NBER WORKING PAPER SERIES

TRADING IN TWILIGHT:
SLEEP, MENTAL ALERTNESS, AND STOCK MARKET TRADING

Hee Seo Han
David Hirshleifer
Jinfei Sheng
Zheng Sun

Working Paper 33477
http://www.nber.org/papers/w33477

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 2025

We thank Yong Chen, Michael Gallmeyer, Andrew Glover (Discussant), Tianyi Huang, Mark Kamstra, Lisa Kramer (Discussant), Holger Muller, Chris Schwarz, Chen Wang (Discussant), Wanyi Wang, Chishen Wei (Discussant), Jun Yang, Lu Zheng, Qiaoqiao Zhu (Discussant), and seminar and conference participants at University of California Irvine, the 2024 Conference on Financial Economics and Accounting, the 2024 Midwest Finance Association Conference, the 2024 China International Conference in Finance, the 2024 ANU Summer Research Camp, and the 2024 California Corporate Finance Conference for helpful comments and suggestions. We thank Terry Odean for sharing the data. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Trading in Twilight: Sleep, Mental Alertness, and Stock Market Trading
Hee Seo Han, David Hirshleifer, Jinfei Sheng, and Zheng Sun
NBER Working Paper No. 33477
February 2025
JEL No. D03, D91, G11, G12, G4, G40, G41, G5, G50

ABSTRACT

We test whether mental alertness, as proxied by sleep disruption, impairs investor trading performance. Using four complementary approaches, we document that retail investors who experience a later sunset time on average earn lower abnormal returns on their trades. These approaches include panel regression with household fixed effects, RDD based on time zone borders, comparison of different seasons and latitudes, and daylight saving changes. Further tests suggest that the sleep disruption effect derives from impaired investor attention.

Hee Seo Han
University of California, Irvine
heesh1@uci.edu

David Hirshleifer
Marshall School of Business
University of Southern California
3670 Trousdale Pkwy
Los Angeles, CA 90089
and NBER
hirshlei@marshall.usc.edu

Jinfei Sheng
Merage School of Business
University of California, Irvine
Irvine, CA 92697
jinfei.sheng@uci.edu

Zheng Sun
Paul Merage School of Business
University of California, Irvine
Irvine, CA 92617
zhengs@uci.edu

1. Introduction

We study here how mental alertness affects investor trading behavior and profitability. By "mental alertness" we refer to as what psychologists describe as cognitive alertness, attentional capacity, and/or arousal. Research in cognitive psychology has consistently found that mental alertness in this sense improves judgements and decisions (e.g., Kahneman 1973; Pilcher and Huffcutt 1996; Dinges et al. 1997; Posner and Petersen 1990; Diamond 2013).

Most behavioral economics and finance models have focused on heuristics and biases that are static and given, whereas in fact the susceptibility to bias varies continually, owing, for example, to shifts in mood and alertness. Such variation is extensively documented by research in psychology, as well as research in finance on mood and stock returns (Hirshleifer and Shumway 2003; Kamstra, Kramer, and Levi 2003; Edmans, Garcia, and Norli 2007; Edmans et al. 2022). However, being alert is conceptually distinct from experiencing a mood such as joy or anger. It is therefore important to understand whether investor mental alertness affects investor attitudes, behavior, and profitability outcomes.

To capture the effects of mental alertness, we focus on sleep disruption, which is both prevalent and known to reduce effectiveness in judgments and decisions. In the United States, the Centers for Disease Control and Prevention (CDC) has declared insufficient sleep a public health problem.[1] More than a third of American adults do not get enough sleep on a regular basis (Liu et al. 2016) and the proportion of people sleeping less than the recommended hour of sleep is rising (Roenneberg 2013). As discussed by Kahneman (2011), people with insufficient sleep tend to rely more on intuitive and heuristic rather than analytical decision-making processes. Studies in the fields of psychology and medicine have consistently found that lack of sleep or poor sleep impairs decision making abilities in both simple and complex tasks (Harrison and Horne 2000).

Our tests focus on retail investors, for whom sleep disruption effects may be especially great. Retail investors lack the formal support systems and team decision processes that can check impulsive decision making by institutional investors. Our focus has the further benefit that retail investors are widely distributed spatially, in contrast with the concentration of institutional

[1] American Association for the Advancement of Science. (2014, March 8). Sleep deprivation described as a serious public health problem. https://www.aaas.org/news/sleep-deprivation-described-serious-public-health-problem

investors at financial hubs. We exploit the spatial dispersion of retail investors to identify causality.[2]

Our main hypothesis is that retail investors are more prone to trading mistakes when they are less mentally alert owing to disrupted sleep, thereby impairing trading performance. To test this hypothesis, we use transaction-level data of retail investors from a large brokerage account in the 1990s as in Barber and Odean (2000). Following previous studies (Gibson and Shrader 2018; Giuntella and Mazzonna 2019), our proxy for investor sleep disruption is local sunset time, which has been shown to reduce sleep time and quality.

It is well-documented that natural sleep cycles are influenced by the length of evening of darkness people are exposed to before bedtime. A longer period of darkness before bedtime triggers the body's production of melatonin, the hormone involved in regulating the sleep-wake cycle (Roenneberg et al. 2007). The period of darkness is longer when the sunset time is earlier, owing either to seasonal variations in daylight or to differences across the time zone border. In either case, earlier sunset times result in greater sleep length and better sleep quality (e.g., Hamermesh et al. 2008, 2018; Giuntella and Mazzonna 2019; Sun and Zhang 2019; Owen et al. 2022).[3] We therefore geocode households' locations and calculate their local sunset time at a daily frequency to test whether local sunset time affects trading performance.

As in Barber and Odean (2000), we measure retail investor trading performance as the subsequent average abnormal returns of the stocks bought or sold by the investors on each day calculated based on Fama-French three-factor model. A stock trading decision is measured to be profitable when a household buys a stock that subsequently has positive future average daily abnormal returns or sells a stock that has negative average daily abnormal returns.

[2] Retail investors often trade less actively than certain classes of institutional investors. However, as events such as the GameStop episode of 2021 make clear, retail investors also play an important role in stock market trading and price setting.

[3] Roenneberg et al. (2007) find that the human circadian rhythm is more closely synchronized with solar time than social time. Hamermesh et al. (2008) suggest that work schedules do not adjust to track seasonal shifts in sunset time. Social schedules constrain the morning wakeup time for workers, so a later sunset and later bedtime can cause shorter sleep duration. Therefore, assuming the average worker to be a retail investor population, late sunset time can be an indicator of shorter sleep length. Gibson and Shrader (2018) find that a one-hour delay in sunset time within a location reduces sleep duration by approximately 20 minutes per week. Giuntella and Mazzonna (2019) show that residing on the late sunset side of a time zone border leads to an average reduction in sleep duration of 19 minutes per day and increases the likelihood of reporting insufficient sleep. Together, these findings suggest that later sunsets, whether within a location or at time zone boundaries, are consistently associated with reduced sleep duration.

Although sunset time is exogenous to the economy, it may be correlated with variables other than sleep that might also affect trading performance. For example, seasonal variations in mood may be correlated with both sunset time and trading performance (Kamstra, Kramer, and Levi 2003). In addition, different geographical locations have different sunset times, and trading performance may be correlated with location for many reasons.

We use four complementary identification strategies to address this endogeneity, each with its own strengths and limitations. Collectively, we view these tests as providing a clear answer to the question of whether sleep affects trading performance.

The first identification method is based on seasonal variation in sunset times within households. This method uses household fixed effects to test for the effect of seasonal variations in sunset times on trade performance. A strength of this method is that it controls for all time-invariant differences across households. A drawback of the approach (which we address by other means) is that it does not control for other possible seasonally-varying determinants of trading.

Using this method, we find a negative relationship between sunset time and trading performance within a household in different seasonal periods. On average, when the sunset occurs approximately one hour later, a household's stock trades result in 2.1 basis points lower average daily abnormal return over the next 21 trading days. This is statistically significant (t = 5.31) and economically substantial. The effect is equivalent to 0.44 percentage points monthly abnormal return, which is comparable to the effect of overconfidence (0.31 percentage points monthly abnormal return) in Barber and Odean (2000).

The seasonal effects estimated using this approach could derive from a different source--the effect of mood as influenced by Seasonal Affective Disorder (SAD). Kamstra, Kramer and Levi (2003) find a SAD effect on stock returns owing to seasonal variations in daytime hours. Sunset time and daytime hours both follow a seasonal cycle and are therefore highly negatively correlated.

However, our sleep disruption hypothesis predicts different seasonal variation from that predicted by the SAD hypothesis. Kamstra, Kramer and Levi (2003) document that the SAD effect mainly applies to Fall and Winter because of declining daylight hours, whereas, as discussed previously, the sleep disruption effect concentrates in Summer, the season with the shortest duration of darkness. Our results are robust to including a SAD variable following Kamstra, Kramer and Levi (2003) as a control in our panel regression test, indicating that sleep and mood are distinct channels that affect trading performance.

The second strategy is a regression discontinuity design (RDD) based on the local discontinuity in sunset time at time zone borders. Time zone borders have been used for RDD in previous studies of the effects of sleep (e.g., Giuntella and Mazzonna 2019; Bahar 2020), but such tests require refinement to achieve credible identification. We first describe a basic RDD test, and then describe how we refine the RDD test strategy to achieve identification.

The starting point of the RDD approach is that households located on opposite sides of the border experience different sunset times (a difference of one hour, in our sample) from those on the other side, despite being in close spatial proximity. Being on the late sunset side of a time zone border is associated with a substantially lower amount of sleep and worse sleep quality. We set a bandwidth restriction of 200km from the relevant time zone border to minimize any possible effects of other geographical factors that could affect trading performance.

An advantage of the RDD approach controls for various factors that correlate with both the location and the trading performance. For example, locations with different sunset times may also have different weather, which has been found to affect securities market outcomes (Hirshleifer and Shumway 2003). In the RDD, the close proximity of the early and late side of the time zone border greatly reduces differences in weather. Further controls in our tests include the latitude of the location, household characteristics, and state, date, and financial center fixed effects.

By comparing across the time zone border, we estimate the relationship between sunset times and trading performance. Retail investors residing on the late sunset side of the time zone border on average earn 11.3 basis points lower daily abnormal returns on their trades over the next 21 trading days. Although this result is only marginally statistically significant (t = 2.03), the economic magnitude is substantial, a 2.4 percentage point difference in the first month. This indicates that the statistical power of our RDD approach is limited due to the smaller sample size.

The endogeneity of time zone borders in our RDD test is mitigated by the inclusion of household characteristics, and state fixed effects to account for differences in law, regulation, and history across time zone borders. Nevertheless, a concern remains that U.S. time zone borders are not randomly assigned.[4] The underlying determinants of time zone borders could cause differences in trading performance even of nearby households on opposite sides of a border.

We address this problem with three validation tests. First, we perform tests restricted to a subsample where time zone borders do not overlap with state borders. In these tests, the effect is qualitatively and quantitatively similar to the full sample. Second, as a placebo test, we consider households within the same time zone but in different states. To do so, we create pseudo-time-zone borders along state lines that divide each time zone in half. Unlike the RDD results using actual time zone borders, being on the east sides of the pseudo-time-zone borders has no significant effect on trading performance. These results suggest that state effects are not a major source of endogeneity.

The third way we address endogeneity of time zone borders in the RDD approach is based on predicted variation in effects across seasons. Based on chronobiological research, we hypothesize (for reasons discussed in detail later) that the adverse effect of being on the late side of the time zone rather than the early side will be greater during Summer than in Winter. Consistent with the prediction, the effect of time zone on trading performance is present only in Summer. This approach mitigates endogeneity concerns because there is no special reason for cross-state differences in governance, law or culture to vary cyclically by season. This seasonally varying effect of time zone borders is, however, consistent with sunset time driving the performance.

Our third identification strategy compares locations with similar longitudes but different latitudes (North vs. South). Northernly cities have later sunset times than southernly ones during the summer but earlier sunset times during the winter. This implies directional predictions that reverse across cities through the seasons each year. Such variation and reversal are not implied by locational factors other than sunset, so such variation identifies the effects of variation in sunset times. This approach also allows us to conduct tests using the full sample, rather than the restricted sample inherent in the RDD approach.

We regress the trading performance on an indicator variable that equals one if a household is in the top 25% latitude and zero if in the bottom 25%. Consistent with our hypothesis, we find

[4] U.S. time zones remain a legacy of transportation networks, commerce, and community decisions. U.S. time zone borders were initially shaped by practical needs originating from the railroad industry's push for standardized time in the 19th century. Over time, these borders shifted to reflect trade connections, commuting patterns, and regional preferences (U.S. Department of Transportation. (2025, January 14) Uniform Time. https://www.transportation.gov/regulations/time-act.).

that the coefficient is significantly negative during the summer, indicating that investors in northernly cities underperform their peers in southernly cities, and positive but not significant during the winter, suggesting a reverse relationship.

A subtler hypothesis is that sunset time will have a nonlinear effect on sleep disruption owing to the timing of onset of melatonin production. Melatonin is asleep-aiding hormone that the human brain produces in response to darkness. The Centers for Disease Control and Prevention (CDC) reports that melatonin production typically begins around two hours before an individual's usual sleep time. Therefore, as long as the dark hours between sunset time and bedtime exceed two hours – a condition that is likely to be satisfied for all locations during winter – the differences in sunset time may have little effect upon sleep time and quality. This implies that latitude will affect trading performance in the summer but not the winter. Consistent with this hypothesis, we find a stronger effect of latitude in the summer than in the winter. The North-South difference in trading performance is significant during the summer, but not in the winter.

Lastly, as our fourth identification method, we use Daylight Saving Time (DST) changes, building on the approach of Kamstra, Kramer, and Levi (2000). DST changes offer a natural experiment for assessing the causal effect of sleep disruption and mental alertness on trading performance. Kamstra, Kramer, and Levi (2000) provide evidence that sleep disruption from DST changes cause negative weekend returns in the U.S. stock market. In contrast, we examine whether DST changes affect investors' trading performance. The test focuses on a narrow window around DST adjustments that occur at sharply defined switch-over dates. An advantage of this identification method is that it controls for any slow-moving factors that may correlate with both sunset time and investor trading performance, such as gradual shifts in market sentiment or seasonal changes in mood.

In most of the contiguous U.S., clocks are adjusted twice annually forward and back, and the Spring transition has a substantial effect on sleep disruption. For example, Barnes and Wagner (2009) find that the Spring shift reduces sleep duration, while the Fall change does not produce a substantial increase in sleep. Similarly, Bazley, Cuculiza, and Pisciotta (2024) find an adverse effect of sleep disruption on information processing and accuracy of earnings forecasts following Spring DST changes, but not after Fall changes. Consistent with the Spring/Fall asymmetry identified in these studies, we find that households in DST-observing counties experience a 20.9 basis-point decline in trading performance over the five days following the Spring DST change compared to the five days preceding it. Also consistent with this asymmetry, we find that the effects of Fall DST changes on trading performance are economically small and statistically insignificant.

We next explore the underlying mechanism through which sleep affects investors' trading performance. We conduct mechanism tests using a regression discontinuity design (RDD) to ensure robust identification.

The first potential explanation for the adverse effect of sleep disruption is that disruption interferes with investor attention. Evidence from psychology suggests that sleep deprivation harms cognitive processing resources, resulting in slower performance of tasks and a greater number of errors (Pilcher and Huffcutt 1996; Alhola and Polo-Kantola 2007; Hudson et al. 2020; Van Dongen et al. 2003). This suggests that sleep disruption may impair investor attention to relevant public information about stock prices.

To test for this, we use trading in relation to corporate earnings announcements. Evidence of systematic underreaction to earnings news is called post-earnings announcement drift (Bernard and Thomas 1990). This effect is consistent with models of limited investor attention to earnings news (Hirshleifer, Lim, and Teoh 2011). To evaluate the extent to which retail investors allocate attention to earnings news, we estimate the propensity to trade a stock on the quarterly earnings announcement day and two days after. We find that people who live on the later sunset side of the time zone border are less likely to trade during that period.

We expect lower reactivity to earnings news to harm trading performance because the post-earnings announcement drift phenomenon suggests a tendency to underreact to earnings news. Indeed, we find that the trades made by sleep-disrupted investors on earnings announcement days are significantly worse than those made by their peers. Moreover, this relative underperformance is 3 times of their underperformance on non-earnings days. This finding supports the hypothesis that inattention is a key mechanism linking sleep disruption to lower trade performance.

Sleep disruption can affect heuristic decision-making for reasons other than impairment of attentional resources. We therefore test for other behavioral effects that have not been attributed primarily to investor attention. First, we investigate whether sleep disruption causes overreaction to news. It has been hypothesized that overreaction to good news causes stocks to become growth stocks, and overreaction to bad news causes firms to become value stocks. Such overreaction has been attributed to either overconfidence (Daniel, Hirshleifer, and Subrahmanyam 1998) or extrapolation of past performance (Lakonishok, Shleifer, and Vishny 1994).

A consequence of such theories is that investors who overreact especially strongly to news will be especially attracted to growth stocks and will shun value stocks especially strongly. Therefore, to test whether sleep disruption exacerbates the tendency of investors to overreact to news, we compare monthly net purchase of growth stocks and value stocks among investors living on the early and late sunset sides of time zone borders. We defined growth and value stocks as in Lakonishok, Shleifer, and Vishny (1994).

Consistent with existing studies, we find evidence of overreaction in our sample, in the sense that retail investors make higher net purchases of growth stocks than value stocks. However, there is no evidence that sleep disruption exacerbates overreaction. This indicates that investor alertness does not reduce the tendency to overreact to news. This is reasonable if overreaction is a problem of excessive investor arousal rather than a problem of inadequate arousal.

We also examine whether sleep disruption influences retail investors' attraction to lottery stocks – stocks with positively skewed returns (Kumar 2009). Theoretical models have derived such behavior under nontraditional preferences that induce attraction to skewness (Brunnermeier and Parker 2005; Barberis and Huang 2008). In the model of Han, Hirshleifer, and Walden 2022, social transmission bias causes an attraction of investors to stocks with high volatility and high skewness. We define lottery stocks as those with above-median idiosyncratic volatility or above-median idiosyncratic skewness. We find no statistically significant difference in the buy trade volume of lottery stocks, under either definition, across time zone borders. This suggests that even mentally alert investors may be attracted to lottery stocks.

Finally, we examine whether sleep disruption amplifies the disposition effect, one of the most well-documented trading anomalies (e.g., Shefrin and Statman 1985, Odean 1998). The disposition effect is the finding that investors are more likely to sell winning stocks (those with gains since purchase) than losing stocks (those with losses since purchase). The disposition effect is associated with trading losses (Odean 1998). Several behavioral biases have been proposed as possible explanations, including realization preference (Barberis and Xiong 2009), mental accounting (Shefrin and Statman 1985), and confirmation bias (Gervais and Odean 2001; Feng and Seasholes 2005).

To investigate whether sleep disruption exacerbates the disposition effect, we examine how time zone border discontinuities affect investor behavior. We find that sleep disruption does not significantly intensify the disposition effect. This suggests that even alert investors are subject to whatever biases generate the disposition effect. This is reasonable if the disposition effect is driven, for example, by disutility from realizing losses, rather than from a lack of sufficient alertness to consider carefully whether to sell stocks.

In summary, our tests for underlying mechanism suggest that sleep disruption reduces trading profitability by impairing investor attention. We find no evidence that sleep disruption causes greater overreaction, increased attraction to lottery stocks, nor a stronger disposition effect. A caveat is that our RDD design has limited statistical power, so the absence of significant findings does not definitively rule out the influence of these alternative mechanisms.

Our research contributes to the literature on the influence of sleep on stock markets. One common setting for testing the effects of changes in sleep is daylight savings time (DST) changes (e.g., Kamstra, Kramer, and Levi 2000, 2002; Berument and Dogan 2011). Our paper makes three new contributions to this literature. First, we examine a different context, the variation in sunset time, to identify the effect of sleep on trading performance. This allows us to capture a more continuous variation in sleep disruption in a larger sample.

Second, we study the effect of sleep on individual investor trading behaviors and outcomes, rather than on the aggregate stock market. This context allows us to employ RDD in tandem with other identification methods to establish a causal effect between sleep and trading performance. Finally, we provide novel evidence on the economic channels through which sleep and mental alertness affect trading performance.

More broadly, our paper is part of a stream of research on how environmental factors influence the stock market. Saunders (1993) and Hirshleifer and Shumway (2003) find that sunshine affects stock investor mood and market returns. Kamstra, Kramer, and Levi (2003) test the relationship between length of daylight hours and stock returns.

Our paper differs from the existing literature in at least three dimensions. First, existing papers focus on how environmental factors affect stock prices, whereas our paper examines how sunset time affects the quality of individual investment decisions. Second, the channels through which environmental factors affect the stock market are different. The current literature has mainly focused on how environmental factors influence investor's moods, which in turn affects their stock trading decisions. Our paper focuses on sleep and consequences for mental alertness. Third, we use a set of complementary identification methods to test for the effect of sleep disruption on retail trading performance.

Finally, this paper contributes to the limited attention literature by providing novel evidence on the effect of cognitive resource constraints on attention. Existing research finds that investor attention is negatively influenced by cognitive load imposed by weekend activities planning or distracting news arrivals (e.g., DellaVigna and Pollet 2009; Hirshleifer, Lim, and Teoh 2009; Hirshleifer and Sheng 2022)—i.e., by substitution of cognitive resources between different targets of attention. Our paper examines how sleep disruption reduces the stock of mental resources—the attentional budget available for use in all activities.

2. Data and Measures

We next discuss data on retail investor trading and location. Then, in Subsection 2.3, we discuss data on local sunset time. Finally, we propose a daily trading performance measure in Subsection 2.4.

2.1 Retail Investors Data

The primary data used in this study is a panel of stock trades by households spanning six years from 1991 to 1996, provided by a large discount brokerage firm. This retail investor data has been widely used in finance literature, starting with Barber and Odean (2000). The data includes daily trading records and monthly holding records for 77,995 households. The key information for this study is the location of each household. Therefore, we only consider households with valid coordinates derived from their zip code information. We convert zip codes into coordinates mainly using the 1990 Census U.S. Gazetteer, following Seasholes and Zhu (2010), and complement with Sashelp.Zipcode file and USPS zip code database. The locations of 52,051 households are identified.

We construct household-day-level panel data. Daily stock information is obtained from CRSP (Center for Research in Security Prices). Using the historic CUSIP codes, we combine the trading records with stock information and identify 10,601 different common stocks with valid price information. To adjust stock returns for risk, we obtain returns of the market portfolio, risk-free rate, and the SMB and HML factors from Kenneth French's website. Additionally, we include the daily CRSP value-weighted index total return and the daily VIX level from CBOE.

As we focus on the stock trading performance of retail investors, the final sample is restricted to households that trade common stocks with valid price information. Furthermore, to exploit the discontinuity design of time zones, we restrict the household located in the contiguous United States. After filtering the sample, 41,131 households remain with their location and common stock trading records.

Figure 1 displays the geographic distribution of households in the final sample, along with the location of the time zone border. Based on the time zone border, we categorize households into four time zone areas, Pacific, Mountain, Central, and Eastern.

Table 1 presents a summary of the final sample, which is divided into these four time zone areas. Panel A of Table 1 shows the number and percentage of households in each time zone area. The Eastern time zone has the largest number of households, accounting for 39.68% of the entire sample, followed by the Pacific time zone with 33.11%. The Mountain time zone has the least number of households, comprising only about 5.76% of the entire sample. Over the six years of the sample period, households trade 29.22 times on average. Panel B of Table 1 describes the sample related to the common stock trades. The number of transaction observations varies across the different time zones, as expected given the number of households. The summary statistics of trading behavior reveal that retail investors execute more buying orders than selling orders, irrespective of the time zone.

2.2 Data on Distance from the Time Zone Border

The contiguous United States is divided into four different time zones by three time zone borders. To measure the distance from the closest time zone border in kilometers for each household, we used the ArcGIS program to combine the coordination of each household with the American time zone border shapefile. The spatial discontinuity in sunset time at the time zone border provides a natural experiment that allows us to compare households that experience similar levels of daylight exposure but have different local sunset times due to being in different time zones. This allows us to isolate the effect of sleep on trading performance, assuming households located nearby share common characteristics.

We use the following procedure to assign signed distance values, a variable called *SignedDistance*, to households from the closest time zone border. If a household is on the left side of a time zone border, a negative distance value is assigned. For instance, a household located in the Pacific time zone only has one *SignedDistance* value from the Pacific/Mountain time zone border, which is a negative value. If a household is in the Central zone, it may have two different

SignedDistance values: one positive number from Mountain/Central and the other negative number from the Central/Eastern time zone border. In this case, we keep the lowest absolute value of *SignedDistance*. This process ensures that the spatial discontinuity cut-off is set at 0 based on the distance measure.

Figure 2 visually depicts the sharp discontinuity in average sunset time at the time zone border, creating a natural experiment where households on either side of the border experience a difference in sunset time. The summary statistics of *SignedDistance* measure are in Panel A of Table 2, which spans from -864.10 to 1510.31 kilometers.

2.3 Local Sunset Time Data

Our proxy for sleep disruption of investors is motivated by the finding that sleep is influenced positively or negatively by the presence of sunlight at different times of day. To identify the location of retail investors, we use the zip code information of each household to obtain the corresponding longitude and latitude coordinates. Using these coordinates, we calculate the local sunset time of each household based on solar mechanics algorithms outlined in Meeus (1991). As defined by Gibson and Shrader (2018), the local sunset time in this study refers to the sunset time of a specific location, taking into account its time zone and daylight saving period. By using this methodology, we are able to obtain a reasonable approximation of the sleep hours of each household based on the time of sunset in their location.

Specifically, we calculate the daily local sunset time for each household in the sample, using the geocoded longitude and latitude coordinates obtained from their zip code information. The sunset time is measured in hours, where a higher value of the variable Sunset indicates a later sunset time. As shown in Panel A of Table 2, the average daily local sunset time across the sample period is 18.71, which is approximately 6:42 p.m. in local time. This information provides the timing of the transition from daylight to darkness at each investor's location, serving as a proxy for sleep time.

2.4 The Trading Performance Measure

To measure a retail investor's trading performance at a daily frequency, we use the ex-post risk-adjusted performance of stocks that the investor trades. Barber and Odean (2000) suggest that Fama-French three-factor model is a reasonable model for evaluating retail investors' investment quality because they tilt towards small stocks and the model accounts for that. Thus, we use a 250-day rolling window to estimate the Fama-French three-factor model as follows:

$$R_{it} = \alpha_i + \beta_{i1}(R_{mt} - R_{ft}) + \beta_{i2}SMB_t + \beta_{i3}HML_t + \varepsilon_{it}, \tag{1}$$

where R_{it} is daily excess return of stock i on day t, which equals stock return minus risk-free rate; R_{ft} and R_{mt} are risk-free return and market return on day t, respectively; and SMB and HML denote size and book-to-market factors of the Fama-French three-factor model. Once we estimate β_{i1}, β_{i2} and β_{i3}, we calculate the risk-adjusted expected excess return, $\widehat{R}_{it}$, using respective returns and factors on day t.

Next, we consider the direction of each trade. If an investor buys a stock that has positive future abnormal returns, it is an ex post good decision. Similarly, if an investor sells a stock that has negative future abnormal returns, it is an ex post good decision. In contrast, if an investor buys a stock that has negative future abnormal returns, it is an ex post bad decision. It is also an ex post bad decision if an investor sells a stock that has positive future excess returns. For each executed trading, the retail investor j's trading performance is calculated as Equation (2).

$$StockPerform_{ijt,k} = (2Buy_{ijt} - 1)(\tfrac{1}{k})\textstyle\sum_{\tau=1}^{k}(R_{i,t+\tau} - \widehat{R}_{i,t+\tau}), \tag{2}$$

where Buy_{ijt} is a dummy variable equaling one if a household j buys stock i on day t and equaling zero if a household j sells; and $\frac{1}{k}\sum_{\tau=1}^{k}(R_{i,t+\tau} - \widehat{R}_{i,t+\tau})$ refers to the average abnormal return of stock i over k days after the trade is executed. Therefore, $StockPerform_{ijt,k}$ is positive when a household buys a stock that will provide a positive average excess return or sells a stock that will generate a negative average excess return in the near future.

As each household may trade stocks several times a day, we aggregate $StockPerform_{ijt,k}$ into household-day-level, using the trade-quantity weighted average as follows:

$$TradePerform_{jt,k} = \textstyle\sum_i(\frac{TQ_{ijt}}{TQ_{jt}})StockPerform_{ijt,k}, \tag{3}$$

where TQ_{ijt} and TQ_{jt} are the stock i's trade quantity traded by household j on day t, and the total quantity traded at day t by a household j, respectively. $TradePerform_{jt,k}$ is the difference in performance over day $t+1$ to $t+k$ of stocks that are bought and sold by investor j on day t, weighted by the corresponding trade quantity. We consider different values of k, from 10 to 21 trading. We use $TradePerform_{jt,k}$ as a primary dependent variable, which measures household j's daily decision quality. $TradePerform_{jt,k}$ is winsorized at 1% and 99%.

The $TradePerform_{jt,k}$ measure focuses on how the stocks traded by investor j on day t perform during the subsequent k days. It is a measure of the decision quality of investors on that day. Intuitively, this measure is high if an investor buys stocks that subsequently earn high abnormal returns or sells stocks that earn low subsequent returns. A similar methodology is commonly used in the mutual fund literature, wherein a fund's trading performance in quarter t is measured by comparing the performance in subsequent quarters of stocks bought and sold in quarter t (e.g., Chen, Jegadeesh, and Wermers 2000).

Panel A of Table 2 presents the summary statistics of our primary dependent variables. As expected, our results align with the literature on retail investors, with household stock trading producing negative outcomes on average. Panel B of Table 2 provides insight into the correlation between the main variables. Our measures of trading performance show a negative correlation with the daily local sunset time. This suggests that circadian rhythms may influence the decision-making of retail investors.

3. Main Results: The Sleep Disruption Effect

In this section, we test the effect of sleep disruption on retail investors' trading performance using four empirical approaches: (1) panel regression on sunset time with household fixed effects, (2) a regression discontinuity design (RDD) around time zone borders and the differences in these effects between Summer and Winter, (3) panel regression across latitude and seasons, and (4) time-series and difference-in-differences (DiD) analysis based on daylight saving time changes.

3.1 Sleep and Trading Performance: Panel Regression

The method is based on seasonal variation in sunset times within households. A strength of this method is that we address the possibility of household time-invariant factors that affect trading performance using household fixed effects. These could include inherent preferences about stocks (Døskeland and Hvide 2011; Grinblatt and Keloharju 2001; Huang 2019; Huberman 2001; Seasholes and Zhu 2010) or trading propensities of households (Barber and Odean 2001; Grinblatt, Keloharju, and Linnainmaa 2012; Korniotis and Kumar 2011). To address this concern, we use a panel regression method with household-level fixed effects.

In addition, the panel data allows us to deal with the seasonality in the cross-sectional stock returns. We control for the well-known weekend effect (Birru 2018; French 1980) by adding the day of the week fixed effects and for the January effect (Keim and Stambaugh 1986; Rozeff and Kinney 1976; Thaler 1987) by including a January dummy variable. We exclude transactions made in December in our main estimations since the retail investors show a tax-motivated selling strategy at the end of the year (Odean 1998).[5] Thus, the following equation tests whether a household's trading performance is explained by its local sunset time:

$$TradePerform_{jt} = \alpha + \beta Sunset_{j,t-1} + X_t'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}, \tag{4}$$

where $Sunset_{jt-1}$ measures a local sunset time on day $t-1$ in household *j*'s location; X_t is a vector of market-level variables, including daily CRSP value-weighted index total return and daily VIX level on day *t*. The coefficient γ_t represents time-fixed effects including the day of week, year, and month; γ_j are household fixed effects and e_{it} is the error term. We hypothesize that later sunset time causes later sleep times, thereby reducing mental alertness and decision-making capacity of the next day. Our hypothesis implies a negative coefficient on the sunset time variable, β in Equation (4), indicating that a later sunset time is associated with lower trading performance.

We control for the effect of daytime hours related to Seasonal Affective Disorder (SAD) in Kamstra, Kramer and Levi (2003). Sunset time and daytime hours both follow a seasonal cycle and are therefore highly negatively correlated.[6] Nevertheless, our sleep hypothesis is empirically distinguishable from the SAD effect owing to predicted differences in effects in different seasonal periods. Kamstra, Kramer, and Levi (2003) document that the SAD effect mainly applies to Fall and Winter seasons because of declining daylight hours, whereas, as mentioned previously, the

[5] The results are robust to including December trades. See Table A3 in the Internet Appendix.

[6] They are not perfectly correlated. For example, SAD is zero in Spring and Summer based on Kamstra, Kramer and Levi (2003) paper, while sunset time has variations in these two seasons.

sleep effect that we focus upon concentrates in Summer as Summer has the shortest duration of darkness. Thus, we construct a SAD variable following Kamstra, Kramer, and Levi (2003) and include it as a control variable in some specifications.[7]

Table 3 reports the results obtained from estimating Equation (4). Columns (1) through (3) and (4) through (6) in Table 3 represent the 10-day and 21-day trade performance windows, respectively, used to assess the effect of sleep disruption. By integrating household fixed effects into the model, we evaluate the influence of sunset time on daily trading performance of households, controlling for household-specific characteristics.

We find a robust negative effect of sunset time on investor performance. For instance, in Column (1), when the sunset time is delayed by approximately an hour and twenty minutes (equivalent to one standard deviation in Sunset), households tend to trade stocks that yield an average daily abnormal return that is 1.1 basis points lower over the next ten days which is statistically significant (t = -5.52). We include household fixed effects, so this finding indicates that, for the same household, later sunset time leads to worse trading performance. The result is stronger when controlling for the market return, VIX, and the January effect in Column (2). Column (3) shows that the effect of sunset time on trading performance still holds after controlling for the SAD effect, indicating that sleep and mood are two distinct influences upon trading performance (t = -5.33).

We also look at the monthly window (i.e., 21 trading days). In Column (6), the average daily abnormal return decreases by 2.3 basis points and continues for 21 trading days. This is equivalent to 0.48 percentage points monthly abnormal return, which is comparable to the effect of overconfidence (0.31 percentage points monthly abnormal return) in Barber and Odean (2000). These findings support that sleep disruption has a statistically and economically significant effect on households' trading performance.

Overall, the results from panel regression with household fixed effects provide further support for the sleep disruption effect documented from the RDD test. Importantly, the panel regression results show that this effect is not likely driven by household characteristics or seasonality.

---

[7] Our results are also robust to orthogonalizing the sunset time variable with respect to the SAD variable. See Table A8 in the Internet Appendix.

3.2 Sleep Disruption and Trading Performance: An RDD Test

To test whether sleep affects trading performance, we employ our second approach, a regression discontinuity design (RDD) that uses spatial discontinuity in sunset time at the border of different time zones. The time zone border creates a quasi-natural experiment where we can compare households located near the border that experience different sunset times despite being in proximity. About an hour difference in local sunset time across the time zone border allows us to isolate the effect of sunset time on trading performance while holding at least some other factors constant. Under the null hypothesis, late sunset time will have no effect on mental alertness or trading performance, so there will be no discontinuity in the slope at the time zone border. We estimate the following regression to investigate the discontinuity at the time zone border:

$$TradePerform_{jt} = \alpha + \beta_1 LateSide_j + \beta_2 SignedDistance_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}, \quad (5)$$

where $LateSide_j$ equals one if the household *j* locates on the right side of the corresponding time zone border, which has the later sunset time by construction. The variable $SignedDistance_j$ measures the signed distance from the household *j* to the corresponding time zone border in kilometers. Because $LateSide_j$ is a persistent household-level variable, including the household fixed effects would subsume it. Therefore, we exploit the available household characteristics variables in the data, to minimize the potential confounding factors that could influence trading behavior. To estimate the local discontinuity, the main analysis uses a 200-kilometer bandwidth based on the absolute value of $SignedDistance_j$.[8] We cluster standard errors by distance from the time zone border, with households grouped in 10-kilometer increments.

The vector of variables X_j includes household characteristics such as the log of number of trades, client segment, age, gender, income, number of stocks traded, average number of stocks held in the monthly portfolio, and average equity value held in the monthly portfolio, and linear control for latitude.[9] Odean (1999) provides evidence that retail investors trade excessively in the

[8] The results are robust to using 300 km. See Table A5 in the Internet Appendix.

[9] Client segment information is provided by the discount brokerage firm. As described in Barber and Odean (2000), the firm labels households as general, affluent, or active trader. A household is classified as an active trader if it makes more than 48 trades in any year, as affluent if it holds more than $100,000 in equity at any point, and as general for all other households.

sense that on average they lose from trading. Furthermore, Barber and Odean (2000) provide evidence that the more investors trade, the worse their net performance. deHaan and Glover (2024) find that a decrease in waking trading hours is associated with lower trading activity and increased capital gains for retail investors. Thus, we control for trading frequency ($ln(Trade_j)$).

The coefficient γ_t captures trade date fixed effects to compare the trades on the same day, which addresses the possibility that seasonal factors other than sunset time that affect trading performance. We also include an indicator for the entire daylight saving time period to capture variation due to time changes because Arizona and some counties in Indiana do not observe daylight saving time during our sample period. The coefficient γ_j captures state fixed effects and geographical group fixed effects consisting of nine categorical groups. We create these groups by dividing the area around each time zone border into three equal latitude bands, ensuring that households compared are at similar latitude levels. We also include an indicator for financial hubs counties such as Cook County (IL), New York County (NY), Philadelphia County (PA), Suffolk County (MA), Washington DC, and Financial districts in San Francisco and Los Angeles (CA), under the assumption that households living near financial centers may show different trading patterns than the other households.

With Equation (5), we examine the relationship between sunset time and households' trading performance. If the later sunset time induces lower trading performance, β_1 is expected to be negative.

Table 4 presents the results of the RDD test, which estimates Equation (5), with 10-day $TradePerform_{jt}$ as the dependent variable for Column (1). We find a negative coefficient of the *LateSide* variable, indicating being on the late sunset side of the time zone border negatively affects the trading performance of retail investors. The economic magnitude of this effect is substantial. Comparing two households that are similar in terms of available characteristics but located on different sides of the time zone border, sleep disruption due to a one-hour later sunset leads to a 0.121 percentage points (12.1 basis points) reduction in average daily abnormal returns during the first ten days after trades. Column (2) of Table 4 shows the results of 21-day $TradePerform_{jt}$, a longer performance window. The coefficient of $LateSide_j$ is again negative (-0.113).

The effects are only marginally statistically significant (t = -2.16 for Column (1) and t = -2.03 for Column (2)) because the sample size is smaller in the RDD tests—only 11% of the sample size in the panel regressions.[10] However, the economic magnitudes are substantial. For example, an 11.3 basis point reduction in returns from Column (2) of Table 4 corresponds to a 2.4 percentage point difference in the first month's returns, on average, between early and late sunset side investors. This indicates that the reason that the statistical significance is marginal is limited power and sample size, not from a weak point-estimate effect.

We also provide a graphical depiction of the discontinuity of trade performance at the time zone border in Figure 3. This graphs trade performance as a function of signed distance from the time zone border. We create 20 bins on each side of the border with bin sample sizes equalized as much as possible. Circles represent the average 10-day $TradePerform_{jt}$ within $SignedDistance_j$ bins. The two lines are based on the regression estimates from Equation (5). They depict the marginal effects of $SignedDistance_j$ on 10-day $TradePerform_{jt}$ by $LateSide_j$, while holding other controls at their mean values. There is discontinuity at 0, as seen in the vertical gap between the two lines. This reflects the inferior trade performance of investors on the later-sunset side (i.e., the east side) of the time zone border.

As discussed in the introduction, U.S. time zone borders are not randomly assigned, so the RDD approach is still subject to endogeneity. In addition to controlling for household characteristics, we partially address this concern by including state fixed effects. Furthermore, for better identification, we perform three further tests.

First, we focus on households who are in the same state but in different time zones. Among the 13 states in the contiguous U.S. that span two time zones, 10 states have sufficient sample from both time zones in proximity to time zone borders. We focus on the households in these 10 states having more than 10 trades during six years of our sample period. In Table 5, RDD analysis of these 10 states indicates that households on the later sunset side have trading performance that is lower by 9.8 basis points (a statistically significant difference). As the sample ensures that the comparison is across time zone borders and not across state borders, this finding supports the hypothesis that sleep disruption impairs trading performance.

Next, to address the same concern, we run a placebo test of the difference between households in the same time zone but in different states. We define three vertical pseudo-time-zone borders, north to south. These borders divide the original time zones and perfectly align with state

[10] The results are similar when using equal-weighted average daily abnormal returns for trading performance measure. See Table A4 in the Internet Appendix.

borders as in Figure 4. Accordingly, we calculate households' *SignedDistance* from these pseudo-time-zone borders similarly to the previous RDD setting. We assign households within 200 km on the east side of the pseudo-time-zone borders to the *LateSide* sample, while households within 200 km on the west side are assigned as counterparties. Therefore, we use RDD to compare households that are in the same time zone but in different states. The regression discontinuity estimates using the pseudo-time-zone borders are in Table 6. It contrasts with the results using the real time zone borders, being on the east side of these pseudo-time-zone borders has no significant effect on trading performance. This suggests that the effects in our main test derive from the effects of time zone differences, not from the effects of state borders.

Our third validation test of RDD compares the effect of time zone borders across different seasons. We hypothesize that the time zone effect will be stronger in Summer than in Winter because melatonin production responds to hours of darkness. Melatonin production, a hormone that helps people to fall asleep, requires around two hours of darkness to have a good quality of sleep. As long as two hours of darkness is provided before bedtime, sleep disruption could be reduced even if the sun sets one hour later. In Winter, all locations in our sample experience longer dark hours between sunset and bedtime compared to Summer. This is likely to reduce the effect of a one-hour difference in sunset time on sleep disruption. Thus, we hypothesize that a one-hour difference in sunset time will have a smaller effect on sleep disruption in Winter. In contrast, the effects of differing laws and cultures across state borders are not expected to vary across seasons.

In Table 7, we estimate Equation (5) for Summer and Winter separately. Sleep disruption during Summer, in Column (2), shows 14.6 basis points lower average daily abnormal returns over the ten-day period, which is statistically significant. In contrast, during Winter in Columns (3), sleep disruption lowers trading performance by 9.6 basis points which is not statistically significant. Thus, the sleep effect is only presented in the summer. These findings indicate that the underperformance on the late side is driven by sunset time rather than differences in laws and cultures, which are not expected to vary cyclically with the seasons.

3.3 Trading Performance across Latitude and Seasons

Our next identification approach exploits the effect of latitude rather than longitude, on sunset time. In the contiguous United States, the northern areas observe a later sunset in the summer season than the southern areas. In contrast, during Winter, the southern areas have later sunset times. In consequence, seasonal variation is predicted to have opposing effects on households living in different latitudes.

Consider the example of Buffalo, NY versus Miami, FL. Both cities are in the Eastern time zone and located in similar longitude, -78.8784 and -80.1918, respectively. However, their latitude coordinates are distant, 42.8864 and 25.7617, respectively. Figure 5 presents the variation in sunset time over a year in Buffalo and Miami. Two lines cross each other twice around March and September. For example, on July 1, Buffalo observes sunset at 20.97 (8:58 p.m.) and Miami does at 20.27 (8:16 p.m.). On January 2, local sunset time is at 16.86 (4:51 p.m.) and 17.68 (5:40 p.m.) in Buffalo and Miami respectively. From this illustration, we can run the regression test using a dummy variable indicating households in the northern part of the U.S.

$$TradePerform_{jt} = \alpha + \beta NorthernPart_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}, \tag{6}$$

where $NorthernPart_j$ equals one if the household j locates in the top 25% latitude or zero if the household j in the bottom 25% latitude in the contiguous US. Other specifications are the same as in Equation (5), such as characteristics control variables and fixed effects. If sleep disruption, measured by later sunset time, negatively influences the trading decision and trading results, β will be negative during the Spring to Summer period (April, May, June, July, and August) and positive during the Fall to Winter period (October, November, December, January, and February).[11]

The regression estimates of Equation (6) are presented in Table 8. The coefficient of $NorthernPart_j$ in the regression captures the comparison between the average 10-day $TradePerform_{jt}$ of the top 25% latitudes and the bottom 25% latitudes.[12] Notably, the analysis takes into account the influence of seasonal variations.

Unconditionally, whether a household is in the northern part or southern part does not affect trading performance, as seen in Column (1). However, for the summer season, the coefficient of $NorthernPart_j$ in Column (2) of Table 8 is negative and significant. It indicates that the stocks traded by households in the northern part of the United States exhibit 41 basis points significantly

[11] We exclude March and September when two areas' local sunset time cross each other.

[12] The result of estimating regression using 21-day window is in the Internet Appendix Table A6. The results are consistent with Table 8.

lower daily performance compared to those in the southern part. In contrast, in Column (3) which focuses on the winter season, the coefficient of $NorthernPart_j$ is positive and insignificant. This finding aligns with the fact that the northern part experiences earlier local sunset times during the winter season, leading to a smaller or insignificant sleep disruption effect.[13]

In sum, these findings indicate that the timing of sunset influences trading performance, with greater magnitudes in the summer than in the winter. The difference in trading performance between the northern and southern United States is statistically significant only during the summer, not during the winter. This implies that the relationship between sunset time and trading performance is nonlinear, depending on the duration of dark hours between sunset and bedtime.

3.4 The Effect of Daylight Saving Time Changes

Daylight Saving Time (DST) changes provide a natural experiment to test the causal effect of sleep disruption on trading performance. Most states in the contiguous U.S. adjust their clocks twice a year, moving from Standard Time to DST in the spring and back to Standard Time in the fall. These time changes cause desynchronization, leading to adverse effects. Kamstra, Kramer, and Levi (2000) demonstrate that sleep desynchronization due to DST significantly contributes to negative weekend returns in the U.S. stock market. We use DST changes as an alternative to time zone tests to test whether sleep disruption affects investors' trading decisions and performance.

The Spring transition, in particular, has a significant effect on sleep disruption due to two factors: the loss of an hour at night and the additional hour of daylight compared to Standard Time. Economic literature underscores the negative consequences of this transition. For example, Barnes and Wagner (2009) find that the spring shift results in 40 minutes less sleep, while the fall change, despite the extra hour, does not produce a significant increase in sleep. Wagner et al. (2012) find that the shift to DST leads to sleep loss and a significant increase in cyberloafing behavior at work. Similarly, Smith (2016) shows that the spring transition into DST increases car crash risk, attributing this rise to sleep deprivation.

For households in DST-observing counties, we compare the 10-day trading performance measure over the five trading days following the spring DST change to the five days preceding it.

[13] The reversal effect is economically large. The average daily performance of investors living in northern cities relative to their southern counterparts drops by 33 basis points from Winter to Summer. However, this point estimate is statistically insignificant (t = 1.38) owing to a lack of statistical power.

Consistent with the past studies mentioned above, relative to the five days before the DST change, households in DST-observing counties experience a 20.9 basis-point decline in trading performance over the five days following the Spring DST (Panel A of Table 9). Additionally, we observe insignificant effects of Fall DST changes on trading performance.

To further explore the effect of sleep disruption on trading performance, we take advantage of variations in DST policies across states. Our control group consists of households in Arizona, a state without DST changes. Following the existing literature (e.g., Janakiraman et al. 2024), we use California as a treatment state because it is adjacent to Arizona. The difference in DST policy across these states provides identification of the effects of DST that addresses the possibility that market-wide events influenced trading performance during the DST change period. DST changes only affect the sleep of households living in counties that observe DST because these changes disturb circadian rhythm and cause sleep disruption. Therefore, we hypothesize that households in DST-observing counties perform worse in the stock market immediately after both Fall and Spring DST changes compared to households in non-observing counties. However, we expect these adverse effects to be more pronounced following the Spring changes than the Fall changes because the Spring changes lead to shorter sleep time. To test this idea, we run the following DiD regression:

$$\begin{aligned} &TradePerform_{jt} \\ &\quad = \alpha + \beta_1 AfterDST_t + \beta_2 DSTcounty_j + \beta_3 AfterDST_t \times DSTcounty_j \\ &\qquad + X_t'\delta_1 + X_j'\delta_2 + \gamma_t + \varepsilon_{jt}, \end{aligned} \tag{7}$$

where $AfterDST_t$ equals one if a trade date *t* is within 5 trading days after daylight saving time transitions and zero if within 5 trading days before the transitions. The variable $DSTcounty_j$ equals one if a household *j* lives in a county that observes daylight saving time and zero otherwise. The vector of variables X_t includes daily CRSP value-weighted index total return and daily VIX level on day *t*. The vector X_j includes household characteristics such as the log of the number of trades, client segment, age, gender, income, number of stocks traded, average number of stocks held in the monthly portfolio, and average equity value held in the monthly portfolio. The coefficient γ_t represent time fixed-effects including the year and day of the week.

We are mainly interested in the interaction term, $AfterDST_t \times DSTcounty_j$, which compares two differences: (1) DST counties vs. non-DST counties; and (2) before vs. after DST changes. Panel B of Table 9 presents the results of estimating Equation (7). Column (1) tests the effect of Spring sleep disruption on trading performance over a 10-day window, while Column (2) examines the effect of Fall sleep disruption. Consistent with our hypothesis, the coefficient estimates for the interaction term are negative, indicating worse trading performance following sleep disruption caused by the time changes. Furthermore, the Spring changes have a more statistically and economically significant effect on trading performance (-0.28) compared to the Fall changes (-0.19). This is consistent with our hypothesis that DST changes are in general disruptive, and that Spring changes are worse as they lead to a later sunset time. The results remain consistent when we extend the analysis to a 21-day trading performance, as shown in Columns (3) and (4).

4. Mechanisms

In this section, we explore potential mechanisms that might contribute to the effect of sleep disruption on investor trading performance. We examine several potential mechanisms: (1) investor attention, (2) overreaction, (3) attraction to lottery stocks, and (4) the disposition effect. We use a regression discontinuity design (RDD) for our mechanism tests to ensure robust identification. Despite the lower statistical power of RDD, we detect significant effects for one of the potential mechanisms.

4.1 Cognitive Capacity and Attention

A well-documented consequence of impaired sleep in neuroscience and psychology is the reduction of cognitive capacity and attention. A classic study by Pilcher and Huffcutt (1996) finds that sleep deprivation leads to significant impairments in cognitive performance, including attention, memory, and decision-making. They show that sleep-deprived individuals often perform tasks at a slower pace and make more errors. We refer to this as a loss of mental alertness. Dinges et al. (1997) explore how sleep deprivation affects attention and vigilance, critical components of cognitive alertness. Their study finds that even moderate sleep loss leads to lapses in attention, increased reaction times, and reduced vigilance. Research on circadian rhythms shows that human alertness levels fluctuate naturally throughout the day based on our biological clock. Dijk and Lockley (2002) argue that disruptions to the circadian rhythm, such as shift work or jet lag, can impair cognitive alertness and performance.

We expect impairment of cognitive resources to cause investors to respond more sluggishly to new information. To test this, we therefore examine the effect of sleep disruption on the likelihood of trading a stock shortly after quarterly earnings announcements. We hypothesize that sleep disruption reduces cognitive resources, resulting in less trading around earnings announcements for individuals in areas with later sunset times compared to those in areas with earlier sunsets.

We further hypothesize that this reduction in reactivity is adverse for trading performance in relation to earnings surprises. Abnormal trading performance—either positive or negative—is possible owing to the post-earnings-announcement drift anomaly (Bernard and Thomas 1990). The leading interpretation of post-earnings announcement drift in past literature is that this reflects underreaction by investors to earnings surprises (Bernard and Thomas 1990; DellaVigna and Pollet 2009; Hirshleifer, Lim, and Teoh 2009; Hirshleifer and Sheng 2022; Hirshleifer and Teoh 2003). This suggests that lower reactivity to earnings news is detrimental to trading performance.

We therefore hypothesize that investors buy less after positive surprises (which positively predict future returns) and sell less after negative surprises (which negatively predict future returns). Taken together, this implies that investors with later sunset times will on average have lower trading profitability on trades made on the date of earnings surprises.

To test this hypothesis, we use quarterly earnings announcements as a setting to test this mechanism. We obtain earnings data from the CRSP/Compustat Merged database and I/B/E/S, spanning from 1991 to 1996. We compile a comprehensive list of earnings announcement dates from both databases. In instances where I/B/E/S provides a different announcement date than Compustat, we follow the approach of DellaVigna and Pollet (2009) and choose the earlier date. To focus on circumstances requiring prompt attention to news, we exclude earnings announcements made on days when the market is closed.

$$EAtrading_{jt} = \alpha + \beta_1 LateSide_j + \beta_2 Distance_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}, \qquad (8)$$

where $EAtrading_{jt}$ is a binary indicator that equals to 1 if household j trades at least one stock on day t which has announced its quarterly earnings few days prior. Conversely, if household j does not trade any stocks on day t that have recently announced earnings, $EAtrading_{jt}$ is set to 0. Other variables remain the same as Equation (5). For this analysis, we exclude the trading in March, June, September, and December, when the earnings announcements are not frequent.[14] According to our hypothesis, we anticipate that the coefficient β_1 would be negative in cases where trades occur shortly after earnings announcements. This would suggest that households with better sleep are more responsive to new information in the stock market, adjusting their trading activities accordingly. Reflecting on the earnings announcements literature, we cluster the standard errors at both 10-kilometer groups from time zone borders and day levels.

Table 10 displays the estimates of Equation (8) with various trading windows. Column (1) shows that before earnings announcements, there is no significant difference between the west and east sides of the time zone border. Focusing on the 0 to 2 days following earnings announcements in Column (2), investors residing on the east side of the time zone border are less inclined to trade stocks based on new information. Living on the east side reduces the likelihood of trading in response to earnings announcements by 2.7 percentage points (t = -2.50), a significant shift considering the average predicted value of trading during earnings announcements is 14.64 percent. This is consistent with the hypothesis that sleep disruption leads to slower reactions. Beyond this period, as indicated in Columns (3) and (4), the effect becomes insignificant, suggesting that outside of the earnings announcement window, investors on both sides trade similarly.

For robustness, we test the same hypothesis using a panel regression with household fixed effects. This alternative approach offers complementary evidence that an average investor experiences lower reactivity to earnings announcements when the sun sets later. Table A1 in the Internet Appendix shows that later sunset times are associated with a lower likelihood of trading stocks with recently announced earnings (within 0 to 2 days). Specifically, a one-hour increase in local sunset time corresponds to a 0.4 percentage point decrease in the probability of trading (t = -4.41). This supports the hypothesis that impaired cognitive resources lead investors to respond more sluggishly to new information.

We next turn to the effect of sleep-disruption on trading performance conditional upon an earnings announcement. This conditioning is crucial. In general, individual investors trade too actively, in the sense that on average they lose money on their trades (Barber and Odean 2000), perhaps owing to overconfidence about their private information or analyses about a stock. In our

[14] Table A7 in the Internet Appendix shows the estimation of Equation (8) using the entire sample. The results are similar.

RDD test, we do not find sleep-disrupted investors trade less unconditionally.[15] However, as we have reported, they do trade less conditioning on the earnings announcement date.

We therefore hypothesize that the effect of sleep disruption will be detrimental conditional upon an earnings announcement date relative to other dates because the post-earnings announcement drift phenomenon reflects investor underreaction to earnings news (e.g., Bernard and Thomas 1990). Specifically, after a positive earnings surprise investors can on average profit by buying, but an underreacting investor will not do so, and after a negative earnings surprise investors can on average profit by selling, but an underreacting investor will not do so.

To directly link trade performance to inattention as a mechanism of sleep disruption, we therefore test whether the lower trade performance of late-sunset-side investors is concentrated among trades made at the time of earnings announcements. We modify our RDD regression from Equation (5) by interacting $EAtrading_{jt}$, the indicator for trades occurring during 0 to 2 days following earnings announcements as previously defined, with the existing RDD variables and household characteristics variables. Similarly to the main RDD analysis, we restrict the sample to a bandwidth of -200 km to 200 km around the time zone border and include only those who trade at least 11 times during the sample period. Specifically, we run the following test:

$$\begin{aligned} &TradePerform_{jt} \\ &\qquad = \alpha + \beta_1 EAtrading_{jt} + \beta_2 LateSide_j + \beta_3 SignedDistance_j \\ &\qquad + \beta_4 EAtrading_{jt} \times LateSide_j \\ &\qquad + \beta_5 EAtrading_{jt} \times SignedDistance_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt} \end{aligned} \tag{9}$$

In Table 11, our trade performance measures are, on average, positive but not significant for trades within two days after earnings announcements in Columns (1) and (3). More importantly, Columns (2) and (4) show that the underperformance of sleep-disrupted investors is concentrated in trades around the earnings announcement dates. We find that the trades made by sleep-disrupted investors on earnings announcement days is significantly worse than those made by their peers. More importantly, this relatively underperformance is 3 times of their underperformance on non-

[15] We find that the difference in trading frequency (sleep-disrupted investors – non-disrupted investors) is economically small (-2.28) and statistically insignificant (t = -0.66).

earnings announcement dates.[16] This finding supports the hypothesis that inattention is a key mechanism linking sleep disruption to lower trade performance. In summary, these results indicate that sleep disruption reduces investors' attention to earnings news, particularly negative earnings news, despite the adverse effect of this inattention on their trading performance.

4.2 Overreaction

Another potential mechanism for the effects of sleep is overreaction to news, perhaps because of extrapolation or overconfidence. To investigate this channel, we test overreaction using measures of value in Lakonishok, Shleifer, and Vishny (1994). If investors overreact to news, they are likely to buy growth stocks (which have experienced good news) more than value stocks (which have experienced bad news).

To define value versus growth stocks, we obtain the monthly ratios of book-to-market value of equity, cash flow-to-market value of equity, and earnings-to-market value of equity from WRDS. We modify the RDD test in Equation (5) to have relevant variables. The dependent variable, $NetPurchase_{ijm}$ is the cumulative net purchases (the number of shares of stock *i* purchased minus the number of shares sold by investor *j*) in month *m*. The main independent variable is $Glamour_{im}$ which equals one if stock i is in the bottom decile of the financial ratio in month m and zero if stock i is in the top decile. If sleep disruption increases the overreaction, then we expect positive coefficient estimates of the interaction term between $Glamour_{im}$ and $LateSide_j$.

Table 12 presents the results of testing for overreaction. On average, investors within 200 km of the boundaries are net buyers of Growth stocks, as shown in Columns (1), (3), and (5), indicating the presence of overreaction. However, the effect of sleep disruption on the magnitude of overreaction remains inconclusive. While sleep disruption appears to magnify overreaction when measuring Growth stocks based on book-to-market ratio (Column (2)), there is no significant difference between the two groups of investors when we use C/P and E/P to measure Growth stocks (Columns (4) and (6)).

In addition, we explore extrapolation as a source of sleep-induced performance effects using another measure. Specifically, we focus on extreme returns of stocks and test whether

[16] The coefficient on the *LateSide* is -0.328 (= -0.099 - 0.229) on the earnings days, compared with the coefficient of the *LateSide* on non-earnings days (-0.099).

investors believe such rare events will happen again in the future. We adopt the frequency measure of return crashes and jumps from Chang et al. (2022) and Hutton, Marcus, and Tehranian (2009).

Following Chang et al. (2022), log market-adjusted returns are computed as $log(1 + \varepsilon_{it})$, where ε_{it} represents the residual from regressing stock i's return on day t, r_{it}, on the current (t), leading ($t - 1$), and lagging ($t + 1$) market and industry returns. $Crash_{it}$ is equal to 1 if a stock i experiences one or more daily log market-adjusted returns falling approximately k standard deviations below its mean return in the period $[t - 31,\ t - 1]$. $Jump_{it}$ is equal to 1 if a stock i experiences one or more daily log market-adjusted returns that are k standard deviations above its mean return in $[t - 31,\ t - 1]$ period. The threshold, k standard deviations, is chosen to represent extreme outcomes, corresponding to the frequency of either 0.01%, 0.1%, or 1% in the normal distribution.

To test whether sleep disruption influences trading performance through extrapolation, we then construct an indicator $TrendChasing_{jt}$ to capture trend-chasing trading by households; the purchase of stocks with extreme positive past return and the sale of stocks with extreme negative past return. The indicator $TrendChasing_{jt}$ equals one on a given day if a household j either buys a jump stock or sells a crash stock, and zero otherwise.

We use a regression discontinuity design and estimate Equation (5) with the dependent variable, $TrendChasing_{jt}$. The results are in Table A2 in the Internet Appendix. Our hypothesis is that the coefficient β_1 will be positive, indicating that investors living on the later sunset side are more likely to buy jump stocks and sell crash stocks when they trade. However, the coefficient estimates of $LateSide_j$ is not significant and the sign of it is not stable with different k.

Taken together, the tests in this subsection indicate that there is no strong evidence that sleep disruption affects investor trading overreaction, whether resulting from overconfidence or from extrapolation of past returns.

4.3 Attraction to Lottery Stocks

One of the trading behaviors exhibited by retail investors is their strong preference for lottery stocks (stocks with positively skewed returns), and that this results in high valuations of such assets and low subsequent returns (e.g., Kumar 2009). The attraction to lottery stocks is related to theories on skewness-related preferences (Barberis and Huang 2008) and preferences over beliefs (Brunnermeier and Parker 2005), and transmission bias in social interactions (Han, Hirshleifer, and Walden 2022). In this section, we test whether sleep disruption influences this risky behavior among retail investors using a basic regression discontinuity design. We test whether sleep disruption may strengthen the attraction.

We define lottery stocks as those with above-median idiosyncratic volatility or with above-median idiosyncratic skewness in month m following Kumar (2009).[17] To measure how actively investors seek out lottery stocks, we compute LP_{jm}, the ratio of buy volume for lottery stocks to the total buy volume for all stocks by household j in the month m.

The results are presented in Table 13. Investors on the late sunset side do not exhibit statistically significant differences in either Column (1) or (2), which correspond to idiosyncratic volatility and idiosyncratic skewness, respectively. Overall, the effect of sleep disruption on the attraction to lottery stocks is insignificant.

4.4 The Disposition Effect

We also explore whether the sleep disruption effect on trading is related to the disposition effect, which is a robust and widespread trading anomaly (e.g., Shefrin and Statman 1985; Odean 1998; Grinblatt and Keloharju 2000; Kumar 2009). The disposition effect refers to that investors are more likely to sell an asset at a gain than an asset at a loss (Shefrin and Statman 1985). The disposition effect is associated with trading losses. Although the exact cause of the disposition effect is still under debate, research indicates that it can be related to behavioral bias, such as loss aversion from prospect theory (Barberis and Xiong 2009), mental accounting (Shefrin and Statman 1985), overconfidence (Barber and Odean 2001), and confirmation bias (Gervais and Odean 2001; Feng and Seasholes 2005).

Given the potential for external factors to influence behavior patterns, we hypothesize that sleep disruption may exacerbate the disposition effect. Specifically, we investigate whether the discontinuity at time zone borders, which can lead to varying levels of sleep disruption among investors, results in a significant difference in the magnitude of the disposition effect. Sleep-

[17] We compute both idiosyncratic volatility and idiosyncratic skewness using the previous six months of daily returns, following Kumar (2009). Specifically, idiosyncratic volatility is measured as the variance of the residuals obtained by fitting the three Fama-French factors and the momentum factor to the daily stock return time series. Idiosyncratic skewness is defined as a scaled measure of the third moment of the residual obtained by fitting a two-factor model to the daily stock returns, where the factors are the excess market returns and the squared excess market returns.

deprived investors may exhibit an even stronger inclination to engage in suboptimal trading behaviors, selling winners too soon and holding onto losers too long.

To test this hypothesis, we adopt the individual-level disposition effect measure proposed by Dhar and Zhu (2006). This approach allows us to capture cross-sectional variation in the disposition effect across different investors. Odean (1998) quantifies the disposition effect among retail investors using the difference between the proportion of gains realized (PGR) and the proportion of losses realized (PLR). The main finding is that retail investors significantly prefer selling winners and holding losers, except in December due to tax-motivated selling, ultimately to the detriment of their wealth. We calculate each investor's PGR, PLR, and disposition effect (DE), focusing on trades made throughout the year, except for December, to isolate the effect of sleep disruption from tax-related motivations.

Table 14 presents the results of this analysis. The coefficient on *LateSide* is insignificant across specifications. Specifically, Columns (1) and (2) imply that sleep disruption does not have a more pronounced effect on the tendency to sell losing stocks rather than hold onto winners. Column (3) shows that sleep disruption does not intensify the disposition effect. Thus, the sleep disruption effect is not likely driven by the disposition effect.

5. Robustness Checks

We next describe additional tests to address possible concerns about the robustness of the sleep disruption effect.

In the main analysis of using household fixed effects, we exclude transactions made in December. Odean (1998) finds that retail investors exhibit different motivations for stock trading in December compared to the rest of the year, and December trades may introduce noise in analyzing the effects of sleep disruption on trading performance. To provide a comprehensive view, we present results that include December trades in Internet Appendix Table A3. These results are consistent with those in Table 3, confirming the robustness of our main findings. In line with our hypothesis, investors experienced lower trade performance when the sun set later, even when December trades were included. While the significance and economic magnitude of the coefficient estimates are somewhat lower than in the main analyses, this outcome is expected, given the distinct motivations for December trades.

We adopt here a trade-quantity weighted daily Fama-French abnormal returns as the primary measure for trading performance. However, there is a potential concern that using trade-quantity weights might introduce a bias. Specifically, a few high-quality trading decisions with large quantities could disproportionately influence the average. To address this concern, we computed an equal-weighted average daily abnormal returns and re-evaluated our findings using the local regression discontinuity model.

The results of this analysis are presented in Table A4, Column (1) and (2). Notably, the direction of the effects remains consistent, and the levels of statistical significance are stable, reaffirming the robustness of our findings despite the methodological adjustments.

We also test whether the result is robust to excess return. Fama-French three-factor model for abnormal returns accounts for the inclination of retail investors to favor small-cap stocks (Barber and Odean 2000). However, the Fama-French three-factor model may not align with the evaluation methods commonly used by most retail investors, who may focus primarily on the excess returns of stocks over the risk-free rate.

To bridge this gap, we also assess trading performance using excess returns above the risk-free rate, rather than the Fama-French three-factor abnormal returns. The findings, as presented in Table A4, Column (3) and (4), demonstrate consistency between two trade performance measures using abnormal returns and excess returns. This robustness check ensures the understanding of retail investor performance.

We initially set the bandwidth to range from -200 km to 200 km in the regression discontinuity design to assure that we are comparing households in proximity. To test the robustness of this bandwidth setting for local discontinuity, we conducted a series of analyses with bandwidth variations from 200 km to 500 km, as shown in Columns (1) to (4) in Table A5. In this analysis, we take the trading performance measure over the 10-day windows. These analyses align with the principles of local regression discontinuity, revealing that narrower bandwidths generally yield results with greater statistical significance. Notably, even in Column (2), with the 300 km bandwidth, being on the side of later sunset decreases trading performance, at least at a 90% significance level. As expected, the effect fades away when using the 400 km or wider bandwidths.

In our earlier analysis, detailed in Table 8, we explored the relationship between sleep disruption and trading performance, examining trading performance over a 10-day span across various latitudes and seasons. Building on this, Table A6 extends our investigation to a longer period. By adopting a longer 21-day window for assessing trading performance, we confirm that during the summer season, as highlighted in Column (2), trading performance in the northern part of the U.S. tends to be lower than that in the southern part. This underperformance aligns with the variations in sunset time across latitudes and seasons. This extended analysis supports the importance of sleep on retail investors' trading performance.

When investigating attention as a mechanism of the effect of sleep on trading performance, we restrict the trading sample to months typically associated with the quarterly earnings announcements by firms—January, February, April, May, July, August, October, and November. This selection was intended to minimize noise. To confirm that the entire trading sample shows consistency in analysis, we expand our analysis to incorporate the entire sample. The results in Table A7 show consistent results with Table 10.

6. Conclusion

This study investigates the relationship between mental alertness, as influenced by sleep, and retail investors' trading performance. Building upon previous research linking late sunset times to sleep disruption, we adopt local sunset time as a proxy for investor sleep to address data limitations. In our first identification method, which is based on seasonal variation in sunset times within households, we find a later local sunset time is associated with lower trading performance within a household.

We employ three additional identification strategies to test the effect of sleep disruption on trading performance. First, a regression discontinuity design using time zone borders combined with comparisons such as Summer versus Winter provides causal evidence of the effect of sleep disruption on trading performance. Investors on the later sunset side exhibit worse trading performance than their counterparts across the time zone border as a function of seasonal variations in sunset time in ways consistent with the hypothesis that sleep disruption reduces mental alertness. Second, trading performance varies across latitudes and seasons in ways consistent with the hypothesis. Specifically, households in the northern part of the contiguous U.S. tend to trade stocks with lower average abnormal returns during the Summer, as the sun sets later in the north than in the south. No such effect is observed in the Winter, when the sun sets early in both regions. Third, households in DST-observing counties perform worse in the stock market immediately after the time adjustments compared to households in non-observing counties. Collectively, these tests provide consistent evidence that sleep disruption negatively affects retail investors' trading performance.

We also perform tests to distinguish several possible economic mechanisms underlying this effect. These tests identify investor attention as an important mechanism of the sleep disruption effect. In contrast, we do not find evidence supporting the effect of the sleep disruption on biases or trading patterns that are not usually associated with inattention, such as overreaction, attraction to lottery stocks, and the disposition effect.

Overall, our findings indicate that sleep disruption reduces mental alertness and attentional capacity, thereby harming trading performance. Our findings suggest that one source of reduced performance is reduced reactivity to earning news. On the other hand, our evidence suggests that several important behavioral biases that affect trading are not driven by a lack of mental alertness. This suggests that even alert investors are subject to important behavioral biases.

References

Alhola, P., and Polo-Kantola, P. (2007). Sleep Deprivation: Impact on Cognitive Performance. *Neuropsychiatric Disease and Treatment*, 3(5), 553–567.

Bahar, D. (2020). The Hardships of Long Distance Relationships: Time Zone Proximity and the Location of MNC's Knowledge-Intensive Activities. *Journal of International Economics*, 125, 103311.

Barber, B. M., and Odean, T. (2000). Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors. *Journal of Finance*, 55(2), 773–806.

Barber, B. M., and Odean, T. (2001). Boys Will Be Boys: Gender, Overconfidence, and Common Stock Investment. *Quarterly Journal of Economics*, 116(1), 261–292.

Barberis, N., and Huang, M. (2008). Stocks as Lotteries: The Implications of Probability Weighting for Security Prices. *American Economic Review*, 98(5), 2066–2100.

Barberis, N., and Xiong, W. (2009). What Drives the Disposition Effect? An Analysis of a Long-Standing Preference-Based Explanation. *Journal of Finance*, 64(2), 751–784.

Barnes, C. M., and Wagner, D. T. (2009). Changing to Daylight Saving Time Cuts into Sleep and Increases Workplace Injuries. *Journal of Applied Psychology*, 94(5), 1305–1317.

Bazley, W., Cuculiza, C., and Pisciotta, K. (2024). Sleep Disruptions and Information Processing in Financial Markets. *Management Science*.

Bernard, V. L., and Thomas, J. K. (1990). Evidence That Stock Prices Do Not Fully Reflect the Implications of Current Earnings for Future Earnings. *Journal of Accounting and Economics*, 13(4), 305–340.

Berument, H., and Dogan, N. (2011). Effects of Daylight Saving Time Changes on Stock Market Volatility: A Reply. *Psychological Reports*, 109(3), 863–878.

Birru, J. (2018). Day of the Week and the Cross-Section of Returns. *Journal of Financial Economics*, 130(1), 182–214.

Brunnermeier, M. K., and Parker, J. A. (2005). Optimal Expectations. *American Economic Review*, 95(4), 1092–1118.

Chang, Y.-C., Hsiao, P.-J., Ljungqvist, A., and Tseng, K. (2022). Testing Disagreement Models. *Journal of Finance*, 77(4), 2239–2285.

Chen, H., Jegadeesh, N., and Wermers, R. (2000). The Value of Active Mutual Fund Management: An Examination of the Stockholdings and Trades of Fund Managers. *Journal of Financial and Quantitative Analysis*, 35(3), 343–368.

Daniel, K., Hirshleifer, D., and Subrahmanyam, A. (1998). Investor Psychology and Security Market Under- and Overreactions. *Journal of Finance*, 53(6), 1839–1885.

deHaan, E., and Glover, A. (2024). Market Access and Retail Investment Performance. *The Accounting Review*, 99(6), 101–127.

Dhar, R., and Zhu, N. (2006). Up Close and Personal: Investor Sophistication and the Disposition Effect. *Management Science*, 52(5), 726–740.

DellaVigna, S., and Pollet, J. M. (2009). Investor Inattention and Friday Earnings Announcements. *Journal of Finance*, 64(2), 709–749.

Diamond, A. (2013). Executive Functions. *Annual Review of Psychology*, 64(1), 135–168.

Dijk, D. J., and Lockley, S. W. (2002). Invited Review: Integration of Human Sleep-Wake Regulation and Circadian Rhythmicity. *Journal of Applied Physiology*, 92(2), 852–862.

Dinges, D. F., Pack, F., Williams, K., Gillen, K. A., Powell, J. W., Ott, G. E., Aptowicz, C., and Pack, A. I. (1997). Cumulative Sleepiness, Mood Disturbance, and Psychomotor Vigilance Performance Decrements During a Week of Sleep Restricted to 4–5 Hours per Night. *Sleep*, 20(4), 267–277.

Døskeland, T. M., and Hvide, H. K. (2011). Do Individual Investors Have Asymmetric Information Based on Work Experience? *Journal of Finance*, 66(3), 1011–1041.

Edmans, A., Garcia, D., and Norli, Ø. (2007). Sports Sentiment and Stock Returns. *Journal of Finance*, 62(4), 1967–1998.

Edmans, A., Fernandez-Perez, A., Garel, A., and Indriawan, I. (2022). Music Sentiment and Stock Returns Around the World. *Journal of Financial Economics*, 145(2), 234–254.

Feng, L., and Seasholes, M. S. (2005). Do Investor Sophistication and Trading Experience Eliminate Behavioral Biases in Financial Markets? *Review of Finance*, 9(3), 305–351.

French, K. R. (1980). Stock Returns and the Weekend Effect. *Journal of Financial Economics*, 8(1), 55–69.

Gervais, S., and Odean, T. (2001). Learning to Be Overconfident. *Review of Financial Studies*, 14(1), 1–27.

Gibson, M., and Shrader, J. (2018). Time Use and Labor Productivity: The Returns to Sleep. *Review of Economics and Statistics*, 100(5), 783–798.

Giuntella, O., and Mazzonna, F. (2019). Sunset Time and the Economic Effects of Social Jetlag: Evidence from US Time Zone Borders. *Journal of Health Economics*, 65, 210–226.

Grinblatt, M., and Keloharju, M. (2001). How Distance, Language, and Culture Influence Stockholdings and Trades. *Journal of Finance*, 56(3), 1053–1073.

Grinblatt, M., Keloharju, M., and Linnainmaa, J. T. (2012). IQ, Trading Behavior, and Performance. *Journal of Financial Economics*, 104(2), 339–362.

Hamermesh, D. S., Myers, C. K., and Pocock, M. L. (2008). Cues for Timing and Coordination: Latitude, Letterman, and Longitude. *Journal of Labor Economics*, 26(2), 223–246.

Han, B., Hirshleifer, D., and Walden, J. (2022). Social Transmission Bias and Investor Behavior. *Journal of Financial and Quantitative Analysis*, 57(1), 390–412.

Harrison, Y., and Horne, J. A. (2000). The Impact of Sleep Deprivation on Decision Making: A Review. *Journal of Experimental Psychology: Applied*, 6(3), 236–249.

Hirshleifer, D., Lim, S. S., and Teoh, S. H. (2009). Driven to Distraction: Extraneous Events and Underreaction to Earnings News. *Journal of Finance*, 64(5), 2289–2325.

Hirshleifer, D., Lim, S. S., and Teoh, S. H. (2011). Limited Investor Attention and Stock Market Misreactions to Accounting Information. *Review of Asset Pricing Studies*, 1(1), 35–73.

Hirshleifer, D., and Sheng, J. (2022). Macro News and Micro News: Complements or Substitutes? *Journal of Financial Economics*, 145(3), 1006–1024.

Hirshleifer, D., and Shumway, T. (2003). Good Day Sunshine: Stock Returns and the Weather. *Journal of Finance*, 58(3), 1009–1032.

Hirshleifer, D., and Teoh, S. H. (2003). Limited Attention, Information Disclosure, and Financial Reporting. *Journal of Accounting and Economics*, 36(1–3), 337–386.

Huang, X. (2019). Mark Twain's Cat: Investment Experience, Categorical Thinking, and Stock Selection. *Journal of Financial Economics*, 131(2), 404–432.

Huberman, G. (2001). Familiarity Breeds Investment. *Review of Financial Studies*, 14(3), 659–680.

Hudson, A. N., Van Dongen, H. P. A., and Honn, K. A. (2020). Sleep Deprivation, Vigilant Attention, and Brain Function: A Review. *Neuropsychopharmacology*, 45(1), 21–30.

Hutton, A. P., Marcus, A. J., and Tehranian, H. (2009). Opaque Financial Reports, R^2, and Crash Risk. *Journal of Financial Economics*, 94(1), 67–86.

Janakiraman, R., Kamatham, H., Feurer, S., Rishika, R., Phogaat, B., and Girju, M. (2024). Spring Forward = Fall Back? The Effect of Daylight Saving Time Change on Consumers' Unhealthy Behavior. *Journal of Marketing*, 88(6), 64–84.

Kahneman, D. (1973). *Attention and Effort.* Prentice-Hall.

Kahneman, D. (2011). *Thinking, Fast and Slow.* Farrar, Straus and Giroux.

Kamstra, M. J., Kramer, L. A., and Levi, M. D. (2000). Losing Sleep at the Market: The Daylight Saving Anomaly. *American Economic Review*, 90(4), 1005–1011.

Kamstra, M. J., Kramer, L. A., and Levi, M. D. (2002). Losing Sleep at the Market: The Daylight Saving Anomaly: Reply. *American Economic Review*, 92(4), 1257–1263.

Kamstra, M. J., Kramer, L. A., and Levi, M. D. (2003). Winter Blues: A SAD Stock Market Cycle. *American Economic Review*, 93(1), 324–343.

Keim, D. B. (1983). Size-Related Anomalies and Stock Return Seasonality: Further Empirical Evidence. *Journal of Financial Economics*, 12(1), 13–32.

Keim, D. B., and Stambaugh, R. F. (1986). Predicting Returns in the Stock and Bond Markets. *Journal of Financial Economics*, 17(2), 357–390.

Korniotis, G. M., and Kumar, A. (2011). Do Older Investors Make Better Investment Decisions? *Review of Economics and Statistics*, 93(1), 244–265.

Kumar, A. (2009). Who Gambles in the Stock Market? *Journal of Finance*, 64(4), 1889–1933.

Lakonishok, J., Shleifer, A., and Vishny, R. W. (1994). Contrarian Investment, Extrapolation, and Risk. *Journal of Finance*, 49(5), 1541–1578.

Liu, Y., Wheaton, A., Chapman, D., Cunningham, T., and Lu, H. (2016). Prevalence of Healthy Sleep Duration Among Adults—United States, 2014. *Morbidity and Mortality Weekly Report*, 65(6), 137–141.

Meeus, J. H. (1991). *Astronomical Algorithms.* Willmann-Bell.

Odean, T. (1998). Are Investors Reluctant to Realize Their Losses? *Journal of Finance*, 53(5), 1775–1798.

Odean, T. (1999). Do Investors Trade Too Much? *American Economic Review*, 89(5), 1279–1298.

Owen, Z., Saeb, S., Short, S., Ong, N., Angi, G., Ghoreyshi, A., and Sullivan, S. S. (2022). Lingering Impacts on Sleep Following the Daylight Savings Time Transition in the Project Baseline Health Study. *Sleep Science and Practice*, 6(1), 13.

Pilcher, J. J., and Huffcutt, A. I. (1996). Effects of Sleep Deprivation on Performance: A Meta-Analysis. *Sleep*, 19(4), 318–326.

Posner, M. I., and Petersen, S. E. (1990). The Attention System of the Human Brain. *Annual Review of Neuroscience*, 13(1), 25–42.

Roenneberg, T. (2013). Chronobiology: The Human Sleep Project. *Nature*, 498(7455), 427–428.

Roenneberg, T., Kumar, C. J., and Merrow, M. (2007). The Human Circadian Clock Entrains to Sun Time. *Current Biology*, 17(2), R44–R45.

Rozeff, M. S., and Kinney, W. R. (1976). Capital Market Seasonality: The Case of Stock Returns. *Journal of Financial Economics*, 3(4), 379–402.

Saunders, E. M. (1993). Stock Prices and Wall Street Weather. *American Economic Review*, 83(5), 1337–1345.

Seasholes, M. S., and Zhu, N. (2010). Individual Investors and Local Bias. *Journal of Finance*, 65(5), 1987–2010.

Shefrin, H., and Statman, M. (1985). The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence. *Journal of Finance*, 40(3), 777–790.

Smith, A. C. (2016). Spring Forward at Your Own Risk: Daylight Saving Time and Fatal Vehicle Crashes. *American Economic Journal: Applied Economics*, 8(2), 65–91.

Sun, X., and Zhang, D. (2019). Later Sunsets and Disrupted Sleep: Evidence from Geographic Variations in Sunset Times. *Journal of Behavioral and Experimental Economics*, 82, 101495.

Thaler, R. H. (1987). Anomalies: The January Effect. *Journal of Economic Perspectives*, 1(1), 197–201.

Van Dongen, H. P. A., Maislin, G., Mullington, J. M., and Dinges, D. F. (2003). The Cumulative Cost of Additional Wakefulness: Dose-Response Effects on Neurobehavioral Functions and Sleep Physiology from Chronic Sleep Restriction and Total Sleep Deprivation. *Sleep*, 26(2), 117–126.

Wagner, D. T., Barnes, C. M., Lim, V. K. G., and Ferris, D. L. (2012). Lost Sleep and Cyberloafing: Evidence from the Laboratory and a Daylight Saving Time Quasi-Experiment. *Journal of Applied Psychology*, 97(5), 1068–1076.

Figure 1: Distribution of Households and Time Zone Borders

The figure presents the geographical distribution of 41,131 households in the contiguous United States based on the zip code information from the large discount brokerage data. The sample is located over four time zones (from left to right: Pacific, Mountain, Central, and Eastern time zone) and three different time zone borders dividing the time zones.

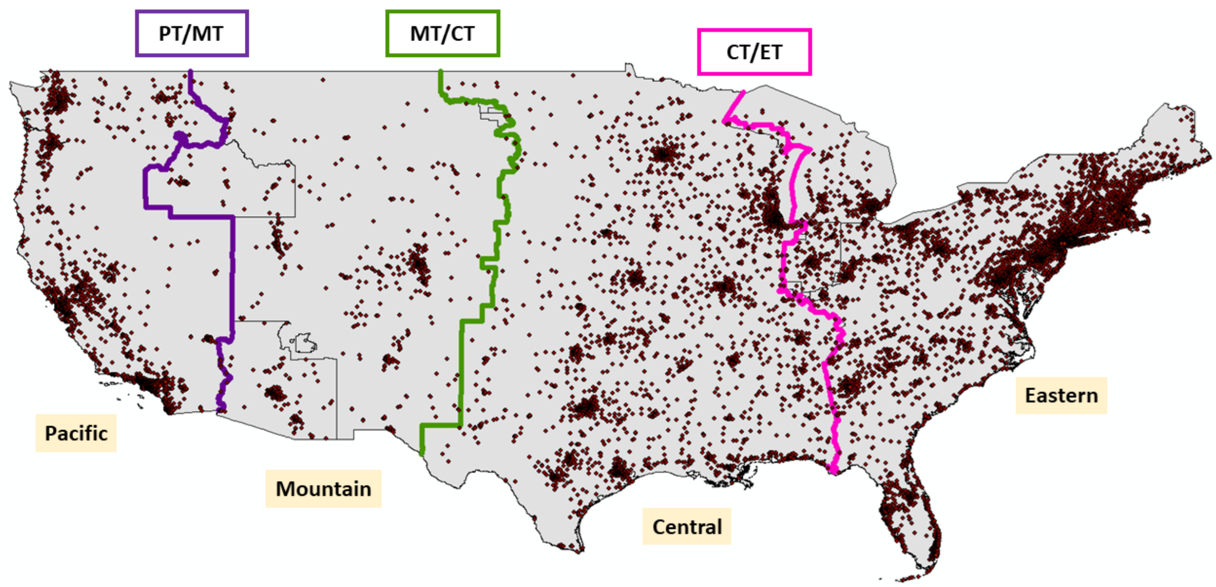

Figure 2: Local Sunset Discontinuity at Time Zone Border

The figure presents discontinuity of local sunset time at time zone border. Local sunset time is calculated based on the latitude and longitude of the zip code centroids in the sample. $LateSide_j$ is an indicator variable for households located on the east side of the relevant time zone, where the local sunset time is later compared to the west side. $SignedDistance_j$ measures how far a household is from the closest time zone border, with negative values indicating west side locations. The border, at $SignedDistance_j = 0$, is marked by a dashed reference line. 20 bins are created on each side of the border with sample sizes equalized across bins as much as possible. Circles represent the average local sunset time within $SignedDistance_j$ bins and are placed according to the mean $SignedDistance_j$ value of each bin. The two solid lines depict the regression relation between the average local sunset time and the $SignedDistance_j$ on either side of time zone borders derived by the following equation:

$$AverageLocalSunsetTime_j = \alpha + \beta_1 LateSide_j + \beta_2 SignedDistance_j + \varepsilon_j$$

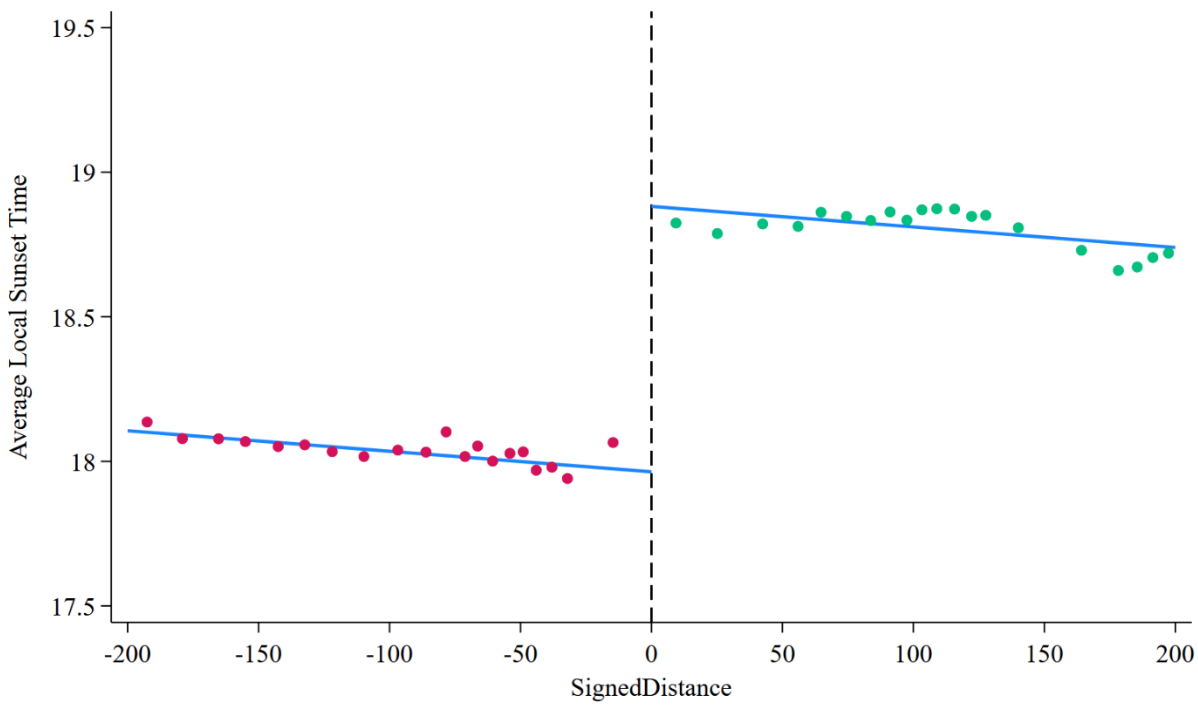

Figure 3: Trade Performance Discontinuity at Time Zone Border

This figure illustrates the discontinuity in trade performance at time zone border estimated by Equation (5). $TradePerform_{jt}$ is calculated using Equation (3) over 10-day windows. $LateSide_j$ is an indicator variable for households located on the east side of the relevant time zone, where the local sunset time is later compared to the west side. $SignedDistance_j$ measures how far a household is from the closest time zone border, with negative values indicating west side locations. The border, at $SignedDistance_j = 0$, is indicated by a dashed reference line. 20 bins are created on each side of the border with sample sizes equalized across bins as much as possible. Circles represent the average 10-day $TradePerform_{jt}$ within $SignedDistance_j$ bins and are placed according to the mean $SignedDistance_j$ value of each bin. $TradePerform_{jt}$ is orthogonalized with respect to control variables. The two solid lines depict the marginal effects of $SignedDistance_j$ on 10-day $TradePerform_{jt}$ by $LateSide_j$, while holding other control variables at their mean values. The marginal effects are estimated using the following regression:

$$TradePerform_{jt} = \alpha + \beta_1 LateSide_j + \beta_2 SignedDistance_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

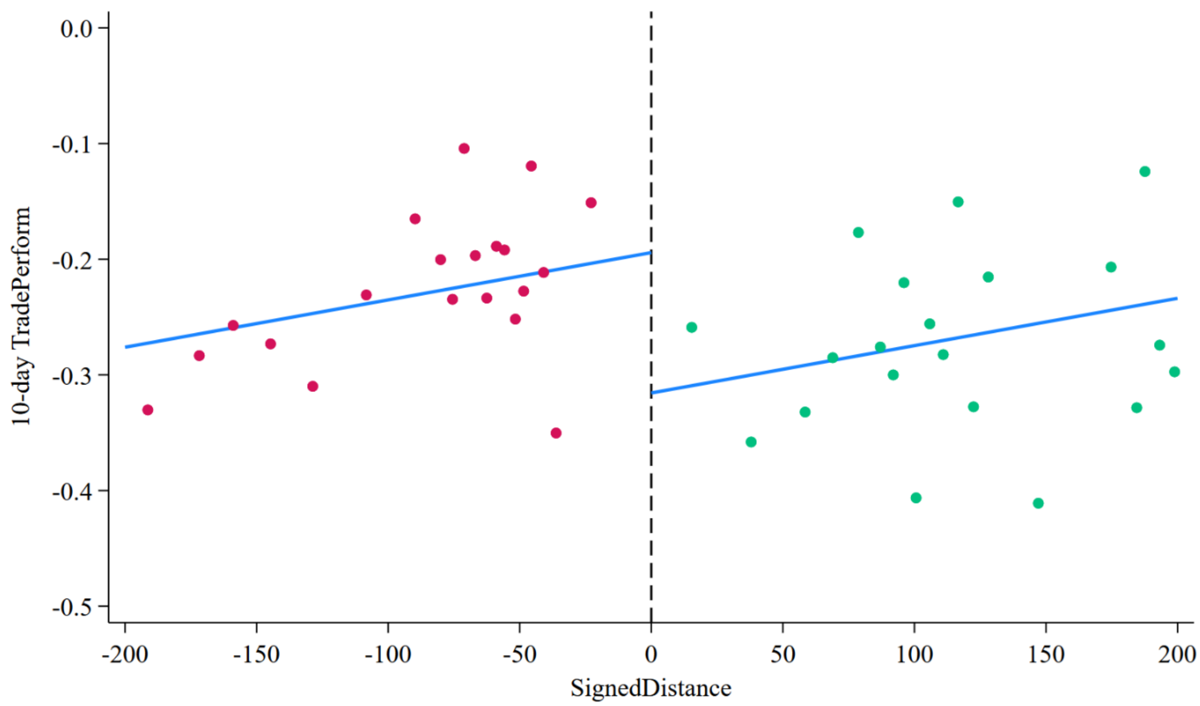

Figure 4: Pseudo-Time-Zone Borders

This figure illustrates three pseudo-time zone borders represented by colored lines (green, blue, and red) that align perfectly with state boundaries. The lighter and darker shades represent the original time zones.

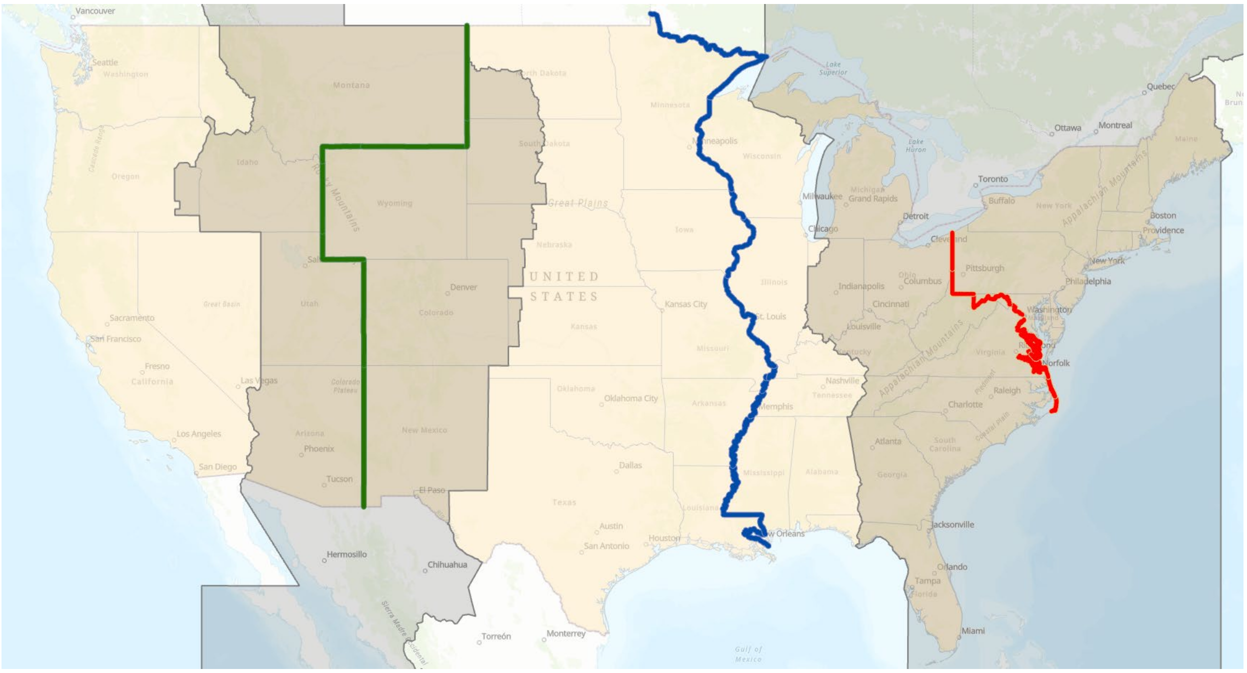

Figure 5: Sunset Variations across Latitudes: Northern vs. Southern Regions

This figure illustrates the variation in local sunset time over the year 1994 of two locations, Miami, Florida and Buffalo, New York. The center of Miami and Buffalo have coordinates (25.7617, -80.1918) and (42.8864, -78.8784) respectively. They share similar longitudes but have large differences in latitudes, i.e., Buffalo is located in the northern area and Miami in the southern area. This difference in latitude creates two intersects in the local sunset time over a year, in March and September.

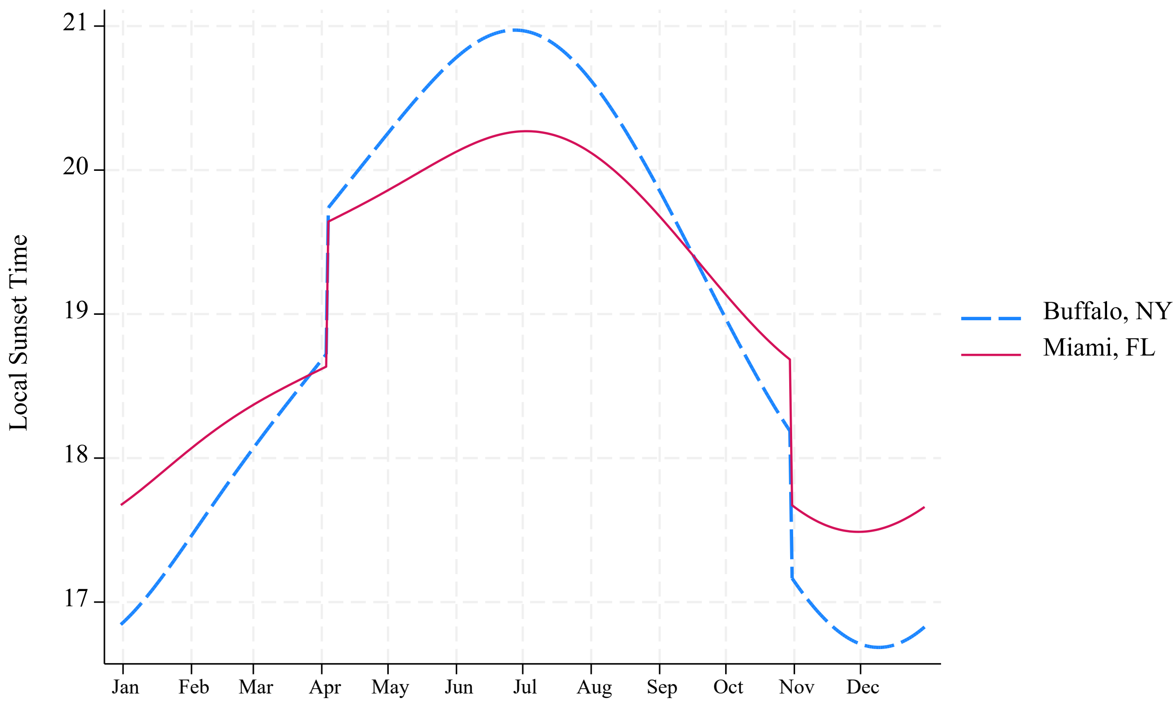

Table 1: Sample Distribution by Time Zone

This table presents summary statistics for the retail investors' trading data from a large discount brokerage. Household location is based on each household's zip code and its center coordinates. Stock information is obtained from CRSP. Each column represents the subsample from the specific time zone. In Panel A, households' location-related information is presented. Each row in panel A shows the number of distinct values of each variable. % in this table means the portion each subsample takes up in the entire sample. In Panel B, households' transaction-related information is presented. The standard deviations are in brackets.

Panel A: Household Distribution by areas

	(1)	(2)	(3)	(4)	(5)
	Pacific	Mountain	Central	Eastern	Entire
Households	13,619	2,369	8,821	16,322	41,131
	33.11%	5.76%	21.45%	39.68%	
Household-day Observation	279,042	44,866	178,432	339,967	842,307
	33.13%	5.33%	21.18%	40.36%	
Average # of transactions in 6 yr	29.13	26.54	29.10	29.75	29.22
State	6	11	21	24	49
County	142	162	766	787	1,853
Zip Code	1,798	651	2,712	5,086	10,247

Panel B: Transaction Distribution by areas

	(1)	(2)	(3)	(4)	(5)
	Pacific	Mountain	Central	Eastern	Entire
Transactions	381,323	60,009	246,625	465,403	1,153,360
	33.06%	5.20%	21.38%	40.35%	
Buys	207,371	32,699	136,082	256,983	633,135
Sells	173,952	27,310	110,543	208,420	520,225
Common Stocks Traded	7,560	4,650	7,417	8,542	9,722
Average Trade Volume	695.7412	639.9132	610.7390	621.5754	644.7330
	[1648.11]	[1874.37]	[1473.31]	[1682.37]	[1639.64]
Average Trade Price	30.4073	30.5936	29.6375	30.2711	30.1974
	[93.78]	[85.03]	[92.76]	[95.72]	[93.92]

Table 2: Summary Statistics

This table presents the description of main variables in empiric analyses. Panel A shows the summary statistics of variables and Panel B shows the correlation between variables. *Sunset* is the local sunset time of each household, measured in hours. *SignedDistance* measures how far a household is located from the closest time zone border, assigned negative if a household lies on the left side of the border. *TradePerform* variables are estimated by Equation (3). The market return is the daily CRSP value-weighted index total return and VIX is the daily VIX level from CBOE.

Panel A: Summary statistics of Main Variables

	Mean	std. dev.	Min	Max
Sunset (in hours)	18.71	1.37	15.74	21.94
SignedDistance (in kilometers)	180.56	625.24	-864.10	1510.31
10-day TradePerform (in %)	-0.190	1.882	-4.532	4.532
21-day TradePerform (in %)	-0.188	1.767	-3.657	3.657
Mktret (in %)	0.059	0.655	-3.407	3.307
VIX	14.909	2.953	9.310	36.200

Panel B: Correlation between Main Variables

	Sunset (in hours)	10-day TradePerform (in %)	21-day TradePerform (in %)	Mktret (in %)
10-day TradePerform (in %)	-0.014***			
21-day TradePerform (in %)	-0.015***	0.943***		
Mktret (in %)	-0.037***	0.031**	0.033***	
VIX	-0.087***	-0.037***	-0.038***	-0.121***

Table 3: Trading Performance and Sunset Time: Panel Regression

This table presents the results from estimating Equation (4). The dependent variable, $TradePerform_{jt}$, is calculated using Equation (3) over 10-day and 21-day window, indicated at the top of each column. $Sunset_{jt-1}$ is the local sunset time of each household on day t - 1, measured in hours. $Mktret_t$ and VIX_t are CRSP daily value-weighted market return and daily VIX level, respectively. $January_t$ is a dummy variable that equals 1 if day t is in January and 0 otherwise. SAD_t is measured following Kamstra, Kramer, and Levi (2003). We calculate the number of nighttime hours for each household's location and date, then subtract 12 (approximately the average number of nighttime hours over the entire year at any location). $Fall_t$ is a dummy variable equal to 1 if the trade date falls between September 21 and December 20, following Kamstra, Kramer, and Levi (2003). We incorporate household fixed effects. All regressions include the year and day of the week fixed effects. We restrict the household to having at least 11 transactions over 6 years. Transactions in December are excluded. Standard errors are clustered at the household level. *t*-statistics in parentheses. Significance is indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

$$TradePerform_{jt} = \alpha + \beta Sunset_{j,t-1} + X_t'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable		10 days			21 days	
Sunset	-0.011***	-0.014***	-0.020***	-0.009***	-0.012***	-0.021***
	(-5.52)	(-6.38)	(-4.83)	(-4.86)	(-5.93)	(-5.31)
Mktret		0.069***	0.069***		0.072***	0.071***
		(12.91)	(12.82)		(13.63)	(13.57)
VIX		-0.007***	-0.008***		-0.006***	-0.006***
		(-5.50)	(-5.76)		(-4.33)	(-4.61)
January		-0.018**	-0.038***		-0.025***	-0.035***
		(-2.02)	(-3.12)		(-2.90)	(-3.07)
SAD			0.000			-0.007
			(0.03)			(-1.02)
Fall			-0.032***			-0.027***
			(-4.24)			(-3.77)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.0312	0.0319	0.0320	0.0345	0.0353	0.0354
Obs.	654,089	653,587	653,587	652,481	651,979	651,979

Table 4: The Effect of Sleep on Trading: RDD

This table presents the results from estimating Equation (5). The dependent variable, $TradePerform_{jt}$, is calculated using Equation (3) over various 10-day and 21-day windows, indicated at the top of each column. $LateSide_j$ is an indicator variable for households located on the east side of the relevant time zone, where the local sunset time is later compared to the west side. $SignedDistance_j$ measures how far a household is from the closest time zone border, with negative values indicating west side locations. Bandwidths for $SignedDistance_j$ range from -200km to 200km, with time zone borders set at 0 as cutoffs. We control for household characteristics such as the log of number of trades, client segment, age, gender, income, number of stocks traded, average number of stocks held in the monthly portfolio, and average equity value held in the monthly portfolio. All columns include trade date fixed effects, state fixed effects, and geographical group fixed effects. An indicator for financial hubs is included. The sample is restricted to households with at least 11 transactions over 6 years. We exclude transactions in December from this analysis. Standard errors are robust and clustered by distance from the time zone border, with households grouped in 10-kilometer increments. *t*-statistics are shown in parentheses. Significance is indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

$$TradePerform_{jt} = \alpha + \beta_1 LateSide_j + \beta_2 SignedDistance_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

Dependent Variable	(1) 10 days	(2) 21 days
LateSide	-0.121**	-0.113**
	(-2.16)	(-2.03)
SignedDistance	0.000	0.000
	(1.36)	(1.38)
Latitude	0.006	0.005
	(0.36)	(0.32)
$\ln(Trade)$	0.014	0.016
	(0.78)	(0.89)
Client segment: Affluent	-0.176***	-0.178***
	(-5.99)	(-6.03)
Client segment: Active	-0.115***	-0.116***
	(-4.93)	(-4.59)
Age	-0.001	-0.001
	(-1.41)	(-1.61)
Gender	-0.076*	-0.056
	(-1.87)	(-1.43)
Income	-0.000	-0.001
	(-1.22)	(-1.43)
Number of Stocks Traded	0.001	0.001
	(1.24)	(1.27)
Average Number of Stocks Held	-0.008***	-0.009***
	(-3.80)	(-4.06)
Average Equity Held	0.093	0.087
	(1.53)	(1.45)
Trade date FE	Yes	Yes
State FE	Yes	Yes
Financial Hubs FE	Yes	Yes
Adj.R^2	0.0193	0.0212
Obs.	73,334	73,155

Table 5: RDD Using States Spanning Two Time Zones

This table presents the results from estimating Equation (5) using samples from states that observe two time zones. The dependent variable, $TradePerform_{jt}$, is calculated using Equation (3) over 10-day windows. $LateSide_j$ is an indicator variable for households located on the east side of the relevant time zone, where the local sunset time is later compared to the west side. $SignedDistance_j$ measures how far a household is from the closest time zone border, with negative values indicating west side locations. We control household characteristics such as the log of number of trades, client segment, age, gender, income, number of stocks traded, average number of stocks held in the monthly portfolio, and average equity value held in the monthly portfolio. All columns include trade date fixed effects, state fixed effects, and geographical group fixed effects. An indicator for financial hubs is included. The sample is restricted to households with at least 11 transactions over 6 years. We exclude transactions in December from this analysis. Standard errors are robust and clustered by distance from the time zone border, with households grouped in 10-kilometer increments. t-statistics are shown in parentheses. Significance is indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

$$TradePerform_{jt} = \alpha + \beta_1 LateSide_j + \beta_2 SignedDistance_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

	(1) Two time zone states
LateSide	-0.098**
	(-2.09)
SignedDistance	0.000*
	(1.92)
Latitude	0.012
	(0.71)
$\ln(Trade)$	0.047**
	(2.22)
Client segment: Affluent	-0.197***
	(-4.67)
Client segment: Active	-0.158***
	(-5.23)
Age	-0.001
	(-0.84)
Gender	-0.016
	(-0.38)
Income	-0.000
	(-1.40)
Number of Stocks Traded	-0.000
	(-0.03)
Average Number of Stocks Held	-0.004
	(-1.12)
Average Equity Held	-0.154
	(-0.87)
Trade date FE	Yes
State FE	Yes
Financial Hubs FE	Yes
Adj. R^2	0.0232
Obs.	40,500

Table 6: RDD Using Pseudo-Time-Zone Borders

This table presents the results from estimating Equation (5) using pseudo time zone borders to measure cut point and running variable of RDD. The dependent variable, $TradePerform_{jt}$, is calculated using Equation (3) over 10-day windows. $LateSide_j$ is an indicator variable for households located on the east side of the relevant pseudo time zone, where the local sunset time is later compared to the west side. $SignedDistance_j$ measures how far a household is from the closest pseudo time zone border, with negative values indicating west side locations. Bandwidths for $SignedDistance_j$ range from -200km to 200km, with pseudo time zone borders set at 0 as cutoffs. We control for household characteristics such as the log of number of trades, client segment, age, gender, income, number of stocks traded, average number of stocks held in the monthly portfolio, and average equity value held in the monthly portfolio. All columns include trade date fixed effects, state fixed effects, and geographical group fixed effects. An indicator for financial hubs is included. The sample is restricted to households with at least 11 transactions over 6 years. We exclude transactions in December from this analysis. Standard errors are robust and clustered by distance from the time zone border, with households grouped in 10-kilometer increments. *t*-statistics are shown in parentheses. Significance is indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

$$TradePerform_{jt} = \alpha + \beta_1 LateSide_j + \beta_2 SignedDistance_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

	(1) Pseudo Time zone borders
LateSide	-0.064
	(-0.34)
SignedDistance	0.000
	(0.82)
Latitude	0.012
	(0.75)
$\ln(Trade)$	0.012
	(0.54)
Client segment: Affluent	-0.186***
	(-6.24)
Client segment: Active	-0.126***
	(-5.13)
Age	-0.001
	(-1.06)
Gender	-0.070
	(-1.62)
Income	-0.000
	(-1.17)
Number of Stocks Traded	0.001
	(1.27)
Average Number of Stocks Held	-0.009***
	(-3.91)
Average Equity Held	0.095
	(1.53)
Trade date FE	Yes
State FE	Yes
Financial Hubs FE	Yes
Adj. R^2	0.0209
Obs.	68,308

Table 7: RDD with Seasonal Changes

This table presents the results from estimating Equation (5). Column (1) shows the result of the entire sample. Column (2) only includes the summer season, April, May, June, July, August, and September. Column (3) includes the Winter season, October, November, January, February, and March. The dependent variable, $TradePerform_{jt}$, is calculated using Equation (3) over 10-day window. $LateSide_j$ is an indicator variable for households located on the east side of the relevant time zone, where the local sunset time is later compared to the west side. $SignedDistance_j$ measures how far a household is from the closest time zone border, with negative values indicating west side locations. Bandwidths for $SignedDistance_j$ range from -200km to 200km, with time zone borders set at 0 as cutoffs. We control for household characteristics such as the log of number of trades, client segment, age, gender, income, number of stocks traded, average number of stocks held in the monthly portfolio, and average equity value held in the monthly portfolio. All columns include trade date fixed effects, state fixed effects, and geographical group fixed effects. An indicator for financial hubs is included. The sample is restricted to households with at least 11 transactions over 6 years. We exclude transactions in December from this analysis. Standard errors are robust and clustered by distance from the time zone border, with households grouped in 10-kilometer increments. *t*-statistics are shown in parentheses. Significance is indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

$$TradePerform_{jt} = \alpha + \beta_1 LateSide_j + \beta_2 SignedDistance_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

	(1) Entire	(2) Summer	(3) Winter
LateSide	-0.121**	-0.146*	-0.096
	(-2.16)	(-1.92)	(-1.31)
SignedDistance	0.000	0.001	0.000
	(1.36)	(1.64)	(0.71)
Latitude	0.006	0.005	0.006
	(0.36)	(0.27)	(0.30)
$\ln(Trade)$	0.014	0.042*	-0.015
	(0.78)	(1.82)	(-0.71)
Client segment: Affluent	-0.176***	-0.170***	-0.184***
	(-5.99)	(-4.09)	(-4.95)
Client segment: Active	-0.115***	-0.130***	-0.097***
	(-4.93)	(-4.35)	(-3.33)
Age	-0.001	-0.002*	-0.001
	(-1.41)	(-1.74)	(-0.62)
Gender	-0.076*	-0.106**	-0.041
	(-1.87)	(-2.17)	(-0.90)
Income	-0.000	-0.001	-0.000
	(-1.22)	(-1.31)	(-0.85)
Number of Stocks Traded	0.001	0.000	0.001**
	(1.24)	(0.44)	(2.03)
Average Number of Stocks Held	-0.008***	-0.007**	-0.010***
	(-3.80)	(-2.40)	(-4.93)
Average Equity Held	0.093	0.082	0.101
	(1.53)	(1.01)	(1.62)
Trade date FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Financial Hubs FE	Yes	Yes	Yes
Adj. R^2	0.0193	0.0206	0.0181
Obs.	73,334	37,985	35,349

Table 8: Northern vs. Southern Depending on Sunset Seasonality

This table presents the results from estimating Equation (6). The dependent variable $TradePerform_{jt}$ is calculated by Equation (3) over 10-day window. $NorthernPart_j$ equals one if a household is in the top 25% latitude and zero if in the bottom 25%. Column (1) shows the result of the entire sample excluding March and September transactions. Column (2) only includes the summer season, April, May, June, July, and August. Column (3) includes the Winter season, October, November, December, January, and February. We control for household characteristics such as the log of number of trades, client segment, age, gender, income, number of stocks traded, average number of stocks held in the monthly portfolio, and average equity value held in the monthly portfolio. We include trade date fixed effects and state fixed effects. Longitude control includes linear longitude and categorical groups dividing each time zone into three parts by two vertical longitude lines. We also include an indicator for financial hubs counties. We restrict the household to having at least 11 transactions over 6 years. Standard errors are robust and clustered at county level. *t*-statistics are shown in parentheses. Significance is indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

$$TradePerform_{jt} = \alpha + \beta NorthernPart_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

	(1) Entire	(2) Summer	(3) Winter
NorthernPart	-0.129	-0.410***	0.051
	(-0.73)	(-3.57)	(0.18)
Longitude	-0.005	-0.003	-0.006
	(-0.58)	(-0.33)	(-0.54)
$\ln(Trade)$	0.006	0.048***	-0.034***
	(0.59)	(3.63)	(-2.77)
Client segment: Affluent	-0.142***	-0.153***	-0.133***
	(-9.63)	(-7.95)	(-6.86)
Client segment: Active	-0.117***	-0.130***	-0.104***
	(-7.47)	(-6.78)	(-5.21)
Age	-0.001***	-0.003***	-0.000
	(-2.88)	(-3.58)	(-0.85)
Gender	-0.014	0.000	-0.026
	(-0.73)	(0.02)	(-1.10)
Income	-0.000*	-0.000	-0.000
	(-1.81)	(-1.65)	(-1.38)
Number of Stocks Traded	0.000	-0.000	0.001***
	(0.71)	(-1.16)	(2.66)
Average Number of Stocks Held	-0.003***	-0.003**	-0.003**
	(-2.79)	(-2.55)	(-2.47)
Average Equity Held	0.037***	0.055***	0.022
	(3.12)	(4.02)	(1.56)
Trade date FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Longitude group FE	Yes	Yes	Yes
Financial Hubs FE	Yes	Yes	Yes
Adj. R^2	0.0157	0.0171	0.0143
Obs.	224,100	108,938	115,162

Table 9: Time-Series and Difference-in-Differences Analysis of DST Changes

This table presents the effect of Daylight Saving Times (DST) changes on trade performance. The dependent variables $TradePerform_{jt}$ is calculated by Equation (3) over 10-day and 21-day window. Column (1) and (2) use 10-day trade performance as a dependent variable. Column (1) includes trades around spring daylight saving time transitions and Column (2) includes trades around fall daylight saving time transitions. Column (3) and (4) use 21-day trade performance measure as a dependent variable and include trades around the spring and fall transitions, respectively. In Panel A, we compare the trading performance of all households in DST-observing states before and after DST changes. $AfterDST_t$ equals one if a trade date *t* is within 5 trading days after daylight saving time transitions and zero if within 5 trading days before the transitions. Panel B presents the results from Difference-in-Difference analysis based on Equation (7). $DSTcounty_j$ equals one if a household j lives in a county that observes daylight saving time and zero otherwise. We use households located in Arizona and California where Arizona does not observe daylight saving time, but California does. We control for household characteristics such as the log of number of trades, client segment, age, gender, income, number of stocks traded, average number of stocks held in the monthly portfolio, and average equity value held in the monthly portfolio. We include $Mktret_t$ and VIX_t to control for CRSP daily value-weighted market return and daily VIX level and incorporate year fixed effects and day of the week fixed effects. We focus on the household having at least 11 transactions over 6 years. Standard errors are robust and clustered at county level. *t*-statistics are shown in parentheses. Significance is indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

$$TradePerform_{jt} = \alpha + \beta_1 AfterDST_t + X_t'\delta_1 + X_j'\delta_2 + \gamma_t + \varepsilon_{jt}$$

Panel A: Time-Series Analysis of DST changes				
	(1)	(2)	(3)	(4)
Dependent Variable	10-days		21-days	
	Spring	Fall	Spring	Fall
After DST	-0.209***	0.036	-0.205***	0.058**
	(-7.03)	(1.29)	(-6.93)	(2.25)
Mktret	0.056***	-0.005	0.059***	0.003
	(3.66)	(-0.21)	(4.02)	(0.13)
VIX	0.019*	-0.047***	0.021**	-0.042***
	(1.75)	(-2.94)	(2.07)	(-3.02)
Household Characteristics	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Adj. R^2	0.0143	0.0116	0.0162	0.0124
Obs.	23,823	23,229	23,760	23,192

(Table 9 continued.)

$$TradePerform_{jt} = \alpha + \beta_1 AfterDST_t + \beta_2 DSTcounty_j + \beta_3 AfterDST_t \times DSTcounty_j$$
$$+X_t'\delta_1 + X_j'\delta_2 + \gamma_t + \varepsilon_{jt}$$

Panel B: Difference-in-Difference Analysis of DST changes using Two States				
	(1)	(2)	(3)	(4)
Dependent Variable	10 days		21 days	
	Spring	Fall	Spring	Fall
After DST $\times$ DST county	-0.280***	-0.191*	-0.295**	-0.096
	(-3.62)	(-1.83)	(-2.07)	(-1.08)
After DST	0.059	0.226***	0.079	0.148**
	(0.96)	(2.84)	(0.60)	(2.29)
DST county	0.035	0.028	0.009	0.005
	(0.59)	(0.49)	(0.09)	(0.09)
Mktret	0.071**	-0.008	0.077***	0.002
	(2.65)	(-0.29)	(3.10)	(0.06)
VIX	0.035*	-0.068**	0.036**	-0.053**
	(1.87)	(-2.40)	(2.02)	(-2.09)
Household Characteristics	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes
Adj. R^2	0.0170	0.0084	0.0180	0.0099
Obs.	7,150	7,146	7,135	7,135

Table 10: Mental Alertness: Evidence from Earnings News

This table presents the results from estimating Equation (8). The dependent variable $EAtrading_{jt}$ takes value 1 if household j trades at least one stock on day t which has announced its quarterly earnings, given household j trades any stock on day t. At the top of each column, the numbers in brackets represent the number of days relative to quarterly earnings announcement dates. For this analysis, we exclude the trading in March, June, September, and December, when the earnings announcements are typically rare. $LateSide_j$ is an indicator variable for households located on the east side of the relevant time zone, where the local sunset time is later compared to the west side. $SignedDistance_j$ measures how far a household is from the closest time zone border, with negative values indicating west side locations. Bandwidths for $SignedDistance_j$ range from -200km to 200km, with time zone borders set at 0 as cutoffs. We control for household characteristics such as the log of number of trades, client segment, age, gender, income, number of stocks traded, average number of stocks held in the monthly portfolio, and average equity value held in the monthly portfolio. All columns include trade date fixed effects, state fixed effects, and geographical group fixed effects. An indicator for financial hubs is included. The sample is restricted to households with at least 11 transactions over 6 years. Standard errors are robust and clustered by distance from the time zone border, with households grouped in 10-kilometer increments and by trading day. *t*-statistics are shown in parentheses. Significance is indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

$$EAtrading_{jt} = \alpha + \beta_1 LateSide_j + \beta_2 SignedDistance_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

	(1) [-5, -1]	(2) [0, 2]	(3) [3, 5]	(4) [6, 10]
LateSide	-0.014	-0.027**	-0.014	-0.012
	(-0.98)	(-2.50)	(-1.20)	(-0.97)
SignedDistance	0.000	0.000	0.000**	0.000*
	(0.86)	(1.67)	(2.36)	(1.73)
Latitude	-0.007*	0.002	-0.002	-0.003
	(-1.92)	(0.71)	(-0.81)	(-0.91)
$\ln(Trade)$	-0.004	-0.001	-0.007***	-0.005*
	(-0.91)	(-0.27)	(-2.82)	(-1.77)
Client segment: Affluent	0.004	0.006	0.005	0.008*
	(0.83)	(1.09)	(1.25)	(1.98)
Client segment: Active	0.001	0.007	0.001	0.009**
	(0.15)	(1.37)	(0.35)	(2.34)
Age	0.000	-0.000	0.000	0.000
	(0.88)	(-0.85)	(0.16)	(1.11)
Gender	0.006	0.002	0.002	0.014*
	(0.65)	(0.29)	(0.32)	(1.74)
Income	0.000	-0.000	0.000	0.000
	(0.52)	(-0.55)	(0.33)	(0.94)
Number of Stocks Traded	0.000**	0.000**	0.000***	0.000**
	(2.29)	(2.55)	(3.00)	(2.68)
Average Number of Stocks Held	0.000	0.000	0.000	0.000
	(0.92)	(1.12)	(1.41)	(1.23)
Average Equity Held	-0.009	-0.019**	-0.011	-0.019
	(-0.73)	(-2.53)	(-1.12)	(-1.62)
Trade date FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Financial Hubs FE	Yes	Yes	Yes	Yes
Adj. R^2	0.0574	0.0572	0.0419	0.0685
Obs.	58,358	58,358	58,358	58,358

Table 11: Effect of Investor Attention on Trade Performance

This table presents the results from estimating Equation (9), interacting $EAtrading_{jt}$ with the existing RDD variables and household characteristics variables. The dependent variable $TradePerform_{jt}$ is calculated by Equation (3) over 10-day and 21-day window. The independent variable $EAtrading_{jt}$ equals 1 if household j trades at least one stock on day t that announced its quarterly earnings within the previous two days, given that household j trades any stock on day t. In Columns (2) and (4), we use regression discontinuity design. $LateSide_j$ is an indicator variable for households located on the east side of the relevant time zone, where the local sunset time is later compared to the west side. $SignedDistance_j$ measures how far a household is from the closest time zone border, with negative values indicating west side locations. In all columns, we analyze households within bandwidths of $SignedDistance_j$, ranging from -200 km to 200 km, using time zone borders set at 0 as the cutoffs. We control for household characteristics such as the log of number of trades, client segment, age, gender, income, number of stocks traded, average number of stocks held in the monthly portfolio, and average equity value held in the monthly portfolio. All columns include trade date fixed effects, state fixed effects, and geographical group fixed effects. An indicator for financial hubs is included. The sample is restricted to households with at least 11 transactions over 6 years. We exclude transactions in December from this analysis. Standard errors are robust and clustered by distance from the time zone border, with households grouped in 10-kilometer increments. *t*-statistics are shown in parentheses. Significance is indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

$$TradePerform_{jt} = \alpha + \beta_1 EAtrading_{jt} + \beta_2 LateSide_j + \beta_3 SignedDistance_j$$
$$+\beta_4 EAtrading_{jt} \times LateSide_j + \beta_5 EAtrading_{jt} \times SignedDistance_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

	(1)	(2)	(3)	(4)
Dependent Variable	10-days		21-days	
EAtrading	0.031	0.120**	0.018	0.097*
	(1.22)	(2.42)	(0.68)	(1.70)
LateSide		-0.099		-0.093
		(-1.63)		(-1.51)
SignedDistance		0.001		0.001
		(1.63)		(1.39)
EAtrading × LateSide		-0.229**		-0.202*
		(-2.12)		(-1.80)
EAtrading × SignedDistance		0.001		0.001
		(1.63)		(1.39)
Household Characteristics	Yes	Yes	Yes	Yes
Trade date FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Financial Hubs	Yes	Yes	Yes	Yes
Bandwidth	200km	200km	200km	200km
Adj. R^2	0.0193	0.0194	0.0211	0.0212
Obs.	73,334	73,334	73,155	73,155

Table 12: Sleep Disruption and Overreaction

This table presents results of regression discontinuity model in Equation (5) with different dependent variables. The dependent variable $NetPurchase_{ijm}$ is the cumulative net purchases (the number of shares of stock i purchased minus the number of shares sold by investor j) in month m. $Glamour_{im}$ indicates whether stock i is in the bottom decile of the financial ratio in month m. For Columns (1) and (2), it takes the value of one if stock i is in the bottom decile of B/M in month m and zero if stock i is in the top decile. For Columns (3) and (4), it takes the value of one if stock i is in the bottom decile of C/P in month m and zero if stock i is in the top decile. For Columns (5) and (6), it takes the value of one if stock i is in the bottom decile of E/P in month m and zero if stock i is in the top decile. $LateSide_j$ is an indicator variable for households located on the east side of the relevant time zone, where the local sunset time is later compared to the west side. $SignedDistance_j$ measures how far a household is from the closest time zone border, with negative values indicating west side locations. Bandwidths for $SignedDistance_j$ range from -200km to 200km, with time zone borders set at 0 as cutoffs. We control for household characteristics such as the log of number of trades, client segment, age, gender, income, number of stocks traded, average number of stocks held in the monthly portfolio, and average equity value held in the monthly portfolio. All columns include year-month fixed effects, state fixed effects, and geographical group fixed effects. An indicator for financial hubs is included. The sample is restricted to households with at least 11 transactions over 6 years. Standard errors are robust and clustered by distance from the time zone border, with households grouped in 10-kilometer increments, and month level. *t*-statistics are shown in parentheses. Significance is indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

$$\begin{aligned} NetPurchase_{ijm} = {} & \alpha + \beta_1 Glamour_{im} + \beta_2 LateSide_j + \beta_3 SignedDistance_j \\ & + \beta_4 Glamour_{im} \times LateSide_j + \beta_5 Glamour_{im} \times SignedDistance_j + X_j'\delta + \gamma_m + \gamma_j + \varepsilon_{ijm} \end{aligned}$$

	(1)	(2)	(3)	(4)	(5)	(6)
	B/M		C/P		E/P	
Glamour	1.831	-13.566	13.568***	-3.620	22.092***	-19.936
	(0.33)	(-0.34)	(3.30)	(-0.38)	(4.05)	(-0.63)
LateSide		-24.456**		-0.495		13.044
		(-2.70)		(-0.04)		(1.31)
SignedDistance		0.145***		-0.015		-0.032
		(2.92)		(-0.22)		(-0.81)
Glamour × LateSide		24.474***		-3.620		-5.094
		(2.83)		(-0.38)		(-0.25)
Glamour × SignedDistance		-0.148***		-3.954		-0.016
		(-2.84)		(-0.23)		(-0.21)
Firm FE	No	Yes	No	Yes	No	Yes
Year-Month FE	No	Yes	No	Yes	No	Yes
Adj.R^2	0.00	0.130	0.00	0.075	0.002	0.203
Obs.	17,898	17,898	10,219	10,219	8,201	8,201

Table 13: Sleep Disruption and Attraction to Lottery Stocks

This table presents the results of regression discontinuity model in Equation (5) with various dependent variables. The dependent variable LP_{jm} is the ratio of buy volume for lottery stocks to total buy volume for all stocks in the month m portfolio. Following Kumar (2009), we define lottery stocks as those with either above-median idiosyncratic volatility or above-median idiosyncratic skewness in month m. In Column (1), LP_{jm} is calculated using stocks with above-median idiosyncratic volatility, while in Column (2) it is calculated using stocks with above-median idiosyncratic skewness. $LateSide_j$ is an indicator variable for households located on the east side of the relevant time zone, where the local sunset time is later compared to the west side. $SignedDistance_j$ measures how far a household is from the closest time zone border, with negative values indicating west side locations. Bandwidths for $SignedDistance_j$ range from -200km to 200km, with time zone borders set at 0 as cutoffs. We control for household characteristics such as the log of number of trades, client segment, age, gender, income, number of stocks traded, average number of stocks held in the monthly portfolio, and average equity value held in the monthly portfolio. All columns include year-month fixed effects, state fixed effects, and geographical group fixed effects. An indicator for financial hubs is included. The sample is restricted to households with at least 11 transactions over 6 years. We exclude transactions in December from this analysis. Standard errors are robust and clustered by distance from the time zone border, with households grouped in 10-kilometer increments. t-statistics are shown in parentheses. Significance is indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

$$LP_{jm} = \alpha + \beta_1 LateSide_j + \beta_2 SignedDistance_j + X_j'\delta + \gamma_m + \gamma_j + \varepsilon_{jm}$$

Dependent Variable	(1) Idiosyncratic Volatility	(2) Idiosyncratic Skewness
LateSide	0.754	-0.339
	(0.62)	(-0.51)
SignedDistance	0.000	0.001
	(0.07)	(0.40)
Latitude	0.238	-0.021
	(0.96)	(-0.12)
$\ln(Trade)$	6.255***	5.505***
	(13.88)	(16.70)
Client segment: Affluent	-1.964***	-0.795***
	(-7.34)	(-4.11)
Client segment: Active	-1.157	-0.629
	(-1.42)	(-1.05)
Age	-0.037***	0.016**
	(-3.60)	(2.48)
Gender	0.969	0.870**
	(1.22)	(2.02)
Income	-0.008*	-0.003
	(-1.78)	(-0.97)
Number of Stocks Traded	0.056**	0.072***
	(2.43)	(5.58)
Average Number of Stocks Held	-0.127***	-0.079***
	(-2.87)	(-3.33)
Average Equity Held	-1.177	0.000*
	(-0.59)	(1.76)
Year-Month FE	Yes	Yes
State FE	Yes	Yes
Financial Hubs FE	Yes	Yes
Adj.R^2	0.0610	0.0549
Obs.	105,349	105,349

Table 14: Sleep Disruption and Disposition Effect

This table presents the results of regression discontinuity model in Equation (5) with various dependent variables. The dependent variable $Disposition_j$ represents one of the disposition effect measures for household j Following Dhar and Zhu (2006), we calculate each investor's proportion of gains realized (PGR), proportion of losses realized (PLR), and the disposition effect (DE), which are used in Columns (1), (2), and (3), respectively. $LateSide_j$ is an indicator variable for households located on the east side of the relevant time zone, where the local sunset time is later compared to the west side. $SignedDistance_j$ measures how far a household is from the closest time zone border, with negative values indicating west side locations. Bandwidths for $SignedDistance_j$ range from -200km to 200km, with time zone borders set at 0 as cutoffs. We control for household characteristics such as the log of number of trades, client segment, age, gender, income, number of stocks traded, average number of stocks held in the monthly portfolio, and average equity value held in the monthly portfolio. All columns include state fixed effects and geographical group fixed effects. An indicator for financial hubs is included. The sample is restricted to households with at least 11 transactions over 6 years. Standard errors are robust and clustered by distance from the time zone border, with households grouped in 10-kilometer increments. *t*-statistics are shown in parentheses. Significance is indicated by * (p < 0.10), ** (p < 0.05), and *** (p < 0.01).

$$Disposition_j = \alpha + \beta_1 LateSide_j + \beta_2 SignedDistance_j + X_j'\delta + \gamma_j + \varepsilon_j$$

Dependent Variable	(1) PGR	(2) PLR	(3) DE
LateSide	0.009	-0.070	0.079
	(0.30)	(-1.25)	(1.49)
SignedDistance	0.000	0.000	-0.000
	(1.04)	(1.65)	(-1.01)
Latitude	0.003	0.002	0.001
	(0.29)	(0.14)	(0.08)
$\ln(Trade)$	-0.031***	0.036**	-0.067***
	(-3.30)	(2.26)	(-4.44)
Client segment: Affluent	-0.072***	-0.109***	0.037
	(-4.38)	(-6.25)	(1.44)
Client segment: Active	-0.011	-0.055***	0.044
	(-0.54)	(-2.75)	(1.53)
Age	-0.001	0.000	-0.001
	(-1.68)	(0.97)	(-1.63)
Gender	-0.009	-0.024	0.015
	(-0.42)	(-1.00)	(0.46)
Income	-0.000	-0.000	-0.000
	(-0.67)	(-0.29)	(-0.24)
Number of Stocks Traded	-0.002***	-0.002***	0.000
	(-5.11)	(-3.27)	(0.09)
Average Number of Stocks Held	-0.012***	-0.012***	0.000
	(-7.08)	(-8.01)	(0.34)
Average Equity Held	0.215***	0.244***	-0.029
	(3.19)	(3.09)	(-0.61)
State FE	Yes	Yes	Yes
Financial Hubs FE	Yes	Yes	Yes
Adj. R^2	0.198	0.117	0.0198
Obs.	2,110	2,110	2,110

Internet Appendix for
"Trading in Twilight: Sleep, Mental Alertness, and Stock Market Trading"

This appendix includes additional tables used in the paper:

Table A1: Mental Alertness: Evidence from Earnings News using Panel Regression

This table presents the results from estimating Equation (4) with a different dependent variable. The dependent variable $EAtrading_{jt}$ takes value 1 if household j trades at least one stock on day t which has announced its quarterly earnings, given household j trades any stock on day t. At the top of each column, the numbers in brackets represent the number of days relative to quarterly earnings announcement dates. $Sunset_{jt-1}$ is the local sunset time of each household on day t - 1, measured in hours. $Mktret_t$ and VIX_t are CRSP daily value-weighted market return and daily VIX level, respectively. $NumberofEA_t$ represents the number of earnings announcements released on day t. SAD_t is measured following Kamstra, Kramer, and Levi (2003). We calculate the number of nighttime hours for each household's location and date, then subtract 12 (approximately the average number of nighttime hours over the entire year at any location). $Fall_t$ is a dummy variable equal to 1 if the trade date falls between September 21 and December 20, following Kamstra, Kramer, and Levi (2003). We incorporate household fixed effects. All regressions include the year and day of the week fixed effects. We restrict the sample to households that trade on at least 11 different days over 6 years. Standard errors are clustered at the household level. t-statistics in parentheses. Significance is indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

$$EAtrading_{jt} = \alpha + \beta Sunset_{j,t-1} + X_t'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

	(1) [-5, -1]	(2) [0, 2]	(3) [3, 5]	(4) [6, 10]
Sunset	-0.001	-0.004***	0.000	0.002**
	(-1.42)	(-4.41)	(0.14)	(2.05)
Mktret	0.001	-0.001	0.001*	0.009***
	(1.14)	(-0.76)	(1.88)	(11.36)
VIX	0.003***	-0.002***	-0.001***	0.001***
	(9.63)	(-7.47)	(-5.25)	(2.98)
Number of EA	0.001***	0.001***	0.001***	0.000***
	(76.07)	(99.19)	(70.74)	(53.39)
SAD	-0.000**	-0.000***	-0.000***	-0.000***
	(-2.56)	(-4.80)	(-6.73)	(-7.67)
Fall	-0.017***	-0.016***	-0.013***	-0.010***
	(-11.10)	(-10.81)	(-10.00)	(-6.80)
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes
Adj. R^2	0.0463	0.0721	0.0529	0.0343
Obs.	491,870	492,419	492,238	493,145

Table A2: Sleep Disruption and Extrapolation of Rare Event

This table presents the results of regression discontinuity model in Equation (5) with the dependent variable, $TrendChasing_{jt}$. $TrendChasing_{jt}$ is an indicator variable that equals one on a given day t if a household j either buys a 'jump' stock or sells a 'crash' stock, and zero otherwise. Stock i is defined as a crash (jump) stock when it experiences one or more daily log market-adjusted returns falling approximately k standard deviations below (above) its mean return in the period $[t - 31, t - 1]$. k corresponds to the frequency of either 0.01%, 0.1%, or 1% in the normal distribution, in Column (1), (2), and (3), respectively. $LateSide$ is an indicator if a household is located on the right side of the relevant time zone where the household observes a later local sunset time than one across the time zone border. $SignedDistance$ measures the distance from the household j to the corresponding time zone border in kilometers. Bandwidths are from -200km to 200km when time zone borders are set to 0 as cutoffs. We control for household characteristics such as the log of number of trades, client segment, age, gender, income, number of stocks traded, average number of stocks held in the monthly portfolio, and average equity value held in the monthly portfolio. All columns include trade date fixed effects, state fixed effects, and geographical group fixed effects. An indicator for financial hubs is included. The sample is restricted to households with at least 11 transactions over 6 years. We exclude transactions in December from this analysis. Standard errors are robust and clustered by distance from the time zone border, with households grouped in 10-kilometer increments. t-statistics are shown in parentheses. Significance is indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

$$TrendChasing_{jt_{jt}} = \alpha + \beta_1 LateSide_j + \beta_2 SignedDistance_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

Dependent Variable	(1) 0.01%	(2) 0.1%	(3) 1%
LateSide	-0.002	0.003	-0.012
	(-1.13)	(0.47)	(-0.62)
SignedDistance	0.000**	-0.000	0.000
	(2.06)	(-0.53)	(1.67)
Latitude	-0.000	0.001	0.004
	(-0.80)	(0.62)	(0.74)
$\ln(Trade)$	-0.000	0.003*	0.023***
	(-0.01)	(1.86)	(4.17)
Client segment: Affluent	-0.000	-0.000	-0.005
	(-0.27)	(-0.12)	(-0.81)
Client segment: Active	-0.000	-0.002	-0.003
	(-0.45)	(-0.89)	(-0.39)
Age	-0.000**	-0.000**	-0.001***
	(-2.49)	(-2.37)	(-3.33)
Gender	-0.000	0.000	-0.000
	(-0.24)	(0.00)	(-0.02)
Income	0.000	0.000	0.000
	(0.78)	(0.81)	(1.31)
Number of Stocks Traded	0.000	0.000	0.000
	(0.76)	(1.27)	(1.10)
Average Number of Stocks Held	0.000	-0.000	0.001
	(1.24)	(-0.06)	(1.53)
Average Equity Held	-0.002*	-0.004	-0.016*
	(-1.97)	(-1.18)	(-1.80)
Trade date FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Financial Hubs FE	Yes	Yes	Yes
Adj. R^2	0.0021	0.0041	0.0130
Obs.	79,066	79,066	79,066

Table A3: Trading Performance and Sunset Time including December

This table presents the results from estimating Equation (4). The dependent variable, $TradePerform_{jt}$, is calculated using Equation (3) over 10-day and 21-day window, indicated at the top of each column. $Sunset_{jt-1}$ is the local sunset time of each household on day t - 1, measured in hours. $Mktret_t$ and VIX_t are CRSP daily value-weighted market return and daily VIX level, respectively. SAD_t is measured following Kamstra, Kramer, and Levi (2003). We calculate the number of nighttime hours for each household's location and date, then subtract 12 (approximately the average number of nighttime hours over the entire year at any location). $Fall_t$ is a dummy variable equal to 1 if the trade date falls between September 21 and December 20, following Kamstra, Kramer, and Levi (2003). We incorporate household fixed effects. All regressions include the year and day of the week fixed effects. We restrict the household to having at least 11 transactions over 6 years. Standard errors are clustered at the household level. *t*-statistics in parentheses. Significance is indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

$$TradePerform_{jt} = \alpha + \beta Sunset_{j,t-1} + X_t'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable		10 days			21 days	
Sunset	-0.017***	-0.017***	-0.022***	-0.017***	-0.017***	-0.022***
	(-9.80)	(-9.84)	(-5.30)	(-10.39)	(-10.33)	(-5.49)
Mktret		0.074***	0.073***		0.077***	0.075***
		(14.14)	(13.85)		(14.95)	(14.68)
VIX		-0.010***	-0.010***		-0.009***	-0.009***
		(-7.70)	(-7.82)		(-7.11)	(-7.21)
SAD			0.004			0.004
			(0.68)			(0.68)
Fall			-0.048***			-0.045***
			(-7.58)			(-7.56)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	No	Yes	Yes	No
Adj. R^2	0.0302	0.0310	0.0306	0.0335	0.0343	0.0338
Obs.	706,911	706,409	706,409	705,129	704,627	704,627

Table A4: Local Discontinuity of Equal-Weighted and Excess Return Trade Performance

This table presents the results of regression discontinuity model in Equation (5). The dependent variable for each estimation is indicated at the top of each column. In Columns (1) and (2), $TradePerform_{jt}$ is calculated by modifying Equation (3) to be equal-weighted. In Columns (3) and (4), $TradePerform_{jt}$ is calculated by modifying Equation (2) to be excess return. $LateSide_j$ is an indicator variable for households located on the east side of the relevant time zone, where the local sunset time is later compared to the west side. $SignedDistance_j$ measures how far a household is from the closest time zone border, with negative values indicating west side locations. Bandwidths for $SignedDistance_j$ range from -200km to 200km, with time zone borders set at 0 as cutoffs. We control for household characteristics such as the log of number of trades, client segment, age, gender, income, number of stocks traded, average number of stocks held in the monthly portfolio, and average equity value held in the monthly portfolio. All columns include trade date fixed effects, state fixed effects, and geographical group fixed effects. An indicator for financial hubs is included. The sample is restricted to households with at least 11 transactions over 6 years. We exclude transactions in December from this analysis. Standard errors are robust and clustered by distance from the time zone border, with households grouped in 10-kilometer increments. *t*-statistics are shown in parentheses. Significance is indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

$$TradePerform_{jt} = \alpha + \beta_1 LateSide_j + \beta_2 SignedDistance_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

	(1)	(2)	(3)	(4)
Dependent Variable	Equal-Weighted		Excess Return	
	10 days	21 days	10 days	21 days
LateSide	-0.115**	-0.111*	-0.107**	-0.093*
	(-2.07)	(-2.00)	(-2.13)	(-1.75)
SignedDistance	0.000	0.000	0.000	0.000
	(1.35)	(1.36)	(1.28)	(1.40)
Latitude	0.008	0.006	0.012	0.011
	(0.49)	(0.42)	(0.78)	(0.77)
$\ln(Trade)$	0.015	0.017	0.025	0.024
	(0.78)	(0.93)	(1.36)	(1.35)
Client segment: Affluent	-0.182***	-0.182***	-0.172***	-0.168***
	(-6.16)	(-6.13)	(-5.63)	(-5.40)
Client segment: Active	-0.118***	-0.119***	-0.116***	-0.117***
	(-5.07)	(-4.71)	(-5.44)	(-4.95)
Age	-0.001	-0.001	-0.001	-0.001
	(-1.50)	(-1.68)	(-1.06)	(-1.17)
Gender	-0.079*	-0.061	-0.072*	-0.058
	(-1.97)	(-1.57)	(-1.77)	(-1.48)
Income	-0.000	-0.001	-0.000	-0.001
	(-1.17)	(-1.41)	(-1.15)	(-1.30)
Number of Stocks Traded	0.001	0.001	0.001	0.001
	(1.15)	(1.13)	(1.19)	(1.35)
Average Number of Stocks Held	-0.008***	-0.009***	-0.008***	-0.009***
	(-3.80)	(-4.06)	(-4.03)	(-4.34)
Average Equity Held	0.095	0.090	0.118*	0.103*
	(1.56)	(1.45)	(1.91)	(1.71)
Trade date FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Financial Hubs FE	Yes	Yes	Yes	Yes
Adj.R^2	0.0197	0.0214	0.0189	0.0195
Obs.	73,334	73,155	76,379	76,200

Table A5: Local Discontinuity at Time Zone Borders with Various Bandwidths

This table presents the results of regression discontinuity model in Equation (5) with different bandwidth settings. The dependent variable $TradePerform_{jt}$ is calculated using Equation (3) over 10-day window. $LateSide_j$ is an indicator variable for households located on the east side of the relevant time zone, where the local sunset time is later compared to the west side. $SignedDistance_j$ measures how far a household is from the closest time zone border, with negative values indicating west side locations. From Columns (1) to (4) we gradually increase the bandwidth, the absolute distance from the corresponding time zone border, from 200km to 500km. We control for household characteristics such as client segment, age, gender, income, number of stocks traded, average number of stocks held in the monthly portfolio, and average equity value held in the monthly portfolio. All columns include trade date fixed effects, state fixed effects, and geographical group fixed effects. An indicator for financial hubs is also included. The sample is restricted to households with at least 11 transactions over 6 years. We exclude transactions in December from this analysis. Standard errors are robust and clustered by distance from the time zone border, with households grouped in 10-kilometer increments. *t*-statistics are shown in parentheses. Significance is indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

$$TradePerform_{jt} = \alpha + \beta_1 LateSide_j + \beta_2 SignedDistance_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

	(1)	(2)	(3)	(4)
Dependent Variable	10 days			
LateSide	-0.118**	-0.075*	-0.039	-0.039
	(-2.13)	(-1.68)	(-1.01)	(-1.00)
SignedDistance	0.000	0.000	0.000	0.000
	(1.33)	(0.71)	(0.51)	(0.66)
Latitude	0.006	-0.010	-0.001	-0.002
	(0.37)	(-0.78)	(-0.15)	(-0.17)
Client segment: Affluent	-0.176***	-0.169***	-0.154***	-0.155***
	(-5.96)	(-6.78)	(-7.37)	(-7.40)
Client segment: Active	-0.105***	-0.120***	-0.115***	-0.115***
	(-3.96)	(-6.43)	(-7.62)	(-7.63)
Age	-0.001	-0.002**	-0.002***	-0.002***
	(-1.44)	(-2.50)	(-3.14)	(-3.12)
Gender	-0.075*	-0.031	-0.025	-0.026
	(-1.88)	(-1.09)	(-1.20)	(-1.21)
Income	-0.001	-0.000*	-0.000**	-0.000**
	(-1.28)	(-1.94)	(-2.37)	(-2.38)
Number of Stocks Traded	0.001**	0.001*	0.000**	0.000**
	(2.43)	(1.84)	(2.24)	(2.24)
Average Number of Stocks Held	-0.008***	-0.004**	-0.005***	-0.005***
	(-3.90)	(-2.27)	(-3.21)	(-3.22)
Average Equity Held	0.099	0.038***	0.049***	0.049***
	(1.62)	(3.18)	(4.36)	(4.40)
Trade date FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Financial Hubs FE	Yes	Yes	Yes	Yes
Bandwidth	200km	300km	400km	500km
Adj.R^2	0.0193	0.0189	0.0175	0.0175
Obs.	73,334	133,323	195,592	195,764

Table A6: Longer-term Effect of Sleep across Northern and Southern Regions

This table presents the results from estimating Equation (6). The dependent variable $TradePerform_{jt}$ is calculated by Equation (3) over 21-day window. $NorthernPart_j$ equals one if a household is in the top 25% latitude and zero if in the bottom 25%. Column (1) shows the result of the entire sample excluding March and September transactions. Column (2) only includes the summer season, April, May, June, July, and August. Column (3) includes the Winter season, October, November, December, January, and February. We control for household characteristics such as the log of number of trades, client segment, age, gender, income, number of stocks traded, average number of stocks held in the monthly portfolio, and average equity value held in the monthly portfolio. We include trade date fixed effects and state fixed effects. Longitude control includes linear longitude and categorical groups dividing each time zone into three parts by two vertical longitude lines. We also include an indicator for financial hubs counties. We restrict the household to having at least 11 transactions over 6 years. Standard errors are robust and clustered at county level. *t*-statistics are shown in parentheses. Significance is indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

$$TradePerform_{jt} = \alpha + \beta NorthernPart_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

	(1) Entire	(2) Summer	(3) Winter
NorthernPart	-0.137	-0.451***	0.064
	(-1.30)	(-3.40)	(0.37)
Longitude	-0.004	-0.001	-0.007
	(-0.51)	(-0.07)	(-0.69)
$\ln(Trade)$	0.005	0.046***	-0.034***
	(0.55)	(3.59)	(-3.25)
Client segment: Affluent	-0.144***	-0.151***	-0.137***
	(-9.71)	(-7.61)	(-7.79)
Client segment: Active	-0.113***	-0.129***	-0.097***
	(-7.81)	(-6.77)	(-5.45)
Age	-0.001***	-0.002***	-0.000
	(-2.87)	(-3.63)	(-0.56)
Gender	-0.009	0.007	-0.023
	(-0.50)	(0.30)	(-1.03)
Income	-0.000*	-0.000*	-0.000
	(-1.72)	(-1.86)	(-0.97)
Number of Stocks Traded	0.000	-0.000	0.001***
	(1.00)	(-0.62)	(2.67)
Average Number of Stocks Held	-0.004***	-0.004***	-0.004***
	(-3.29)	(-3.19)	(-2.85)
Average Equity Held	0.031***	0.051***	0.014
	(2.74)	(4.24)	(0.96)
Trade date FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Longitude group FE	Yes	Yes	Yes
Financial Hubs FE	Yes	Yes	Yes
Adj. R^2	0.018	0.0193	0.0169
Obs.	223,514	108,632	114,882

Table A7: Mental Alertness: Evidence from Earnings News with Full Sample

This table presents the results from estimating Equation (8). The dependent variable $EAtrading_{jt}$ takes value 1 if household j trade at least one stock on day *t* which has announced its quarterly earnings, given household j trades any stock on day *t*. At the top of each column, the numbers in brackets represent the number of days relative to quarterly earnings announcement dates. $LateSide_j$ is an indicator variable for households located on the east side of the relevant time zone, where the local sunset time is later than on the west side. $SignedDistance_j$ measures how far a household is from the closest time zone border, with negative values indicating west side locations. Bandwidths for $SignedDistance_j$ range from -200km to 200km, with time zone borders set at 0 as cutoffs. We control for household characteristics such as the log of number of trades, client segment, age, gender, income, number of stocks traded, average number of stocks held in the monthly portfolio, and average equity value held in the monthly portfolio. All columns include trade date fixed effects, state fixed effects, and geographical group fixed effects. An indicator for financial hubs is included. The sample is restricted to households with at least 11 transactions over 6 years. We exclude transactions in December from this analysis. Standard errors are robust and clustered by distance from the time zone border, with households grouped in 10-kilometer increments. *t*-statistics are shown in parentheses. Significance is indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

$$EAtrading_{jt} = \alpha + \beta_1 LateSide_j + \beta_2 SignedDistance_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

	(1) [-5, -1]	(2) [0, 2]	(3) [3, 5]	(4) [6, 10]
LateSide	-0.007	-0.019*	-0.007	-0.013
	(-0.54)	(-1.97)	(-0.56)	(-1.23)
SignedDistance	0.000	0.000	0.000	0.000*
	(0.50)	(1.17)	(1.56)	(1.88)
Latitude	-0.005*	-0.000	-0.003	-0.004
	(-1.80)	(-0.01)	(-1.34)	(-1.23)
$\ln(Trade)$	-0.003	-0.001	-0.006***	-0.005*
	(-0.82)	(-0.50)	(-2.75)	(-1.88)
Client segment: Affluent	0.000	0.002	0.003	0.004
	(0.07)	(0.43)	(0.83)	(1.15)
Client segment: Active	-0.000	0.004	0.001	0.006
	(-0.12)	(0.96)	(0.30)	(1.63)
Age	0.000	-0.000	-0.000	0.000
	(0.72)	(-0.72)	(-0.04)	(0.38)
Gender	0.004	0.003	0.003	0.010
	(0.48)	(0.54)	(0.61)	(1.33)
Income	0.000	-0.000	0.000	0.000
	(0.33)	(-0.63)	(0.38)	(0.48)
Number of Stocks Traded	0.000*	0.000*	0.000**	0.000**
	(1.73)	(1.83)	(2.25)	(2.12)
Average Number of Stocks Held	0.000	0.000*	0.000*	0.000
	(1.29)	(1.82)	(1.74)	(1.53)
Average Equity Held	-0.012	-0.021***	-0.016*	-0.016*
	(-1.32)	(-3.56)	(-1.97)	(-1.87)
Trade date FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Financial Hubs FE	Yes	Yes	Yes	Yes
Adj. R^2	0.0631	0.0597	0.0403	0.0651
Obs.	85,860	85,860	85,860	85,860

Table A8: Trading Performance with Orthogonalized Sunset

This table presents the results from estimating Equation (4). The dependent variable, $TradePerform_{jt}$, is calculated using Equation (3) over 10-day and 21-day window, indicated at the top of each column. $Sunset_{jt-1}$ is the local sunset time of each household on day t - 1, measured in hours. $Mktret_t$ and VIX_t are CRSP daily value-weighted market return and daily VIX level, respectively. $January_t$ is a dummy variable that equals 1 if day t is in January and 0 otherwise. $Sunset_{t-1}^{Orth}$ is the orthogonalized $Sunset_{jt-1}$ with respect to the SAD_t and $Fall_t$, where SAD_t and $Fall_t$ are measured following Kamstra, Kramer, and Levi (2003). We calculate the number of nighttime hours for each household's location and date, then subtract 12 (approximately the average number of nighttime hours over the entire year at any location). We incorporate household fixed effects, the year fixed effects, and day of the week fixed effects. We restrict the household to having at least 11 transactions over 6 years. Transactions in December are excluded. Standard errors are clustered at the household level. t-statistics in parentheses. Significance is indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

$$TradePerform_{jt} = \alpha + \beta Sunset_{j,t-1} + X_t'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable		10 days			21 days	
Sunset	-0.011***	-0.014***		-0.009***	-0.012***	
	(-5.52)	(-6.38)		(-4.86)	(-5.93)	
Mktret		0.069***	0.070***		0.072***	0.072***
		(12.91)	(13.00)		(13.63)	(13.70)
VIX		-0.007***	-0.007***		-0.006***	-0.005***
		(-5.50)	(-5.22)		(-4.33)	(-4.19)
January		-0.018**	0.012		-0.025***	0.003
		(-2.02)	(1.51)		(-2.90)	(0.36)
$Sunset^{Orth}$			-0.023***			-0.023***
			(-5.37)			(-5.74)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of Week FE	No	Yes	Yes	No	Yes	Yes
Adj. R^2	0.0312	0.0319	0.0319	0.0345	0.0353	0.0353
Obs.	654,089	653,587	653,587	652,481	651,979	651,979