaries. As a specific example, from the information in the lending data, I can observe a licensed practical nurse who made five separate, relatively small loans, in five different cities.[7] As such, this design applies individual fixed effects to examine how the same individual's financial behavior changes given variation in the instrument. Overall, I find effects consistent with the baseline.

As a distinct identification strategy to supplement the main design, I examine variation in loan outcomes when applications are filled out following DST shifts. During the spring DST shift, individuals lose an hour of time to sleep, while during the autumn DST shift, individuals gain an hour to sleep. Consistent with the literature on daylight savings shifts and the asymmetric effects of sleep loss/gain, I only find an effect on loan outcomes for the spring DST shift and no effect for the autumn DST shift (Barnes and Wagner, 2009; Smith, 2016). This result is robust to the inclusion of individual fixed effects and there is no impact on loan pricing. Results from a placebo test also rule out confounding pre-trends. Overall, the results in this empirical setting mirror the results of the previous study: the effects of sleep deficiency on loan risk are entirely concentrated in the early morning in the hours following waking and at similar economic magnitudes.

Finally, I test for possible behavioral mechanisms by which sleep loss impacts loan outcomes. I hypothesize heuristic thinking as a potential channel motivated by findings in the psychological and finance literatures, and fundamentally related to the work in Tversky and Kahneman (1974). First, heuristic thinking has been associated with sub-optimal decision-making

[7] An illustration of a sample of borrower relocation is provided in Figure 4.

in several financial settings, and proxies for heuristic thinking have been associated with higher levels of default risk in other online lending settings (Kuo, Lin, and Zhao, 2014; Hirshleifer et al., 2019; Hu et al., 2023). Second, in laboratory settings, insufficient sleep has been strongly associated with higher levels of heuristic thinking in decision-making (Engle-Friedman et al. 2018; Dickinson and McElroy, 2019). Other laboratory studies indicate sleep loss is associated with lower levels of risk aversion in similar settings (Killgore, Balkin, and Wesenten, 2006; Killgore, 2010; Xu, Liu, and Wang, 2021). For example, Mckenna, Dickinson, and Drummond (2007) find in certain instances that sleep deprivation led subjects to take more risks than they would have when normally rested. This research implies when individuals are tired or sleep deprived, they tend to rely on heuristics in their decision-making process, which is associated with individuals taking on more risk than otherwise intended. Overall, these observed relationships suggest heuristic, less deliberative thinking in the choice to take out a loan may be a possible behavioral mechanism for the influence of sleep loss on default risk.

I construct a loan-level index of the pervasiveness of round numbers in loan amount requests, which signals the degree of heuristic thinking. Similar measures have been used in the finance literature to assess decision-making under uncertainty and cognitive deficits, which typically also involve increases in financial risk (Kuo, Lin, and Zhao, 2015; D'Acunto et al, 2022; Pursiainen, 2022; Hu et al., 2023). Using this proxy, I find a strong relationship between sleep loss and heuristic thinking in both the spatial RDD and DST analysis, suggesting that heuristic thinking is a cognitive channel by which sleep loss impacts real financial outcomes, consistent with predictions from laboratory studies (Kilgore, Balkin, and Wesenten, 2006; Mckenna et al., 2007; Killgore, 2010; Xu, Liu, and Wang, 2021).

This study broad contributes to the literature on the determinants of household credit demand (Gross and Souleles, 2002; Agarwal, Chunlin, and Souleles, 2007; Melzer, 2011). More specifically, this paper contributes to the burgeoning literature on credit demand in online markets. Using online lending data, Hertzberg, Liberman, and Paravisini (2018) find that when offered longer term loans, borrowers who take the longer-term loan default less. Additionally, Tang (2019) documents that borrower's use online lending as a substitute for bank debt among infra-marginal bank borrowers but complements bank lending in the small loans market. Hu et al. (2023) use data from a Chinese P2P lending platform and find that round number loans exhibit poor repayment behavior, which they attribute to the borrower's heuristic choices.

This study also directly contributes to the broader literature focusing on identifying behavioral factors that influence financial decision-making. Previous studies identify several such factors. One strand of the literature focuses on the role of gender in financial decision-making and risk aversion (Renate et al., 1999; Huang and Kisgen, 2013; Ke, 2021). Several studies focus on the role of mood on financial decision-making (Bassi, Colacito, and Fulghieri, 2013; Goetzmann et al., 2015 Cortés, Duchin, and Sosyura, 2016; Chhaochharia, et al., 2019). A another strand of the literature examines the role of sentiment both in financial decision-making and investing (Edmans, Garcia, and Norli, 2007; Arif and Lee, 2014; DeVault, Sias, and Starks, 2019; Obaid and Pukthuanthong, 2022).

The study proceeds as follows. Section 2 describes the psychological literature on sleep loss. Section 3 presents the data and main empirical designs. Section 4 presents an analysis of the discontinuity in sleep duration around time zone boundaries. Section 5 details the empirical designs I use in this study. Section 6 presents the main results of the spatial RDD. Section 7 presents additional results applying daylight savings time changes to supplement robustness. Section 8 examines time of day effects. Section 9 examines the relationship between insufficient sleep and heuristic thinking to explore potential mechanisms. Section 10 concludes.

2. Related Psychology Literature

2.1. Insufficient Sleep and Risk Aversion

There is a wide literature on sleep loss in the medical and psychological literatures. One primary area of research is the impact of sleep loss on cognitive performance. Medic, Wille, and Hemels (2017) finds that sleep disruptions lead to cognitive deficits among healthy adults. In one study, subjects were restricted to five hours of sleep per night for four consecutive nights. The subjects' resulting cognitive deficits were compared to that from alcohol consumption and their performance was found to be on par with having a blood alcohol concentration close to the legal limit for driving (Elmenhorst et al., 2009).

More generally, Pilcher and Huffcutt (1996), in a meta-analysis, find that sleep disruptions effects both cognitive functioning and mood. Futhermore, Killgore and Weber (2014) find sleep loss impacts a wide array of cognitive processes, including sensory perception, mood, and cognitive functioning. Other literatures have explored the effects of sleep loss outside of laboratory settings. For example, research finds increases in vehicle crashes and workplace accidents following the shift in daylight savings time (Coren, 1996; Varughese and Allen, 2001; Smith, 2016). This research suggests even the relatively modest change in sleep duration from DST shifts, about a 40 minute decrease the night of the shift, can have large cognitive effects (Barnes and Wagner, 2009). Additionally, Lanaj, Johnson, and Barnes (2014) find sleep loss (stimulated by late night smartphone use) increases individuals' depletion the following morning. The authors also find that this impacts the overall engagement at work the day following the sleep loss.

More significantly, the literature suggests a distinct relationship between sleep loss and risk aversion, which has implications for financial markets. Levels of insufficient sleep have been shown to have distinct effects on financial risk aversion in laboratory settings. For example, after seven consecutive nights of sleep restriction individuals show lower levels of financial risk aversion (Maric et al., 2017). In a broad survey of the sleep literature, Womack et al. (2013) finds that sleep loss is positively associated with risk-taking behavior across 23 studies. Nofsinger and Shank (2019) also examine the relationship between sleep loss and financial decision-making in a laboratory environment, finding that individuals with more sleep have less distortion of probability, a more curved utility function, and are less loss averse. Furthermore, a wide set of laboratory studies suggest that sleep restriction or deprivation increases individuals' uncertainty bearing propensity (Killgore, Balkin, and Wesenten, 2006; Mckenna, Dickinson, and Drummond, 2007; Killgore, 2010). Xu, Liu, and Wang (2021) explore the relationship between sleep loss and individuals risk behavior given uncertain conditions. The authors find that individuals with more sleep show an increased aversion making choices under conditions of uncertainty. Castillo, Dickinson, and Petrie (2016) find that study participants prefer riskier asset bundles when treated with mild sleepiness. In Section 8, I also explore the effect of insufficient sleep on heuristic thinking, which is associated with decision-making under uncertainty and increases in default risk in online financial settings (Pursiainen, 2022; Hu et al., 2023).

2.2. Time of Day Effects

The state of impaired cognition and grogginess experienced following awakening is known as sleep inertia (Wertz, Ronda, and Czeisler, 2006). Overall, a wide array of medical literature suggests that the effects of sleep loss are concentrated in the morning hours as a function of this effect. Wertz, Ronda, and Czeisler (2006) finds that cognitive performance following awakening is worse than all subsequent points measured during an awakened period of 26 hours. The authors find the cognitive declines associated with sleep inertia are detectable for a period of two hours following awakening. Bruck and Pisanti (2002) find that decision-making immediately following awakening is about 51% below optimum, and it remains about 20% optimum after 30 minutes of awakening. An additional laboratory study finds that the negative effects of sleep inertia dissipate in about 2-4 hours (Jewett et al., 2008). The authors find that cognitive performance is significantly impaired upon awakening regardless of whether subjects got out of bed, ate breakfast, showered, and were exposed to indoor room light or whether subjects remained in bed and were exposed to dim light.

Studies also highlight the relationship between sleep loss and sleep inertia. Tassi and Muzet (2000) finds that prior sleep deprivation enhances the negative effects of sleep inertia. In addition, Balkin and Bedia (1998) also find that prior periods of sleep disruption exacerbate the cognitive declines associated with sleep inertia. Another study finds that following a sufficient period of sleep, sleep inertia is moderate and produces only a slight deficit (Tassi et al., 2006). The authors show that sleep inertia leads to dose-dependent negative effects on cognitive performance. Overall, these studies illustrate that sleep inertia is related to sleep loss such that prior sleep loss exacerbates the existing cognitive deficit.

Given the findings in the literature, I hypothesize the effects of sleep loss may be most prevalent in the morning hours around waking, consistent with the cognitive declines associated with sleep inertia, exacerbated under the conditions of sleep loss. As such, this study takes established predictions from laboratory environments and illustrates the real-world household welfare implications of sleep deficits.

3. Data and Variables

3.1. American Time Use Survey (ATUS) Individual Time Use

I first analyze the discontinuity in sleep-related variables across time zone borders using data drawn from the American Time Use Survey (ATUS). The ATUS has been conducted by the US Bureau of Labor Statistics (BLS) since 2003. The sample mirrors the sample in which lending data is available, namely 2007-2021. In the survey, the respondents are asked to record detailed time use information from the previous day, which includes information on time spent sleeping. Given that the ATUS survey does not ask information on county location, I use the ATUS-CPS (Current Population Survey) merged dataset, available from the BLS.

Following Giuntella and Mazzonna (2019), I restrict the sample to people aged 18-55 years to avoid the confounding effect of retirement and any selection issues that may arise from high-school age workers. Further, I limit the analysis to individuals who sleep between 2 and 16 hours per night. I exclude naps from the data, focusing on sleep starting and ending times between 7 a.m. and 7 p.m. Furthermore, I also exclude weekends from the analysis, such that a lack of a typical work schedule does not confound the results.[8] Summary statistics for the key variables related to the ATUS in Table 1. The main variable I source from the ATUS data is *Sleep Duration*, defined as the self-reported number of minutes the respondent slept on the reported day. Given less than six hours of sleep on a consistent basis is the typical definition of chronic sleep restriction, I define *Major Sleep Deficit* as an indicator equal to one if the respondent reports getting less than six hours of sleep (Schoenborn and Adams, 2010). Other key variables include *Late Bedtime*, an indicator variable equal to one if the survey respondent went to bed after 10 p.m. I also define *Early Wake Time*, an indicator variable equal to one if the respondent woke up before 7:30 a.m.

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[8] In addition, in the analyses, I exclude observations from the county containing the city of Las Vegas (Clark County NV), as it is an outlier and unique case in terms of bedtimes. Results are quantitively similar when it is included.

3.2. Loan Data

Data on online loans comes from Prosper.com (Prosper). Prosper has facilitated $22 billion in loans to more than 1.35 million people.[9] It provides consumer loans that range between $2000 to $40,000 with interest rates ranging between 5% and 35% (Balyuk, 2022). The sample period is 2007-2021. To attain a loan, an individual must fill out an online application, in which a specific loan amount must be requested. The individual must also give additional information, such as a home address and employment, and consent must be given for a credit check. Upon being priced, the loan is listed online for investor funding.

I focus on Prosper due to several key features which are conducive to researching the impact of sleep loss. First, the platform gives the exact time (down to the millisecond) an individual is filling out the loan application, allowing me to exploit time of day variation in the effects of sleep of financial decision-making. Second, Prosper requests the individual's home address, and reports the city and state in the data, allowing me to exploit granular geographic details in the main spatial RDD.[10]

I report summary statistics for the key variables from Prosper in Table 1. There are three main dependent variables of interest. The first is *Default*, which I define following Butler, Cornaggia, and Gurun (2017). *Default* takes a value of one if the loan's status is ever "Default (bankruptcy)" or "Charge-off".[11] A loan is charged off when a borrower misses five consecutive monthly payments. I also include a variable for the interest rate on the loan (*Interest Rate*), to

[9] See https://www.prosper.com/about

[10] I match geographic details and loan application times from the Prosper listing dataset into the Prosper loan dataset, two distinct datasets offered by Prosper. Both datasets contain a shared set of identical variables, but the datasets lack a unique identifier. Given the high specificity of the variables, most observations are unique, which allows for an exact match. I remove any loans or listings which an exact match cannot be identified.

[11] Because I focus on loan outcomes, I do not include late payments in *Default* (our measure of loan distress) as does Butler, Cornaggia, and Gurun (2017). I show in Internet Appendix Table IA3 the results are robust to the inclusion of late payments in the measure of loan distress.

capture the extent that the effects of sleep loss may be priced into this financial market. The third is *Heuristic Index*, a which serves as a proxy for uncertain decision-making. It is defined as an index between 0-5 for whether a loan is rounded to the nearest 1000, 5000, 10000, 15000, or 20000, following Pursiainen (2022).

4. Empirical Approaches

To capture the effects of sleep on financial decision-making, this study leverages two primary identification strategies that yield similar results. The main approach is a spatial RDD leveraging exogenous discontinuities in sunset time as an instrument for sleep loss. The second approach utilizes variation in sleep brought on by daylight savings time changes. Both allow for the examination of the effects of sleep deficiencies at different times of day, which is a necessary component in understanding how sleep loss impacts human behavior (Wertz, Ronda, and Czeisler, 2006). In addition, both approaches allow for the inclusion of individual fixed effects, mitigating many confounding factors related to selection.

4.1. Spatial Regression Discontinuity Design

As an instrument for sleep loss, I exploit the sharp discontinuity in sunset times across time zone boundaries. I observe a clear discontinuity in sunset time across the boundaries, which I demonstrate is associated with discontinuities in both bedtimes and sleep duration in Table 2, with other demographic characteristics remaining continuous across time zone boundaries.[12] Figure 1 plots the discontinuity in bedtimes.[13] Unlike a standard regression discontinuity design, given there

[12] I test for discontinuities in demographic and economic characteristics in the ATUS sample in Internet Appendix Table IA2.

[13] Due to a lack of ATUS sample coverage in a wide number of US counties, I illustrate the discontinuity in bedtimes using data from the *Jawbone sleep tracker* website, following Giuntella and Mazzonna (2017).

are three separate time zone boundaries the analysis applies, a standard approach would compare individuals living on opposite sides of *different* time zone boundaries (such as an individual living in Florida to an individual living in California). Furthermore, it would compare individuals who live at different latitudes, which have different sunset times. As such, an important addition to the design is geographic fixed effects, controlling for the specific time zone boundary (such that I only compare individuals across the same boundary), state fixed effects (such that I only compare individuals in the same state), and latitude fixed effects (such that I only compare individuals living in the same 0.25-degree latitude bands). In certain specifications, I also remove observations from 30 miles on either side of the time zone boundary, denoted as *Commuting Zone*, to account for any effects of individuals who may regularly commute across time zone boundaries (following Giuntella and Mazzonna (2017)). I illustrate the results are robust to a wide array of commuting zone sizes in Internet Appendix Table IA4.

Formally, I exploit geographic variation in sunset time using the following specification:

$$Y_{i,t} = \alpha_0 + \alpha_1 LS_c + \alpha_2 f(D_C) + \alpha_3 (LS_{i,c} \times f(D_C)) + \alpha_4 X_{i,t} + \alpha_5 W_t + \alpha_6 Z_c + \varepsilon_{i,t,c} \tag{1}$$

where $Y_{i,t}$ is an outcome of interest, LS_c is an indicator for a county being on the late sunset side of a time zone boundary, and $f(D_C)$ is the distance to the time zone boundary in miles.[14] $X_{i,t}$ is a vector of individual specific control variables. W_t and Z_c are vectors of both time and geographic fixed effects.[15]

This identification strategy rests on the assumption that there are no discontinuities in

[14] This serves as the forcing variable. Specifically, I use the distance to the county centroid.
[15] In Equations (1) and (2), *i* indexes individuals, *t* indexes time, and *c* indexes geography.

observable or unobservable characteristics across the thresholds that may confound the main results. Certain studies apply similar identification strategies to examine the effect of sleep loss on other outcomes, showing that demographic characteristics are smooth across boundaries, but also showing discontinuities in health factors (such as propensities for developing diabetes or heart disease) or labor productivity (Giuntella and Mazzonna, 2017; Gibson and Shrader, 2018; Costa et al., 2022). I mitigate concerns that these discontinuities may be confounding the results in several ways. First, the results illustrate that the effects of sleep loss on loan risk concentrates in those loans filled out during the morning hours following a night of insufficient sleep across multiple empirical strategies. Given this intra-day variation, it is unlikely that a more time-invariant health or labor market characteristic confounds the results. Additionally, I apply individual fixed effects, mitigating concerns relating to selection and other time-invariant individual characteristics. The results also show a distinct increase in heuristics in the loan application consistent with the effect of sleep, but inconsistent with health or demographic effects (see Section 8). Finally, I apply the secondary empirical design utilizing daylight savings time changes and *short-term* disruptions in sleep. This design validates the main regression discontinuity design, and the short-term variation in sleep from DST changes are unlikely to be related to long-term trends in health or labor market productivity.

4.2. Daylight Savings Time Shifts

As an additional specification, this study leverages shifts in daylight savings time (DST) as a disruption to sleep duration. This follows a wide set of literatures which examine the role of daylight savings time shifts, which is strongly linked in sleep disruptions (Lahti et al., 2006; Kantermann et al., 2007; Barnes and Wagner, 2009). The sleep disruptions resulting from DST are associated with numerous outcomes, such as increases in workplace injuries and increases in auto accidents (Coren 1996; Barnes and Wagner, 2009). In the finance literature, DST changes are linked to changes in analyst forecast accuracy and stock market declines (Kamstra, Kramer, and Levi, 2002; Bazley, Cuculiza, and Pisciotta, 2022). Barnes and Wagner (2009) find that daylight savings shifts are associated with about a 40-minute decrease in sleep for the night of the DST shift.

In this setting, I examine the role of the sleep disruptions associated with DST shifts on financial decision-making throughout the day, and I compare these effects to those induced by late sunset discontinuities across time zone borders. I compare the financial behavior of individuals in the days immediately following the spring DST change with those at other points in time. I allow for a four-day period following the spring DST shift, motived by prior research which suggests one hour of sleep loss takes between three and four days to recover from (Harrison, 2013; Kitamura et al., 2016; Bazley, Cuculiza, and Pisciotta, 2022). I show in Internet Appendix Table IA9 that results are robust to using one-, two-, and three-day windows as well.

Formally, I exploit variation in sleep induced by DST shifts using the following specification:

$$Y_{i,t} = \alpha_0 + \alpha_1 Spring\ Shift_t + \alpha_2 X_{i,t} + \alpha_3 W_t + \alpha_4 Z_c + \varepsilon_{i,t,c} \tag{2}$$

where $Y_{i,t}$ is an outcome of interest, $Spring\ Shift_t$ is an indicator variable equal to one during the four-day window following the spring DST shift. $X_{i,t}$ is a vector of individual specific control variables. W_t and Z_c are vectors of both time and geographic fixed effects.

The daylight savings shift design also aids in clarifying possible mechanisms. For example, it could be the case that individuals who are sleep deprived see declines in their labor productivity another economic factor that decreases their ability to pay back the loan. On the other hand, it could be the case that an individual makes an ill-advised choice to take out a loan when sleep-deprived, whereby a lack of sleep inhibits an individual's ability to consider their choice thoughtfully and rationally. While the sunset time (spatial RDD) design could plausibility relate to either mechanism given it acts upon an individual over a long period of time, the DST design is a short-term exogenous event, so it could only relate to an individual at the time they are considering a loan. This provides some evidence that the mechanism must be related to an individual's choices in taking out a loan, rather than any changes in their ability to repay during the lifetime of the loan. I provide analysis relating to possible mechanisms in Section 8.

5. Sunset Time and Sleep Loss

This section examines the relationship between sunset time and sleep loss, following other studies (Giuntella and Mazzonna, 2019). The purpose of this section is to establish the primary discontinuity in sleep duration across time zone borders and illustrate the relationship between bedtime, waking time, and sleep duration. I plot discontinuities in *Late Bedtime* and *Sleep Duration* across time zone boundaries in Panels A and B of Figure 2.

Table 2 presents the results for this analysis. Each model includes demographic controls for a survey respondent's number of children, gender, marital status, education, and income. I also include an array of fixed effects, accounting for geographic characteristics such as time zone border and state, and temporal characteristics such as the day of the week and the year. The analysis follows the form specified in Equation (1).

I investigate the relationship between bedtime and waking time in Columns 1-2.[16] *Late Bedtime* is a dummy variable equal to one if the respondent went to sleep after 10 p.m. and *Early Wake Time* is a dummy variable equal to one if the respondent woke up prior to 7:30 a.m. Consistent with the literature, I find that individuals reported bedtimes are a function of solar cues while their wake times are not, such that being on the late sunset side of a time zone border increases the probability of going to sleep after 10 p.m. by 8.7 percentage points, or about 20% its standard deviation, with no significant effect on waking time (Walch, Cochran, and Forger, 2016).[17] In Column 4, I report the full specification with *Sleep Duration*, defined as the self-reported hours of sleep the respondent had in minutes. I find that being on the late sunset side of the time zone boundary, and thus a higher probability of going to sleep later in the evening, is associated with about a 35.8-minute decrease in sleep duration. I show that the results are robust to excluding a commuting zone around the time zone boundary in Column 5. Additionally, Column 6 illustrates the results are robust to an alternative 100-mile bandwidth. Column 7 reports the results for *Chronic Sleep Deficit*, suggesting being on the late sunset side of the time zone boundary increases the probability of receiving less than six hours of sleep by 11.9 percentage points, or about 33.4% relative to the standard deviation (79.7% relative to the mean). Overall, these results are consistent with the effect sizes found in other studies (Giuntella and Mazzonna, 2019).[18] In addition, I find no discontinuities in demographic or economic characteristics across the time zone boundaries.[19]

In summary, this section demonstrates a clear relationship between time zone boundaries

[16] I show this result is robust to the use of continuous measures of sleep and wake times in Internet Appendix Table IA1.
[17] The economic magnitude of this effect is also equivalent to about 11.6% of the mean.
[18] For example, Giuntella and Mazzonna (2019) find discontinuities in sleep duration between 19 and 36 minutes.
[19] I report these results in Internet Appendix Table IA2.

and sleep duration. Moreover, this section demonstrates the mechanism by which the discontinuity occurs: a later sunset time leads to more individuals staying up late (responding to natural solar cues), which leads to overall less sleep duration. The following section leverages this discontinuity to investigate the effects of sleep loss on financial outcomes throughout the day.

6. Sleep Loss and Default

6.1. Baseline Results

This subsection studies the effect of sleep loss on loan default applying sunset time as an instrument for sleep loss. To examine the effect of sleep loss on loan outcomes, I apply the spatial regression discontinuity model as specified in Equation (1). This section also mirrors the identification strategy in Section 4, such that I can calculate the associated increase in loan risk as a function of the size of the discontinuities found in Table 2.

Figure 3 plots this discontinuity throughout the day. Panel A plots the discontinuity in loan default across the time zone boundary in the early morning (5-10 a.m.), while Panel B plots the discontinuity in default in the afternoon and evening. In Panel A, there is a visual discontinuity in loan outcomes in the early morning, which then begins to close and disappears by afternoon and the evening, as illustrated in Panel B. As such, this discontinuity grows and shrinks throughout the day. I further explore this time-of-day dynamic effect in more detail in Section 7. This figure provides evidence for the hypothesis that the effect of sleep loss on loan outcomes concentrate early in the day following waking.

Table 3 examines the effect of sleep loss (instrumented for by *LS*) on loan default.[20]

[20] Following Giuntella and Mazzonna (2017), I exclude Arizona and Indiana in the main analysis, given these states did not follow DST for the full sample, which leads to a lack of discontinuities at certain times of year. I show in Internet Appendix Table IA5 that the results are robust to the inclusion of these states (DST noncompliers).

Columns 1-3 examine early morning loans (5-10 a.m.), while Column 4 examines afternoon and evening loans (4-9 p.m.)[21]. The first column in Table 3 provides the baseline result without controlling for borrower quality or loan characteristics. Column 2 provides the baseline result applying the full specification of controls and fixed effects. The results suggest applying for a loan the late sunset side of a time zone border, during the morning, increases the likelihood of default by 2.97 percentage points. The economic magnitude of this effect is about 10.46% the standard deviation of *Default*.[22] Column 3 excludes the 30-mile *Commuting Zone* on either side of the time zone border. Column 4 examines the effect of sleep loss on loan risk in the afternoon (4-9 p.m.). I find no effect of sleep loss on loan risk for loans begun in the afternoon following insufficient sleep, given the statistically insignificant coefficient on *LS* in Column 4. The results are also consistent with the evidence that the effects of "social jetlag" influence cognitive performance most in the morning hours, with no detectable effect in the afternoon (Goldstein et al., 2007).

In summary, sleep loss, instrumented for by sunset time, has an economically important effect on loan outcomes, for those loans begun in the morning following a night of insufficient sleep.

6.2. Discontinuities in Borrower Characteristics

It is plausible that sleep loss may also induce changes to the composition of borrowers that are filing loan applications. In this case, sleep loss induced changes in the composition of borrowers may also be responsible for the associated increase in risk. For example, it could be the case that only borrowers with less financial literacy take out loans in the morning, leading to an increase in loan risk due to the shift in borrower composition. In this section, I investigate these possibilities

[21] I further explore the effects across the full day in Section 8.
[22] This is also equivalent to about 33.6% the mean of *Default*.

and test for discontinuities in the individual's loan size, income, risk score, employment, and lending history.

The results are reported in Table 4.[23] Columns 1-5 display the estimated coefficients for the set of individual credit characteristics. There is no significant difference in loan size, income, risk score, employment, or lending history. Overall, I find no discontinuities in these observable credit characteristics. This provides evidence suggesting no clear change in the composition of borrowers across the threshold. I supplement this analysis further in Section 5.6, with the inclusion of individual fixed effects to further eliminate concerns related to selection.

6.3. Alternative Bandwidths and Specifications

The purpose of this subsection is to show the robustness of the results to alternative bandwidths and specifications. I present these results in Table 5.[24]

Columns 1-6 of Table 5 present the results from the baseline specification at varying bandwidths around the time zone boundaries, from 700 miles to 100 miles. I show that estimates across all tested bandwidths are quantitively similar and statistically significant. In addition, I estimate a second-degree global polynomial as an alternative to a local linear regression in Column 7, and I demonstrate the estimate is robust to the application of higher order polynomials.[25] Overall, these results indicate that the estimates are robust to a wide array of bandwidths and estimation using a higher order polynomial regression discontinuity design.

[23] I show these results with a 30-mile commuting zone excluded in Internet Appendix Table IA6.
[24] These results are also robust to the exclusion of a 30-mile commuting zone, which I show in Internet Appendix Table IA7.
[25] I only test a second-degree polynomial given Gelman and Imbens (2018) suggests the application of third- or higher-degree polynomials leads to biased results in regression discontinuity designs.

6.4. Arizona/California Natural Experiment

The time zone boundaries that exist in the US are not always static. The primary example of this is between the states of Arizona, California, and Nevada. California and Nevada abide by daylight savings time and Arizona does not. This implies that during normal time (not during DST), California and Nevada are one hour behind Arizona, and there is a time zone boundary between the states with Arizona being on the late sunset side. During DST, California and Nevada advance one hour, such that both states share the same time with Arizona. In this way, the time zone boundary between these states turns on and off over the course of the year. This provides a unique setting for a natural experiment.

If the discontinuity in the timing of natural light in the evening is a valid instrument, then the effects should only be seen when the time zone boundary is "on" with no effect when the time zone boundary is "off". To perform this analysis, I restrict the sample to Arizona, California, and Nevada and estimate the effect of the sleep loss instrument at different times of day, not during and during DST.[26] I report these results in Table 6.

I find that sleep loss instrument only impacts default risk only when the boundary is "on" and only in the morning, consistent with the main results. I find no effect when time is continuous across the threshold. Overall, this result mitigates concerns related to confounding differences that may coincide with time zone boundaries.

6.5. Individual Relocation

In this subsection, I perform a similar spatial RDD as the baseline design in Table 3, but I constrain the sample to individuals who have variation in the geography of the locations they apply for loans

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[26] Given I focus on three specific states along one time zone boundary, I remove the broader, nationwide geographic fixed effects present in the baseline design (Table 3), namely time zone border, state, and latitude fixed effects.

in. I illustrate a set of borrower relocations in Figure 4. In the figure, I illustrate that individuals can and do make loans on one side of the CST-EST time zone boundary, and then move to the other side of the boundary and make another loan. In other words, I observe individuals moving between the treated (late sunset) and control (early sunset) groups, and I examine variation in their behavior. I report the results in Table 7. Each model includes individual-specific fixed effects.

The evidence shows that the baseline results are robust to including individual-specific fixed effects. Columns 1-3 report the results for the morning (5-10 a.m.), while Column 4 reports the results for the afternoon and evening (4-9 p.m.). The results are consistent with the baseline results in Table 3, such that the effects of sleep loss on loan outcomes are primarily concentrated in the morning hours, with no effect in the afternoon or evening. Overall, this test alleviates concerns that there may be unobserved geographic discontinuities across the time zone boundaries that may be cofounding the results.

6.6. Pricing

In this subsection, I test the pricing implications of the results. If the effects of sleep loss are influencing measurable and well-known risk factors, then the effect on default should also be priced into the interest rate on the loan.[27] Interest rates are assigned by Prosper using a proprietary algorithm.[28] I estimate the baseline analysis examining the effect on the interest rate, varying the bandwidth and the time of day (following the main results in Table 3). I report these results in Table 8.

[27] For example, it could be the case that borrowers are taking out much larger loans than they are able to pay back, or they are taking out an additional contemporary loan. If this is the case, the interest rate would reflect the risk adjustment.

[28] Prior to December 2010, Prosper used an auction-based process of determining the loan rate. Following December 2010, Prosper rates are set by the platform (See Balyuk 2022 and Wei and Lin, 2017).

In all specifications, the coefficient estimates on *LS* are statistically insignificant and near zero. This result suggests that the effects of sleep cannot be adequately priced into this financial market based on observable borrower characteristics and decisions. In other words, the loan pricing is failing to compensate investors for the increased risk. It may be difficult for the platform to price the loan risk given the choice to make a loan under conditions insufficient sleep hold *within* an individual, and is not adequately captured by observable credit characteristics, such as a credit score, as sections 5.5 and 5.2 suggest.

6.7. Investor Effects

In this subsection, I rule out possible concerns related to investor, or supply side, effects. Initially, as a function of the platform, possible confounding factors related to the behavior of the investor appear unlikely. First, most lenders are passive, and loans are funded automatically, removing any behavioral considerations altogether (Balyuk and Davydenko, 2023). However, while there are some active investors, the instrument for sleep loss (sunset time) impacts the borrower's location, and the few active investors are geographically disaggregated and cannot observe the borrower's county or city. Despite this, I perform an analysis to further allay concerns related to confounding investor effects.

I report this results in Internet Appendix Table IA8. I define a variable, *Funded*, which captures whether a listing is funded by investors. Across all specifications, I find no effect of the sleep loss instrument on the probability of loan funding, which rules out possible confounding effects related to the supply of loans, rather than the demand.

7. Daylight Savings Shifts

Sleep disruptions induced by daylight savings time shifts has been used in the financial literature as a proxy for sleep loss and sleep disruptions (Pinegar, 2002; Kamstra, Kramer, and Levi, 2003; Lamb, Zuber, and Gandar, 2004; Berument, Dogan, and Onar, 2010; Bazley, Cuculiza, and Pisciotta, 2022). In this setting, I perform a similar identification strategy as Bazley, Cuculiza, and Pisciotta (2022) by applying DST shifts to estimate the effect of a sleep disruption on borrower financial decision-making and to validate the main regression discontinuity design. In spring, on a Sunday at 2 a.m., clocks shift forward, giving individuals one hour less time to sleep. In autumn, on a Sunday at 2 a.m., clocks shift back one hour, giving individuals one hour more to sleep. Table 9 presents the results for the effect of sleep disruptions. I define *Spring Shift* and *Autumn Shift* as the four-day windows around the spring and autumn daylight savings shifts, respectively. This is motivated by prior research that suggests one hour of sleep loss takes three to four days to recover from m (Kitamura et al., 2016; Harrison, 2013). I show in Internet Appendix Table IA9 that results are robust to using one-, two-, and three-day windows as well.

I report the DST analysis in Table 9. In Column 1, I find no effect of the autumn DST shift, consistent with the literature on the asymmetric effects of sleep loss and gain (Barnes and Wagner, 2009; Smith, 2016; Bazley, Cuculiza, and Pisciotta, 2022). In Column 2, I find that a one-hour discontinuity in time to sleep is associated with a 3.01 percentage point increase in default for applied for in the morning during the treatment window. The economic magnitude is an increase in default relative to 10.6% its standard deviation. Column 3 finds no statistically significant effect on default for loans filled out in the afternoon and evening during the treatment window, consistent with the main results. Column 4 shows that the main result in Column 2 is robust to the inclusion of individual fixed effects. Finally, Columns 5-6 demonstrate that the effect of the sleep disruption is not priced into the interest rate, consistent with the results in Table 8. In the Internet Appendix, I also rule out possible investor effects in this setting following Section 5.7.[29]

I examine whether the results may be due to preexisting weekly or seasonal trends in lending. I augment the regression specification of Table 9, Column 2 with 10 different indicators for four-day event-windows surrounding the spring DST shift. I plot these results in Figure 5. There is no clear trend in the period leading up to spring DST, only the event window during DST sees a sharp increase in loan risk. Additionally, these results also suggest no effect in the afternoon and evening, consistent with Table 9. These results suggest that the spring DST shift, and the associated sleep disruption, casually impacts loan risk.

8. Time of Day

As previous results indicate, the effect of the instrument for sleep loss and loan risk varies throughout the day. As such, I perform a separate analysis to determine the *specific* times of day in which the magnitude and significance of the effects of sleep loss are at their peak. I perform this analysis for both the baseline spatial RDD (Table 3, Column 2) and the DST shift design (Table 9, Column 2).

To perform this analysis, I re-run the respective analyses with the full specification of controls and fixed effects for a series of rolling five-hour windows throughout the day. Each five-hour window being centered on a particular time. For example, in Figure 6, the x-axis tick for 7 corresponds to a regression estimate on the sample period from between 5-10 a.m., the tick for 8 for 6-11 a.m., 9 for 7-12 p.m. and so on. Beginning with the spatial RDD, the coefficient on the sleep loss instrument, *LS*, is plotted throughout the day. The results are shown in Figure 6, Panel A. As the figure suggests, the coefficient estimates are statistically significant only for the period

[29] I report these results in Internet Appendix Table IA10.

in the early morning, diminishing by late morning and afternoon. Following the previous specification., I examine the effect of the spring DST shift on loan outcomes throughout the day. Applying the specification of Table 9, Column 2, I perform the rolling five-hour window analysis for the effect of the DST shift at different times of the day. I plot the results in Figure 6, Panel B.

The coefficient estimates for *Spring Shift* are significant for the early morning. By late morning, the effect diminishes, with no effect in the afternoon or evening. Overall, the estimates of the effect of sleep loss in this section are similar to the estimates using the spatial regression discontinuity model, despite using two entirely different identification strategies. This suggests that both approaches capture the same general effect.

This analysis leads to the general question of why individuals fill out loan applications when tired in the morning at all, assuming individuals are reasonably self-aware of their cognitive deficits and willing to postpone the choice. This reasoning suggests individuals may be less likely to make this financial decision when sleep deprived. This relates to a much broader question on why individuals make choices at all under conditions of insufficient sleep.

A literature in psychology and sleep medicine provides some illustrative evidence on this topic. First, studies often show that individuals are not adequately aware of the extent of their own cognitive deficits resulting from insufficient sleep (Herscovitch and Broughton, 1981; Philip et al. 1997; Philip et al., 1999; Arnedt et al., 2000; Dorrian et al., 2003). Given this, potential borrowers may not see a strong need to thoroughly consider their financial decisions given they do not recognize their own cognitive shortcomings. In addition, individuals may not have ample opportunity to postpone their decisions to a later date or time due to rigid social schedules, so they are more likely to take out a loan even when tired. I provide some suggestive evidence for this hypothesis in the Internet Appendix.[30]

In contrast, there is a wide literature that provides evidence that individuals may be *more* likely to fill out a loan when tired, rather than less likely, due to the relationship between insufficient sleep and impulsive thinking (Altena et al., 2008; Barnes, 2012; Guarana et al., 2021). It could be the case that individuals are making these choices out of impulsivity or little deliberation and are thus *more* likely to take out a poorly considered loan, which the following section provides evidence for.

9. Mechanisms

9.1. Sleep and Heuristic Thinking

Sleep loss is associated with cognitive declines, which manifest in aspects of human decision-making. In the finance literature, cognitive declines have been associated with higher levels of heuristic thinking, and heuristic thinking has been shown to lead to increases in default risk and lower quality financial decision-making in financial markets (Kuo, Lin, and Zhao, 2014; Engle-Friedman et al., 2018; Dickinson and McElroy, 2019; Hirshleifer et al., 2019; Hu et al., 2023). Given the relationship between insufficient sleep and heuristic thinking in the laboratory, and the relationship between heuristic thinking and lower quality financial decision-making and default risk in the finance literature, I hypothesize that this may be a potential behavioral channel by which sleep impacts default risk.

A growing body of research in medicine and neurophysiology finds strong associations

[30] I present results from this analysis in Internet Appendix Table IA11. In this analysis, I generate general proxies for schedule flexibility (*Inflexible Schedule* and *Flexible Schedule*) using within-occupation differences in self-employment status, then controlling for income and credit characteristics. I then examine if having an inflexible or flexible schedule alters the probability of applying for a loan in the early morning (5-10 a.m.). I find that having an inflexible schedule increases the probability, and having a flexible schedule decreases the probability.

between insufficient sleep, lower risk aversion, and heuristic thinking. Principally, laboratory studies have shown that sleep deprived individuals show decreased risk aversion, such that individuals are more likely to take risks, particularly under uncertain future conditions (Killgore, Balkin, and Wesenten, 2006; Mckenna, Dickinson, and Drummond, 2007; Killgore, 2010; Xu, Liu, and Wang, 2021). Engle-Friedman et al. (2018) finds that insufficient sleep increases heuristic thinking among study participants in standard tasks. In a similar study, Dickinson and McElroy (2019) find that lab participants make economic choices in a "less deliberative manner under common adverse sleep states, which gives rise to a relative increase in automatic or heuristic-based decision making." Similarly, research finds that insufficient sleep increases impulsive behavior and reduces self-control (Altena et al., 2008; Barnes, 2012; Guarana et al., 2021). In this setting, choosing to take out a loan thoughtfully requires assessing future probabilities, which takes substantial cognitive resources, and that decision-making process is limited under the conditions of poor sleep.

In other words, in laboratory settings, individuals tend to make less deliberative, sub-optimal, impulsive choices under conditions of poor sleep when they otherwise would not, and participants also take on more risk, such as choosing riskier asset bundles (Castillo, Dickinson, and Petrie, 2017; Dickinson and McElroy, 2019). I hypothesize a similar dynamic is occurring in the online lending environment, whereby individuals who are suffering cognitive limitations from insufficient sleep may engage in less deliberative, sub-optimal decision-making in their choice to take out a loan, and thus an increase in heuristic thinking can at least partially explain the increase in default risk.

I present the results of the behavioral channel analysis in Table 10. I define *Heuristic Index* as the sum of several indicator variables relating to loan rounding.[31] In this way, a pervasiveness of round numbers *signals* less deliberation in the application process. I examine heuristic thinking with both empirical approaches, applying the spatial RDD and DST analyses in Panel A and Panel B, respectively. With both empirical approaches, I observe higher levels of heuristic thinking in the morning hours, with no effect in the afternoon or evening. This result mirrors the timing of the effects of sleep loss on loan risk found in previous sections, providing evidence for the hypothesis that this is a behavioral mechanism by which sleep loss impact defaults risk. I also find these results hold with individual fixed effects, which I report in Internet Appendix Table IA12.[32]

I also test for the effect of sleep loss on heuristic thinking along the extensive margin. I generate a county-day-hour panel from the platform data to examine how the volume of loans that exhibit signs of heuristic thinking changes as a result of insufficient sleep.[33] I report these results in Internet Appendix Table IA13. I find that under conditions of insufficient sleep, in both the spatial RDD and DST shift designs, the proportional volume of loans that exhibit heuristic thinking increases between 1.4% and 3.0%, with no effect in the afternoon and evening.

9.2. Heuristic Thinking and Default

Sleep loss is associated with heuristic thinking, which has been associated with poor financial outcomes and lower quality decision-making in several financial settings, including online lending (Kuo, Lin, and Zhao, 2014; Hirshleifer et al., 2019; Hu et al., 2023). This subsection examines whether the cognitive limitations induced by sleep loss, measured by a pervasiveness of round

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[31] Specifically, I define this variable as an index between 0-5 for whether a loan is rounded to the nearest 1000, 5000, 10000, 15000, or 20000, following Pursiainen (2022).

[32] For the DST shift analysis using individual fixed effects, the initial effect is not statistically significant for the morning hours despite having a relatively high magnitude. When the morning window is expanded to include more hours, the result becomes statistically significant.

[33] Specifically, I define *Heuristic Loan Volume (%)* as the percent of loan volume rounded to the nearest thousand a given county-day-hour.

numbers (*Heuristic Index*) is associated with higher levels of default, as would be consistent with prior findings in online lending markets (Hu et al., 2023).[34] I present these results in Table 11.

With an array of controls and fixed effects, across all models, I find a relationship between heuristic thinking and the probability of default. Notably, the results in Columns 4-5 suggest that the effects of heuristic thinking hold with individual fixed effects, consistent with prior results, and illustrating that within-individual variation in cognitive resources leads to a higher probability of default.

Overall, these results are consistent with the hypothesis that the cognitive declines associated with insufficient sleep leads to higher levels of heuristic thinking, and thus more risk. As such, I can identify one of the predicted channels by which sleep loss impacts decision-making, which then has measurable consequences for household financial well-being.

10. Conclusion

In this paper, I offer empirical evidence that insufficient sleep increases loan risk. Using a large sample of online lending microdata and several distinct identification strategies, I document an economically significant, positive effect of sleep loss on loan risk, for those loans completed in the morning following a night of insufficient sleep. This is consistent with the psychology literature on sleep loss, whereby the most significant cognitive effects associated with sleep loss are in the morning hours after waking. The results suggest that the behavioral channel by which this effect operates is that which is predicted by lab studies: the cognitive declines associated with sleep loss leads to higher levels of heuristic and less deliberative thinking when it comes to making financial

[34] A pervasiveness of round numbers in loan amounts has also been associated with higher levels of borrower misreporting (misconduct), along with heuristic thinking (Pursiainen, 2023; Hu et al., 2023). However, I find no evidence of misreporting in income amounts, which suggests the design is primary capturing heuristic thinking.

decisions.

This study is the first to measure the real effects of sleep on household financial decision-making, and consequently, household welfare. As such, the key contribution of this paper is a clean identification of the impact and influence of sleep on household financial behavior. The effect of insufficient sleep is large, explaining many defaults and poor financial outcomes for individuals. This relationship may contribute to the time use poverty trap analyzed by Banerjee and Mullainathan (2008) and compound the other negative labor and health effects of insufficient sleep found in other studies (Gibson and Shrader, 2018; Giuntella and Mazzonna, 2019).

Surprisingly, despite the significance of sleep as a key determinant of human behavior, the impact of sleep loss on financial outcomes has received limited attention in the field of finance. One of the possible reasons such a discrepancy exists in these fields is a lack of tested identification strategies. Given this study introduces several distinct and consistent identification strategies to the finance literature, further work may benefit by applying similar empirical designs in other financial settings to better understand the influence of sleep loss other financial markets or firm outcomes.

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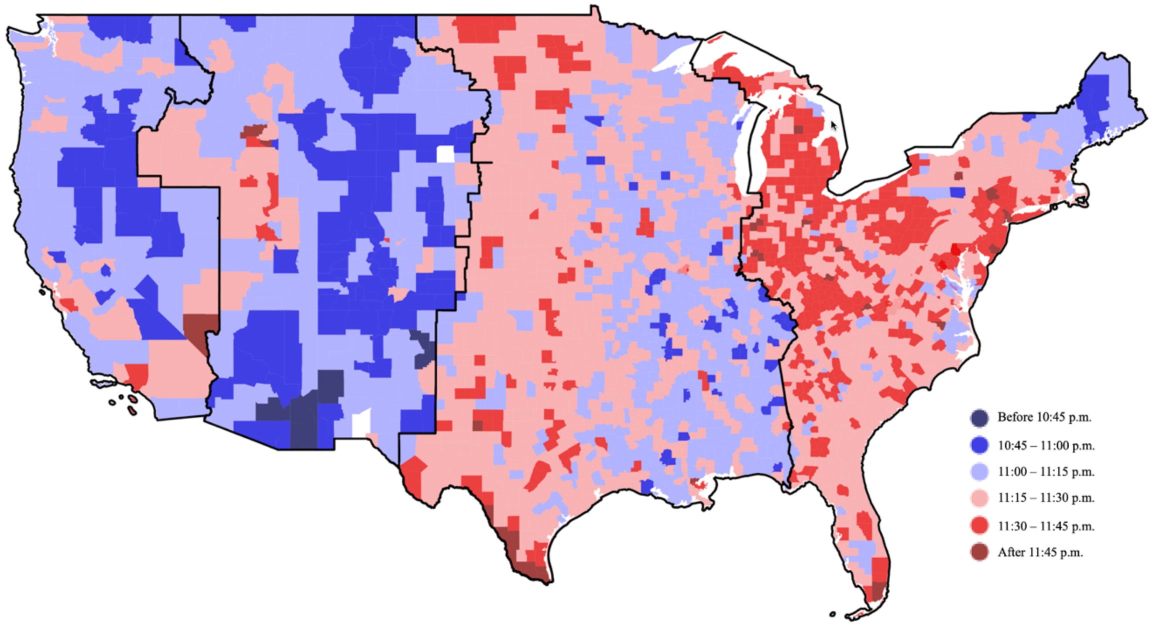
Appendix

Table A1. Key Variable Definitions

Variable name	Definition
	Time Zone Variables
LS	An indicator equal to one if a firm's headquarters falls on the late sunset side of a time zone boundary.
Miles to Boundary.	The number of miles from the firm headquarters to the nearest time zone boundary.
	Daylight Savings Time Variables
Spring Shift	An indicator equal to one during the four days following the Sunday of spring DST.
Autumn Shift	An indicator equal to one during the four days following the Sunday of Autumn DST.
	ATUS Variables
Sleep Duration	The total amount of time the individual reports sleeping, measured in minutes.
Major Sleep Deficit	An indicator equal to one if the respondent reports less than six hours of sleep
Late Bedtime	An indicator equal to one if an individual reports going to sleep after 10 p.m.
Early Wake Time	An indicator equal to one if an individual reports waking up before 7:30 a.m.
Married	An indicator equal to one if an respondent reports being married.
Children	The total number of children in respondent's family.
College	An indicator equal to one if an individual reports having completed a four-year bachelor's degree.
Age	An individual's reported age.
Black	An indicator equal to one if the respondent reports being black or African American.
Household Income	The reported weekly household income of the individual.
	Loan Variables
Default	An indicator equal to one if a loan defaults or is charged-off.
Interest Rate	The annual interest rate on the loan.
Loan Size	The total dollar size of the loan.
Income	A categorical variable 0-6 capturing the size of the borrower's annual income.
Risk Score	The platform constructed variable capturing the total riskiness of the borrower.
Employment	The total number of months the borrower has been employed.
Prior Loans	The total number of prior loans the borrower has made on the platform.
Heuristic Index	An index between 0-5 for whether a loan is rounded to the nearest 1000, 5000, 10000, 15000, or 20000, following Pursiainen (2022).

Figure 1. County Bedtimes and Treatment Areas
This figure reports the average bedtimes by county overlaid with time zone and county borders. Panel A presents the average bedtime by county for the contiguous US. Panel B presents average bedtimes along the CST-EST time zone boundary with state borders shown. The data is sourced from the *Jawbone sleep tracker* website following Giuntella and Mazzonna (2017). Later bedtimes are shown by red hues and earlier bedtimes are shown by blue hues.

Panel A: Bedtime by County



Panel B: CST-EST Boundary

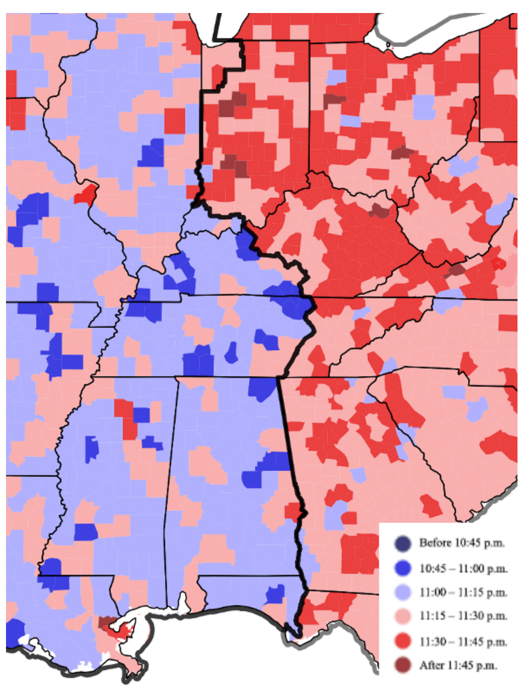
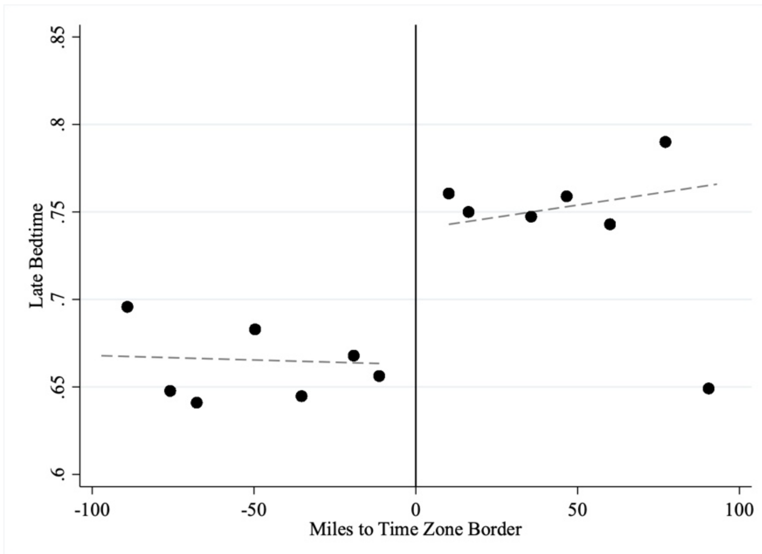


Figure 2. Discontinuities in Sleep-Related Variables

This figure reports the probability of a late bedtime (*Late Bedtime*) and the overall duration of sleep (*Sleep Duration*) around time zone borders. In each panel, the x-axis presents the running variable *Miles to TZ Border*, with a bandwidth of 100 miles around the cutoff. In Panel A, the y-axis corresponds to the probability of a late bedtime (*Late Bedtime*). In Panel B, the y-axis corresponds to the overall duration of sleep (*Sleep Duration*) in minutes. Values along the y-axis are shown in seven equal bins on either side of the threshold. The solid lines represent the fitted values of a first-degree polynomial.

Panel A: Bedtime



Panel B: Sleep Duration

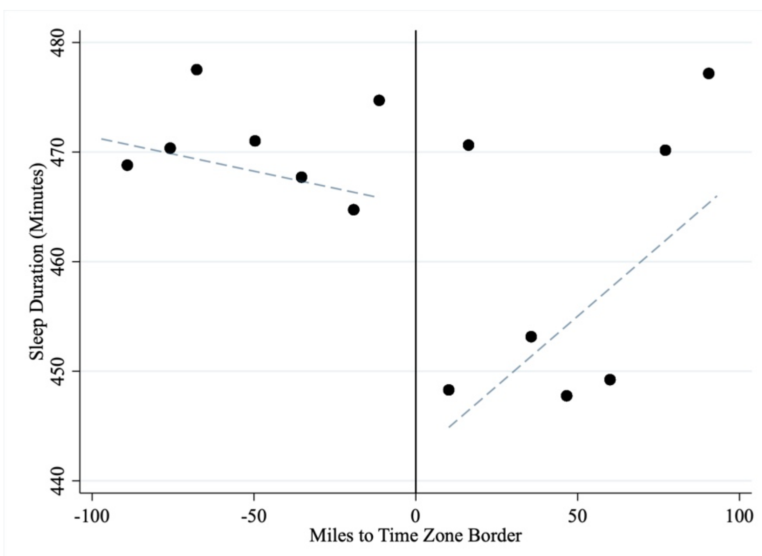
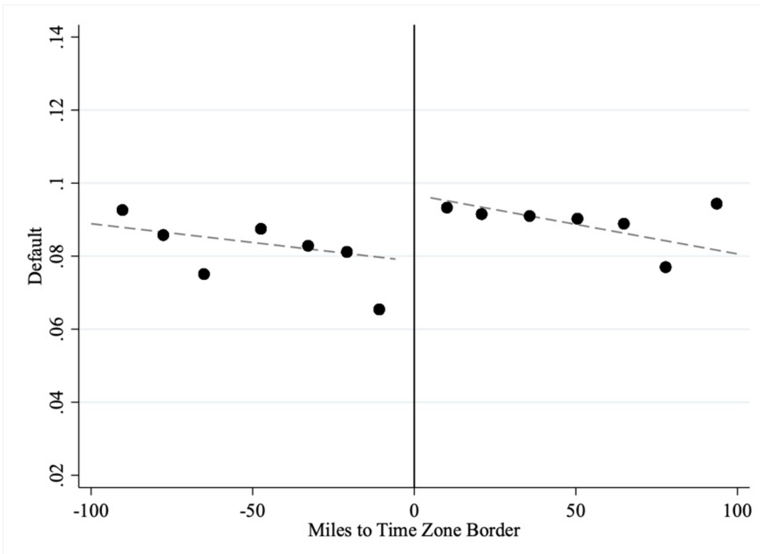


Figure 3. Discontinuities in Default Probability

This figure reports the probability of a loan being defaulting around a time zone border threshold at different times of the day. In each panel, the x-axis presents the running variable *Miles to TZ Border*, with a bandwidth of 100 miles around the cutoff. In Panel A, the y-axis corresponds to the probability of the loan being defaulted (*Default*) between 5-10 a.m. In Panel B, the y-axis corresponds to the probability of the loan being defaulted (*Default*) between 4-9 p.m. Values along the y-axis are shown in seven equal bins on either side of the threshold. The solid lines represent the fitted values of a first-degree polynomial.

Panel A: Early Morning (5-10 a.m.)



Panel B: Afternoon and Evening (4-9 p.m.)

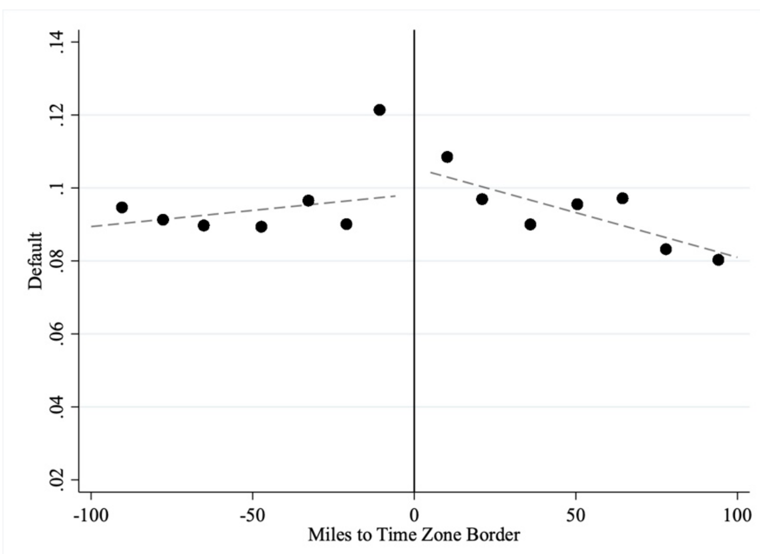


Figure 4. Borrower Relocation

This figure illustrates a sample of borrower relocations across the CST-EST time zone border. The illustrative sample includes two loans per borrower. The blue indicators represent the origin of the borrower (where the prior of the loans is made). The green indicators represent the destination of the borrower (where the latter of the loans is made). Origins and destinations are connected by red lines.

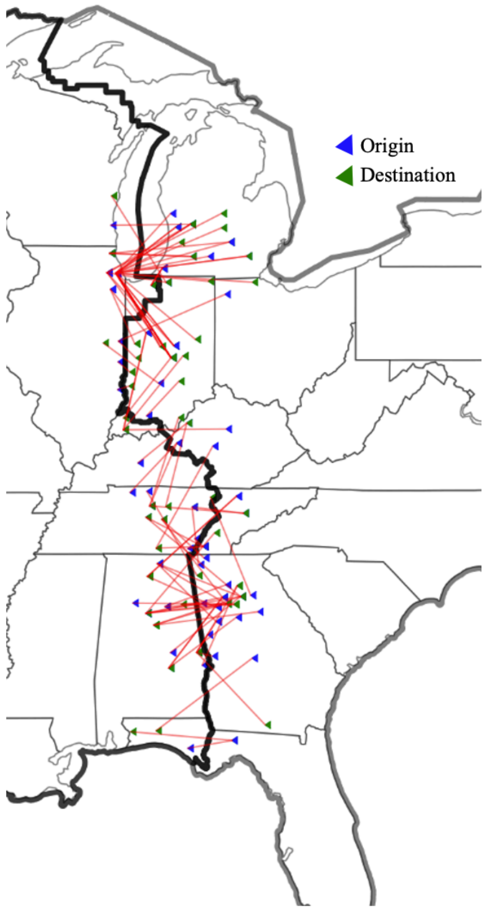
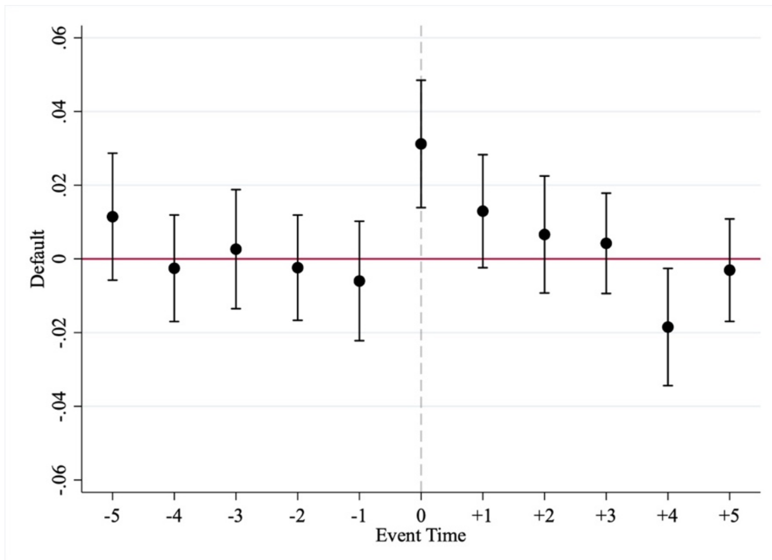


Figure 5. DST Parallel Trends Analysis

This figure plots the coefficients for different event windows relative to the spring daylight savings time shift (*Spring Shift*) and the probability of a loan defaulting (*Default)*. Each regression includes the same control variables included in Column 2 of Table 6. *Spring Shift* is an indicator equal to one during the four days following the Sunday of spring DST. *Default* is defined as whether a loan defaults or is charged-off. The y-axis plots the values of *Default*, while the x-axis plots the event time relative to a spring daylight savings shift (*Spring Shift*). The vertical lines represent the 90% confidence intervals. Panel A presents results from the early morning (5-10 a.m.) while Panel B presents results from the afternoon and evening (4-9 p.m.).

Panel A: Early Morning (5-10 a.m.)



Panel B: Afternoon and Evening (4-9 p.m.)

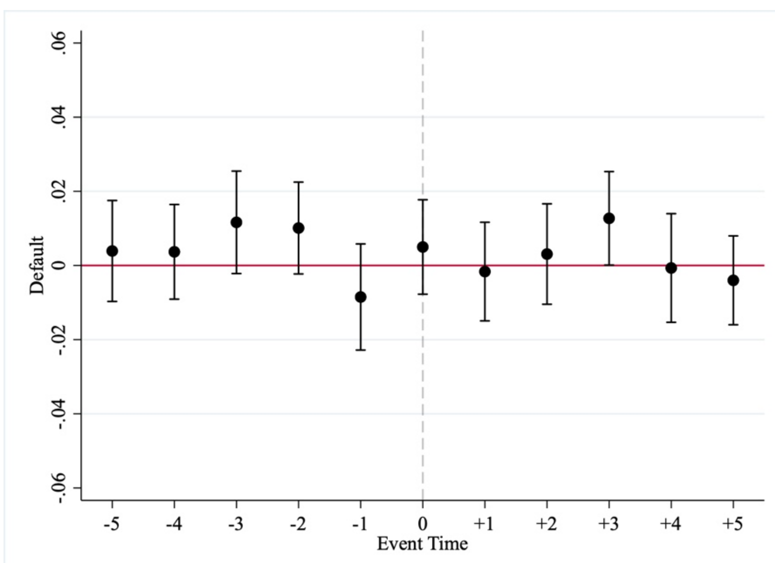
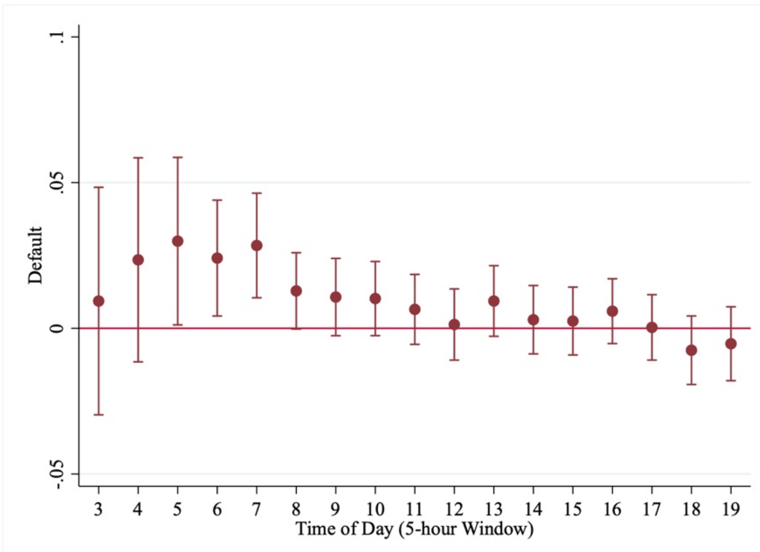


Figure 6. Time of Day

This figure displays the effect of sleep loss on loan outcomes throughout the day. Panel A reports the coefficient values of *LS* (sleep loss instrument) on *Default* for consecutive five-hour windows over the course of the day, consistent with the specification in Table 3, Column 2. Panel B reports the coefficient values of *Spring Shift* on *Default* for consecutive five-hour windows over the course of the day, consistent with the specification in Table 6, Colum 1. In both panels, each x-axis tick corresponds to a regression run for a five-hour window centered around the displayed time. For example, the tick for 7 corresponds to a model run on a sample between 5-10 a.m., while the tick for 8 corresponds to a model run between 6-10 a.m. The main outcome variable is *Default,* an indicator variable equal to one if the borrower's loan defaults or is charged-off. The explanatory variables are *LS* and *Spring Shift* in Panel A and B, respectively. *LS* is an indicator for whether the respondent falls on the late sunset side of a time zone border. *Spring Shift* is defined as the four-day window following the spring daylight savings shift. The vertical lines represent the 90% confidence intervals.

Panel A: Sunset Time (Spatial RDD)



Panel B: Daylight Savings Shifts

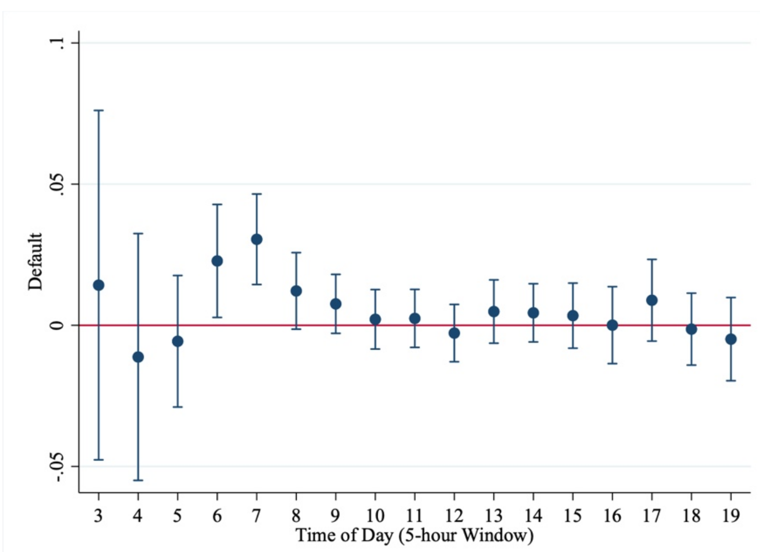


Table 1: Summary Statistics

This figure reports the summary statistics for the key variables used in the study. Variables in Panel A are calculated using US county centroids. Variables in Panel B are calculated using publicly available time change data. Variables in Panel C are sourced from the Census American Time Use Survey (ATUS) public microdata files. The data in Panel D are from Prosper.com.

	Mean	SD	25th	Median	75th
Panel A: Spatial Regression Discontinuity Variables					
LS	0.6228	0.4848	0	1	1
Miles to TZ Border	79.8329	266.3848	-116.7451	76.8698	253.4455
Panel B: Daylight Savings Variables					
Spring Shift	0.0049	0.0697	0	0	0
Autumn Shift	0.0048	0.0692	0	0	0
Panel C: ATUS Sleep Data					
Sleep Duration	468.9497	124.7612	405	480	540
Major Sleep Deficit	0.1494	0.3565	0	0	0
Late Bedtime	0.7462	0.4352	0	1	1
Early Wake Time	0.6318	0.4823	0	1	1
Married	0.5334	0.4989	0	1	1
Gender	0.4414	0.4966	0	0	1
Children	0.8810	1.2810	0	1	2
College	0.4183	0.4933	0	0	1
Household Income	99313.2372	69574.6056	48000	80700	134400
Age	38.8053	9.9705	31	39	47
Black	0.1368	0.3437	0	0	0
Panel D: Online Loan Data					
Default	0.0884	0.2839	0	0	0
Heuristic Index	1.4079	1.2144	1	1	2
Loan Size	12920.4505	8524.7924	6000	10332.50	18000
Income	4.3390	1.1724	3	4	5
Risk Score	7.4648	2.5489	6	8	10
Employment	110.9665	123.4921	29	75	161
Prior Loans	0.4981	1.3794	0	0	1
Interest Rate	0.1511	0.0620	0.1043	0.1380	0.1864

Table 2: Sunset Time and Sleep Duration

This table reports the effect of a late sunset time on several sleep-related outcomes using data from the Census' American Time Use Survey (ATUS). In Column 1, the outcome variable is *Late Bedtime*, an indicator variable equal to one if the survey respondent went to bed after 10 p.m. In Column 2, the outcome variable is *Early Wake Time*, an indicator variable equal to one if the respondent woke up before 7:30 a.m. In Columns 3-6, the outcome variable is *Sleep Duration,* defined as the survey respondent's reported duration of sleep in minutes. In Column 7, *Major Sleep Deficit* is defined as an indicator equal to one if the respondent reports less than six hours of sleep. The explanatory variable is *LS*, an indicator for whether the respondent falls on the late sunset side of a time zone border. Controls include *Married*, *Gender*, *Children*, *College*, and *Income.* Each model includes the variable and interaction term *Miles to TZ Border* and *LS* × *Miles to TZ Border*. Fixed effects are included where indicated. *Commuting Zone* indicates whether a 30-mile commuting zone on either size of the bandwidth is excluded. Weekends are excluded. Standard errors are clustered at geographical level (based on the distance from the time zone border). The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

	(1) Late Bedtime	(2) Early Wake Time	(3) Sleep Duration	(4) Sleep Duration	(5) Sleep Duration	(6) Sleep Duration	(7) Major Sleep Deficit
LS	0.0864***	-0.0252	-38.2460***	-35.8720***	-29.3751***	-31.4979***	0.1197***
	(2.5949)	(-0.8781)	(-5.2533)	(-4.9493)	(-4.1455)	(-3.2924)	(3.8805)
Controls	Yes	Yes	No	Yes	Yes	Yes	Yes
Latitude	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Zone Border	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Zone	No	No	No	No	Yes	No	No
Bandwidth	400	400	400	400	400	100	400
Observations	12992	12992	18878	12992	12780	2098	12992
R-squared	0.0396	0.1210	0.0261	0.0515	0.0444	0.0803	0.0275

Table 3: Sleep Loss and Loan Outcomes

This table reports the effect of the sleep instrument (*LS*) on loan default at different times of the day. The main outcome variable is *Default*, an indicator variable equal to one if the borrower's loan defaults or is charged-off. The explanatory variable of interest and the instrument for sleep loss is *LS*, an indicator variable equal to one if the borrower is on the late sunset side of a time zone border. Controls include: *Risk Score*, *Income*, *ln(Loan Size)*, *Employment*, and *Prior Loans.* Each model includes the variable and interaction term *Miles to TZ Border* and *LS* × *Miles to TZ Border*. Fixed effects are included where indicated. *Commuting Zone* indicates whether a 30-mile commuting zone on either size of the bandwidth is excluded. Weekend loans are excluded. Standard errors are clustered at geographical level (based on the distance from the time zone border). The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

	(1)	(2)	(3)	(4)
Time of Day:	5-10 a.m.	5-10 a.m.	5-10 a.m.	4-9 p.m.
Dependent Variable: Default				
LS	0.0298***	0.0297***	0.0320***	-0.0056
	(2.7762)	(2.7485)	(2.6642)	(-0.8074)
Controls	No	Yes	Yes	Yes
Latitude	Yes	Yes	Yes	Yes
Time Zone Border	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes	Yes
Loan Purpose	No	Yes	Yes	Yes
Term	No	Yes	Yes	Yes
Commuting Zone	No	No	Yes	No
Bandwidth	400	400	400	400
Observations	70517	70517	69143	114046
R-squared	0.0323	0.0561	0.0562	0.0556

Table 4: Discontinuities in Borrower and Loan Characteristics

This table tests for discontinuities in borrower and loan characteristics across time zone borders. The first outcome variable is *ln(Loan Size)*, the log transformed size of the loan in dollars ($). The second outcome variable is *Income*, a categorical variable corresponding to various annual income bins. The third outcome variable is *Risk Score*, a platform calculated metric of a borrower's credit worthiness from all available borrower information. The fourth outcome variable is *Employment*, a continuous variable equal to the number of months a borrower has been employed at her current job. The fifth outcome variable is *Prior Loans*, a variable equal to the number of prior loans the borrower has made on the platform. The explanatory variable of interest and the instrument for sleep loss is *LS*, an indicator variable equal to one if the borrower is on the late sunset side of a time zone border. Each model includes the variable and interaction term *Miles to TZ Border* and *LS* × *Miles to TZ Border*. Fixed effects are included where indicated. *Commuting Zone* indicates whether a 30-mile commuting zone on either size of the bandwidth is excluded. Weekend loans are excluded. Standard errors are clustered at geographical level (based on the distance from the time zone border). The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

	(1)	(2)	(3)	(4)	(5)
Time of Day: 5-10 a.m.					
	ln(Loan Size)	Income Range	Risk Score	Employment	Prior Loans
LS	0.0258	0.0610	-0.0311	7.0381	-0.0111
	(0.8985)	(1.0209)	(-0.3254)	(1.5135)	(-0.2691)
Latitude	Yes	Yes	Yes	Yes	Yes
Time Zone Border	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes	Yes	Yes
Bandwidth	400	400	400	400	400
Observations	70517	70517	70517	70517	70517
R-squared	0.0445	0.0582	0.0707	0.0093	0.0374

Table 5: Alternative Bandwidths and Polynomials

This table reports the effect of the sleep instrument (*LS*) on loan default at various bandwidths around the geographic threshold. The main outcome variable is *Default*, an indicator variable equal to one if the borrower's loan defaults or is charged-off. The explanatory variable of interest and the instrument for sleep loss is *LS*, an indicator variable equal to one if the borrower is on the late sunset side of a time zone border. Controls include: *Risk Score*, *Income*, *ln(Loan Size)*, *Employment*, and *Prior Loans.* Each model includes the variable and interaction term *Miles to TZ Border* and *LS* × *Miles to TZ Border*. Fixed effects are included where indicated. Weekend loans are excluded. Weekend loans are excluded. Column 7 reports a specification using a second-degree polynomial. Standard errors are clustered at geographical level (based on the distance from the time zone border). The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Time of Day: 5-10 a.m.							
Dependent Variable: Default							2nd Degree Polynomial
LS	0.0257**	0.0255**	0.0275***	0.0308***	0.0294**	0.0353*	0.0351***
	(2.5264)	(2.4903)	(2.6606)	(2.5981)	(2.2874)	(1.7979)	(2.6551)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Latitude	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Zone Border	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Term	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth	**700**	**600**	**500**	**300**	**200**	**100**	**400**
Observations	87139	82761	79855	53113	33819	16487	70517
R-squared	0.0553	0.0560	0.0567	0.0558	0.0569	0.0647	0.0561

Table 6: Arizona-California Border

This table reports the effect of the sleep instrument (*LS*) on loan default between the Arizona and California/Nevada border as the time zone boundary turns on and off with DST shifts. The main outcome variable is *Default*, an indicator variable equal to one if the borrower's loan defaults or is charged-off. The explanatory variable of interest and the instrument for sleep loss is *LS*, an indicator variable equal to one if the borrower is on the late sunset side of a time zone border. Controls include: *Risk Score*, *Income*, *ln(Loan Size)*, *Employment*, and *Prior Loans.* Each model includes the variable and interaction term *Miles to TZ Border* and *LS* × *Miles to TZ Border*. Fixed effects are included where indicated. Weekend loans are excluded. Standard errors are clustered at geographical level (based on the distance from the time zone border). The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

	(1)	(2)	(3)	(4)
Time of Day:	5-10 a.m.	4-9 p.m.	5-10 a.m.	4-9 p.m.
Dependent Variable: Default				
	During Regular Time		During DST	
LS	0.0529*	-0.0296	0.0023	-0.0259
	(1.7752)	(-1.3299)	(0.0916)	(-1.5095)
Controls	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes	Yes
Loan Purpose	Yes	Yes	Yes	Yes
Term	Yes	Yes	Yes	Yes
Observations	6269	8005	11444	16124
R-squared	0.0603	0.0754	0.0610	0.0623

Table 7: Borrower Relocation and Individual Fixed Effects

This table reports the effect of the sleep instrument (*LS*) on loan default for borrowers who relocate around time zone boundaries, allowing for the application of individual fixed effects. The main outcome variable is *Default,* an indicator variable equal to one if the borrower's loan defaults or is charged-off. The explanatory variable of interest and the instrument for sleep loss is *LS*, an indicator variable equal to one if the borrower is on the late sunset side of a time zone border. Controls include: *Risk Score*, *Income*, *ln(Loan Size)*, *Employment*, and *Prior Loans.* Each model includes the variable and interaction term *Miles to TZ Border* and *LS* × *Miles to TZ Border*. Fixed effects are included where indicated. Weekend loans are excluded. Standard errors are clustered at geographical level (based on the distance from the time zone border). The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

	(1)	(2)	(3)	(4)
Time of Day:	5-10 a.m.	5-10 a.m.	5-10 a.m.	4-9 p.m.
Dependent Variable: Default				
LS	0.0572*	0.0657*	0.0675*	0.0024
	(1.6543)	(1.7915)	(1.8219)	(0.0629)
Controls	No	No	Yes	Yes
Individual	Yes	Yes	Yes	Yes
Time Zone Border	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes	Yes
Loan Purpose	No	Yes	Yes	Yes
Term	No	Yes	Yes	Yes
Bandwidth	400	400	400	400
Observations	7298	7298	7298	11660
R-squared	0.7169	0.7195	0.7199	0.6955

Table 8: Pricing

This table reports the effect of the sleep instrument (*LS*) on loan default at different times of the day. The outcome variable is *Interest Rate*, defined as the interest rate on the borrower's loan. The explanatory variable of interest and the instrument for sleep loss is *LS*, an indicator variable equal to one if the borrower is on the late sunset side of a time zone border. Controls include: *Risk Score*, *Income*, *ln(Loan Size)*, *Employment*, and *Prior Loans*. Each model includes the variable and interaction term *Miles to TZ Border* and *LS* × *Miles to TZ Border*. Fixed effects are included where indicated. *Commuting Zone* indicates whether a 30-mile commuting zone on either size of the bandwidth is excluded. Weekend loans are excluded. Standard errors are clustered at geographical level (based on the distance from the time zone border). The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

	(1)	(2)	(3)	(4)	(5)
Time of Day:	5-10 a.m.	5-10 a.m.	5-10 a.m.	5-10 a.m.	4-9 p.m.
Dependent Variable: Interest Rate					
LS	0.0003	0.0001	0.0016	-0.0009	-0.0003
	(0.1229)	(0.0650)	(0.7055)	(-0.6200)	(-0.2488)
Controls	No	Yes	Yes	Yes	Yes
Latitude	Yes	Yes	Yes	Yes	Yes
Time Zone Border	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes	Yes	Yes
Loan Purpose	No	Yes	Yes	Yes	Yes
Term	No	Yes	Yes	Yes	Yes
Commuting Zone	No	No	No	Yes	No
Bandwidth	400	400	100	400	400
Observations	70517	70517	16487	69143	114046
R-squared	0.0063	0.0417	0.6154	0.6149	0.6109

Table 9: Daylights Savings Time Shifts, Default, and Pricing

This table reports to the of spring daylight savings time shifts on loan default at different times of the day. The main outcome variable is *Default,* an indicator variable equal to one if the borrower's loan defaults or is charged-off. The main explanatory variable is *Spring Shift*, defined as the four-day window following the spring daylight savings shift. Also included as an explanatory variable is *Autumn Shift*, defined as the four-day window following the autumn daylight savings shift. Controls include: *Risk Score*, *Income*, *ln(Loan Size)*, *Employment*, and *Prior Loans.* Fixed effects are included where indicated. Standard errors are clustered by individual. The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Time of Day:	5-10 a.m.	5-10 a.m.	4-9 p.m.	5-10 a.m.	4-9 p.m.	5-10 a.m.	5-10 a.m.
	Default	Default	Default	Default	Default	Interest Rate	Interest Rate
Spring Shift		0.0301***	-0.0016	0.0723*	-0.0179	-0.0008	-0.0010
		(3.0554)	(-0.2367)	(1.8086)	(-0.7433)	(-0.4051)	(-0.8152)
Autumn Shift	0.0045						
	(0.6062)						
Controls	Yes	Yes	Yes	Yes	Yes	No	Yes
Individual	No	No	No	Yes	Yes	No	No
City × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Term	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	118861	118861	176555	5879	9192	118861	118861
R-squared	0.2162	0.2163	0.1844	0.8554	0.8391	0.2279	0.6888

Table 10: Heuristic Thinking

This table reports the effect of two different instruments for sleep loss on loan heuristics at different times of the day. The main outcome variable is *Heuristic Index,* defined as an index between 0-5 for whether a loan is rounded to the nearest 1000, 5000, 10000, 15000, or 20000 (following Pursiainen, 2022). In Panel A, the explanatory variable of interest and the instrument for sleep loss is *LS*, an indicator variable equal to one if the borrower is on the late sunset side of a time zone border. In Panel B, explanatory variable is *Spring Shift*, defined as the four-day window following the spring daylight savings shift. In Panel A, controls include: *Risk Score*, *Income*, *ln(Loan Size)*, *Employment*, and *Prior Loans*, while Panel A includes the variable and interaction term *Miles to TZ Border* and *LS* × *Miles to TZ Border*. Fixed effects are included where indicated. In Panel A, weekend loans are excluded. Standard errors are clustered at geographical level (based on the distance from the time zone border) in Panel A and at the borrower level in Panel B. The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

Panel A: Sunset Time (Spatial RDD)

	(1)	(2)	(3)
Time of Day:	5-10 a.m.	5-10 a.m.	4-9 p.m.
Dependent Variable: Heuristic Index			
LS	0.0892**	0.0701**	-0.0046
	(2.2949)	(2.1069)	(-0.1535)
Controls	No	Yes	Yes
Latitude	Yes	Yes	Yes
Time Zone Border	Yes	Yes	Yes
State	Yes	Yes	Yes
Year	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes
Loan Purpose	No	Yes	Yes
Term	No	Yes	Yes
Bandwidth	400	400	400
Observations	70517	70517	114046
R-squared	0.0124	0.1710	0.1665

Panel B: Daylight Savings Shifts

	(1)	(2)	(3)
Time of Day:	5-10 a.m.	5-10 a.m.	4-9 p.m.
Dependent Variable: Heuristic Index			
Spring Shift	0.0926**	0.0662*	0.0201
	(2.2288)	(1.7516)	(0.7077)
Controls	No	Yes	Yes
City × Year	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes
Loan Purpose	No	Yes	Yes
Term	No	Yes	Yes
Observations	118861	118861	176555
R-squared	0.1900	0.3162	0.2854

Table 11: Heuristic Thinking and Default

This table corresponds to the association between the loan heuristics and loan outcomes. The main outcome variable is *Default,* an indicator variable equal to one if the borrower's loan defaults or is charged-off. The main explanatory variable is *Heuristic Index,* defined as an index between 0-5 for whether a loan is rounded to the nearest 1000, 5000, 10000, 15000, or 20000 (following Pursiainen, 2022). Controls include: *Risk Score*, *Income*, *ln(Loan Size)*, *Employment*, and *Prior Loans.* Fixed effects are included where indicated. Weekends are excluded. Standard errors are clustered at geographical level (based on the distance from the time zone border). The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

Dependent Variable: Default	(1)	(2)	(3)	(4)	(5)
Heuristic Index	0.0054***	0.0058***	0.0034***	0.0041***	0.0045***
	(22.8233)	(22.9038)	(12.8503)	(2.8180)	(2.8851)
Controls	No	No	Yes	No	Yes
City × Year	No	Yes	Yes	No	No
Individual × Year	No	No	No	Yes	Yes
Day-of-Week	No	Yes	Yes	Yes	Yes
Loan Purpose	No	Yes	Yes	Yes	Yes
Term	No	Yes	Yes	Yes	Yes
Observations	792674	754711	754711	17051	17051
R-squared	0.0007	0.1106	0.1265	0.7359	0.7434

Internet Appendix

Insufficient Sleep and Intra-Day Financial Decision-Making: Evidence from Online Lending

This appendix provides supplemental materials that support the manuscript "Insufficient Sleep and Intra-Day Financial Decision-Making: Evidence from Online Lending."

Table IA1: Continuous Measures of Sleep and Wake Times

This table reports the effect of a late sunset time on continuous measures of sleep and wake time using data from the Census' American Time Use Survey (ATUS). In Column 1, the outcome variable is *Bedtime*, a continuous variable representing the respondent's hour of bedtime. In Column 2, the outcome variable is *Wake Time*, a continuous variable equal to the hour of the respondent's waking time. The explanatory variable is *LS*, an indicator for whether the respondent falls on the late sunset side of a time zone border. Controls include *Married*, *Gender*, *Children*, *College*, and *Income.* Each model includes the variable and interaction term *Miles to TZ Border* and *LS* × *Miles to TZ Border*. Fixed effects are included where indicated. Weekends are excluded. Standard errors are clustered at geographical level (based on the distance from the time zone border). The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively.

	(1) Bedtime	(2) Wake Time
LS	0.4357***	-0.2117
	(3.2333)	(-0.8898)
Controls	Yes	Yes
Latitude	Yes	Yes
Time Zone Border	Yes	Yes
State	Yes	Yes
Year	Yes	Yes
Day-of-Week	Yes	Yes
Bandwidth	400	400
Observations	12992	12992
R-squared	0.0451	0.0834

Table IA2: Discontinuities in Demographic Characteristics

This table tests for discontinuities in ATUS survey respondent characteristics across time zone borders. The outcome variables are the respondent characteristics which are defined Appendix I. The explanatory variable of interest and the instrument for sleep loss is *LS*, an indicator variable equal to one if the borrower is on the late sunset side of a time zone border. Each model includes the variable and interaction term *Miles to TZ Border* and *LS* × *Miles to TZ Border*. *Commuting Zone* indicates whether a 30-mile commuting zone on either size of the bandwidth is excluded. Fixed effects are included where indicated. Standard errors are clustered at geographical level (based on the distance from the time zone border). The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

	(1) Black	(2) Married	(3) Male	(4) Children	(5) Income	(6) Age
LS	0.0269	0.0093	-0.0324	-0.0775	2327.3001	-1.7944
	(0.7875)	(0.2322)	(-1.2665)	(-0.8790)	(0.2207)	(-1.3168)
Latitude	Yes	Yes	Yes	Yes	Yes	Yes
Time Zone Border	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Zone	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth	400	400	400	400	400	100
Observations	18553	18553	18553	18553	12780	18553
R-squared	0.0955	0.0257	0.0107	0.0317	0.0797	0.0133

Table IA3: Alternative Measure of Loan Risk

This table reports the effect of the sleep instrument (*LS*) on loan distress at different times of the day using an alternative measure. The alternative measure and main outcome variable is *Bad Loan* from Butler, Cornaggia, and Gurun (2017), an indicator variable equal to one if the borrower's loan defaults, is charged-off, or has late payments made on it. The explanatory variable of interest and the instrument for sleep loss is *LS*, an indicator variable equal to one if the borrower is on the late sunset side of a time zone border. Controls include: *Risk Score*, *Income*, *ln(Loan Size)*, *Employment*, and *Prior Loans.* Each model includes the variable and interaction term *Miles to TZ Border* and *LS* × *Miles to TZ Border*. Fixed effects are included where indicated. Weekend loans are excluded. Standard errors are clustered at geographical level (based on the distance from the time zone border). The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

	(1)	(2)	(3)
Time of Day:	5-10 a.m.	5-10 a.m.	4-9 p.m.
Dependent Variable: Bad Loan			
LS	0.0305***	0.0302***	0.0065
	(2.6225)	(2.5915)	(0.7221)
Controls	No	Yes	Yes
Latitude	Yes	Yes	Yes
Time Zone Border	Yes	Yes	Yes
State	Yes	Yes	Yes
Year	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes
Loan Purpose	No	Yes	Yes
Term	No	Yes	Yes
Bandwidth	400	400	400
Observations	70517	70517	114046
R-squared	0.0289	0.0631	0.0600

Table IA4: Different Sizes of *Commuting Zone*

This table reports the effect of the sleep instrument (*LS*) on loan default at different times of the day using an array of *Commuting Zone* sizes. The main outcome variable is *Default*, an indicator variable equal to one if the borrower's loan defaults or is charged-off. The explanatory variable of interest and the instrument for sleep loss is *LS*, an indicator variable equal to one if the borrower is on the late sunset side of a time zone border. Controls include: *Risk Score*, *Income*, *ln(Loan Size)*, *Employment*, and *Prior Loans.* Each model includes the variable and interaction term *Miles to TZ Border* and *LS* × *Miles to TZ Border*. Fixed effects are included where indicated. Weekend loans are excluded. Standard errors are clustered at geographical level (based on the distance from the time zone border). The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)
Time of Day:	5-10 a.m.	5-10 a.m.	5-10 a.m.	5-10 a.m.	5-10 a.m.	5-10 a.m.
Commuting Zone Size:	10 miles	20 miles	40 miles	50 miles	75 miles	100 miles
Dependent Variable: Default						
LS	0.0267**	0.0248**	0.0291**	0.0445***	0.0323**	0.0284
	(2.4519)	(2.2316)	(2.2372)	(3.4422)	(2.1582)	(1.4539)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Latitude	Yes	Yes	Yes	Yes	Yes	Yes
Time Zone Border	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose	Yes	Yes	Yes	Yes	Yes	Yes
Term	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Zone	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth	400	400	400	400	400	400
Observations	87139	82761	79855	53113	33819	16487
R-squared	0.0553	0.0560	0.0567	0.0558	0.0569	0.0647

Table IA5: Daylight Savings Time Noncompliers

This table reports the effect of the sleep instrument (*LS*) on loan default at different times of the day including DST noncompliers. The main outcome variable is *Default*, an indicator variable equal to one if the borrower's loan defaults or is charged-off. The explanatory variable of interest and the instrument for sleep loss is *LS*, an indicator variable equal to one if the borrower is on the late sunset side of a time zone border. Controls include: *Risk Score*, *Income*, *ln(Loan Size)*, *Employment*, and *Prior Loans.* Each model includes the variable and interaction term *Miles to TZ Border* and *LS* × *Miles to TZ Border*. Fixed effects are included where indicated. *Commuting Zone* indicates whether a 30-mile commuting zone on either size of the bandwidth is excluded. States indicates which of the DST noncompliers is included/excluded in the sample of 48 contiguous states. Weekend loans are excluded. Standard errors are clustered at geographical level (based on the distance from the time zone border). The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

	(1)	(2)	(3)
Time of Day:	5-10 a.m.	5-10 a.m.	5-10 a.m.
States:	All But Arizona	All But Indiana	All
Dependent Variable: Default			
LS	0.0238**	0.0335***	0.0252**
	(2.0113)	(2.7791)	(2.1278)
Controls	No	Yes	Yes
Latitude	Yes	Yes	Yes
Time Zone Border	Yes	Yes	Yes
State	Yes	Yes	Yes
Year	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes
Loan Purpose	No	Yes	Yes
Term	No	Yes	Yes
Commuting Zone	Yes	Yes	Yes
Bandwidth	400	400	400
Observations	70356	71535	72748
R-squared	0.0564	0.0561	0.0562

Table IA6: Discontinuities in Borrower and Loan Characteristics (Commuting Zone)

This table tests for discontinuities in borrower and loan characteristics across time zone borders with a commuting zone excluded. The first outcome variable is *ln(Loan Size)*, the log transformed size of the loan in dollars ($). The second outcome variable is *Income*, a categorical variable corresponding to various annual income bins. The third outcome variable is *Risk Score*, a platform calculated metric of a borrower's credit worthiness from all available borrower information. The fourth outcome variable is *Employment*, a continuous variable equal to the number of months a borrower has been employed at her current job. The fifth outcome variable is *Prior Loans*, a variable equal to the number of prior loans the borrower has made on the platform. The explanatory variable of interest and the instrument for sleep loss is *LS*, an indicator variable equal to one if the borrower is on the late sunset side of a time zone border. Each model includes the variable and interaction term *Miles to TZ Border* and *LS* × *Miles to TZ Border*. Fixed effects are included where indicated. *Commuting Zone* indicates whether a 30-mile commuting zone on either size of the bandwidth is excluded. Weekend loans are excluded. Standard errors are clustered at geographical level (based on the distance from the time zone border). The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

	(1) ln(Loan Size)	(2) Income Range	(3) Risk Score	(4) Employment	(5) Prior Loans
LS	0.0364	0.0619	-0.0149	6.8552	-0.0009
	(1.0699)	(0.9119)	(-0.1341)	(1.2117)	(-0.0194)
Latitude	Yes	Yes	Yes	Yes	Yes
Time Zone Border	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes	Yes	Yes
Commuting Zone	Yes	Yes	Yes	Yes	Yes
Bandwidth	400	400	400	400	400
Observations	69143	69143	69143	69143	69143
R-squared	0.0447	0.0579	0.0706	0.0093	0.0371

Table IA7: Alternative Bandwidths and Polynomials (Commuting Zone)

This table reports the effect of the sleep instrument (*LS*) on loan default at various bandwidths around the geographic threshold with the excluded commuting zone. The main outcome variable is *Default*, an indicator variable equal to one if the borrower's loan defaults or is charged-off. The explanatory variable of interest and the instrument for sleep loss is *LS*, an indicator variable equal to one if the borrower is on the late sunset side of a time zone border. Controls include: *Risk Score*, *Income*, *ln(Loan Size)*, *Employment*, and *Prior Loans.* Each model includes the variable and interaction term *Miles to TZ Border* and *LS* × *Miles to TZ Border*. Fixed effects are included where indicated. *Commuting Zone* indicates whether a 30-mile commuting zone on either size of the bandwidth is excluded. Weekend loans are excluded. Weekend loans are excluded. Column 7 reports a specification using a second-degree polynomial. Standard errors are clustered at geographical level (based on the distance from the time zone border). The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: Default							2nd Degree Polynomial
LS	0.0276**	0.0273**	0.0295***	0.0332**	0.0348**	0.0721**	0.0366**
	(2.4685)	(2.4296)	(2.5948)	(2.4660)	(2.3209)	(2.4561)	(2.3818)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Latitude	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Zone Border	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Term	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commuting Zone	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth	**700**	**600**	**500**	**300**	**200**	**100**	**400**
Observations	85765	81387	78481	51739	32446	15113	69143
R-squared	0.0554	0.0562	0.0568	0.0559	0.0569	0.0655	0.0562

Table IA8: Loan Supply (Sunset Time)

This table reports the effect of the sleep on the probability of funding. The main outcome variable is *Funded*, defined as an indicator variable equal to one if a listing is funded. The explanatory variable of interest and the instrument for sleep loss is *LS*, an indicator variable equal to one if the borrower is on the late sunset side of a time zone border. Controls include: *Risk Score*, *Income*, *ln(Listing Size)*, *Employment*, and *Prior Loans*. Each model includes the variable and interaction term *Miles to TZ Border* and *LS × Miles to TZ Border*. Fixed effects are included where indicated. Weekend loans are excluded. Standard errors are clustered at geographical level (based on the distance from the time zone border). The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

	(1)	(2)	(3)
Time of Day:	5-10 a.m.	5-10 a.m.	4-9 p.m.
Dependent Variable: Funded			
LS	0.0073	0.0081	0.0004
	(0.6942)	(0.7773)	(0.0417)
Controls	No	Yes	Yes
Latitude	Yes	Yes	Yes
Time Zone Border	Yes	Yes	Yes
State	Yes	Yes	Yes
Year	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes
Loan Purpose	No	Yes	Yes
Term	No	Yes	Yes
Bandwidth	400	400	400
Observations	158746	158746	275378
R-squared	0.1203	0.1338	0.1295

Table IA9: Alternative Daylight Savings Windows

This table corresponds to the effect gains or losses in sleep from daylight savings time shifts on loan default at different times of the day. The main outcome variables are indicators for one-, two-, and three-day windows following the spring daylight savings shift. Controls include: *Risk Score*, *Income*, *ln(Loan Size)*, *Employment*, and *Prior Loans.* Fixed effects are included where indicated. Standard errors are clustered at the borrower level. The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)
Time of Day: 5-10 a.m.						
Dependent Variable: Default						
Spring Shift (1 day)	0.0584*	0.0573*				
	(1.8612)	(1.8698)				
Spring Shift (2 days)			0.0348**	0.0358**		
			(2.0876)	(2.1804)		
Spring Shift (3 days)					0.0236**	0.0230**
					(2.0590)	(2.0282)
Controls	No	Yes	No	Yes	No	No
City × Year	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose	Yes	Yes	Yes	Yes	Yes	Yes
Term	Yes	Yes	Yes	Yes	Yes	Yes
Observations	118861	118861	118861	118861	118861	118861
R-squared	0.2003	0.2163	0.2003	0.2163	0.2003	0.2163

Table IA10: Loan Supply (Daylight Savings Time)

This table reports the effect of the sleep on the probability of funding. The main outcome variable is *Funded*, defined as an indicator variable equal to one if a listing is funded. The explanatory variable is *Spring Shift*, defined as the four-day window following the spring daylight savings shift. Controls include: *Risk Score*, *Income*, *ln(Listing Size)*, *Employment*, and *Prior Loans*. Fixed effects are included where indicated. Standard errors are clustered at the borrower level. The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

	(1)	(2)	(3)
Time of Day:	5-10 a.m.	5-10 a.m.	4-9 p.m.
Dependent Variable: Funded			
Spring Shift	-0.0128	-0.0104	-0.0075
	(-1.4267)	(-1.1747)	(-1.2001)
Controls	No	Yes	Yes
City × Year	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes
Loan Purpose	No	Yes	Yes
Term	No	Yes	Yes
Observations	303918	303918	468604
R-squared	0.2715	0.2815	0.2433

Table IA11: Schedule Flexibility

This table reports the effect of having an inflexible schedule on the probability of taking out a loan in the morning. The main outcome variable is *Morning Loan*, an indicator variable equal to one if the loan application was done between the hours of 5-10 a.m. The explanatory variables are *Inflexible Schedule*, a variable equal to one if the borrower reports being employed but not self-employed, and *Flexible Schedule*, a variable equal to one if the borrower reports being self-employed. Controls include: *Risk Score*, *Income*, *ln(Loan Size)*, *Employment*, and *Prior Loans.* Fixed effects are included where indicated. Weekend loans are excluded. Standard errors are clustered at borrower level. The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

Dependent Variable: Morning Loan	(1)	(2)	(3)	(4)
Inflexible Schedule	0.0100***	0.0146***		
	(5.0555)	(7.2490)		
Flexible Schedule			-0.0091***	-0.0135***
			(-4.0739)	(-5.9798)
Controls	No	Yes	No	Yes
Occupation	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes	Yes
Loan Purpose	No	Yes	No	Yes
Term	No	Yes	No	Yes
Observations	520419	520419	520419	520419
R-squared	0.0070	0.0094	0.0070	0.0094

Table IA12: Within-Individual Heuristic Thinking

This table reports the effect of two different instruments for sleep loss on loan heuristics at different times of the day with individual fixed effects. The main outcome variable is *Heuristic Index,* defined as an index between 0-5 for whether a loan is rounded to the nearest 1000, 5000, 10000, 15000, or 20000 (following Pursiainen, 2022). In Panel A, the explanatory variable of interest and the instrument for sleep loss is *LS*, an indicator variable equal to one if the borrower is on the late sunset side of a time zone border. In Panel B, explanatory variable is *Spring Shift*, defined as the four-day window following the spring daylight savings shift. In Panel A, controls include: *Risk Score*, *Income*, *ln(Loan Size)*, *Employment*, and *Prior Loans*, while Panel A includes the variable and interaction term *Miles to TZ Border* and *LS* × *Miles to TZ Border*. Fixed effects are included where indicated. In Panel A, weekend loans are excluded. Standard errors are clustered at geographical level (based on the distance from the time zone border) in Panel A and at the borrower level in Panel B. The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively. See Table 1 for sample descriptive characteristics.

Panel A: Sunset Time (Spatial RDD)

	(1)	(2)	(3)
Time of Day:	5-10 a.m.	5-10 a.m.	4-9 p.m.
Dependent Variable: Heuristic Index			
LS	1.2388**	1.2903**	0.0891
	(2.2741)	(2.4016)	(0.2820)
Controls	Yes	Yes	Yes
Individual	Yes	Yes	Yes
Time Zone Border	Yes	Yes	Yes
Year	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes
Loan Purpose	Yes	Yes	Yes
Term	Yes	Yes	Yes
Bandwidth	400	400	400
Observations	7298	7298	11660
R-squared	0.5649	0.5677`	0.5746

Panel B: Sunset Time (Spatial RDD)

	(1)	(2)
Time of Day:	5-10 a.m.	Full Day (5 a.m. – 9 p.m.)
Dependent Variable: Heuristic Index		
Spring Shift	0.1430	0.0953**
	(0.4665)	(2.1455)
Controls	Yes	Yes
Individual	Yes	Yes
City × Year	Yes	Yes
Day-of-Week	Yes	Yes
Loan Purpose	Yes	Yes
Term	Yes	Yes
Observations	5879	172123
R-squared	0.7763	0.6561

Table IA13: Extensive Margin Tests

This table reports the effect of sleep loss on loan volume. The outcome variable is *Heuristic Loan Volume (%)*, defined as the percent of loan volume rounded to the nearest thousand a given county-day-hour. In Panel A, the explanatory variable of interest and the instrument for sleep loss is *LS*, an indicator variable equal to one if the borrower is on the late sunset side of a time zone border. Panel A also includes the variables *Miles to TZ Border* and *LS × Miles to TZ Border*. In Panel B, the main explanatory variable is *Spring Shift*, defined as the four-day window following the spring daylight savings shift. The second explanatory variable is *Autumn Shift*, defined as the four-day window following the autumn daylight savings shift. Fixed effects are included where indicated. Weekend loans are excluded in Panel A. In Panel A, standard errors are clustered at geographical level (based on the distance from the time zone border). In Panel B, standard errors are clustered by week. The t-statistics are denoted in parenthesis. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level, respectively.

Panel A: Sunset Time (Spatial RDD)

	(1)	(2)
Time of Day:	5-10 a.m.	4-9 p.m.
Dependent Variable: Heuristic Loan Volume (%)		
LS	0.0227*	0.0023
	(1.6874)	(0.1891)
Latitude	Yes	Yes
Time Zone Boundary	Yes	Yes
State	Yes	Yes
Month-Year	Yes	Yes
Day-of-Week	Yes	Yes
Hour	Yes	Yes
Observations	67865	109907
R-squared	0.0562	0.0456

Panel B: Daylight Savings Shifts

	(1)	(2)	(3)
Time of Day:	5-10 a.m.	5-10 a.m.	4-9 p.m.
Dependent Variable: Heuristic Loan Volume (%)			
Spring Shift		0.0113**	0.0036
		(2.1069)	(0.9035)
Autumn Shift	-0.0024		
	(-0.5452)		
County × Year	Yes	Yes	Yes
Day-of-Week	Yes	Yes	Yes
Hour	Yes	Yes	Yes
Observations	98458	98458	165460
R-squared	0.1037	0.1037	0.0885