Trading in Twilight:
Sleep and Retail Investors' Stock Investment Performance

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Abstract

Lack of sleep poses significant challenges for modern society. Sleep deprivation has been identified not only as a public health problem, but also an economic issue. However, it remains to be empirically investigated whether investors' stock investment, which are voluntary and directly linked to their wealth, are influenced by their sleep. We study the impact of sleep on the trading performance of investors in the stock market, utilizing household-level stock trading panel data from a large discount brokerage. The study documents a substantial negative relationship between sleep, proxied by local sunset time, and lower trading performance. Empirical strategies, including panel regression and regression discontinuity design, establish a causal link. The magnitude of the effect is large. Simply being on the later sunset side of the timezone borders leads to stock investment decisions that generate 2 basis points lower daily abnormal returns over the next 250 days (5% in annum). The study also uncovers potential channels, such as inattention to new information and a 4.5% increase in the probability of asymmetric risk preference. Overall, our research demonstrates that sleep constitutes a significant factor in shaping investor investment behavior and performance. The findings underscore the policy implications of prioritizing adequate sleep for financial decision-makers.

Keywords: Sleep; Retail Investors; Trading performance; Attention, Behavioral finance; Social finance.

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1. Introduction

The Center of Disease and Prevention (CDC) in the United States has declared insufficient sleep a "public health problem." More than a third of American adults are not getting enough sleep on a regular basis (Liu et al., 2016). More concerning, the proportion of people sleeping less than the recommended hour of sleep is rising (Roenneberg, 2013). Sleep deprivation has been identified not only as a public health problem, but also an economic issue. Studies in the fields of psychology and medicine has consistently demonstrated the impact of sleep on decision making abilities, not only in simple tasks but also in complex and multi-dimensional situations (Harrison and Horne, 2000). Although there is growing research on the economic impact of sleep, mainly documenting the lower productivity in workforce (e.g., Daley et. al., 2009; Hafner et al., 2017), there is limited research on the economic consequence of sleep in broader economic activities. This paper extends this literature by investigating the impact of sleep on the trading performance of investors in the stock market.

This paper focuses on studying the effects of sleep on retail investors, for several reasons. First, retail investors trade on a voluntary basis. The evidence will complement existing research focusing on the workforce. Second, retail investors are well documented to be more likely to suffer from behavioral biases in general (e.g., Barber and Odean, 2000; Barber, Huang, Odean, and Schwarz, 2022). Thus, it is natural to study the effect in this setting. Third, the recent GameStop episode suggests that retail investors can exert significant impact on the stock market, hence understanding their behaviors is important for policy makers and investors. Finally, the pool of retail investors is widely distributed geographically, while institutional investors are often located in several financial hubs. Thus, the retail investor setting allows us to utilize geographical identification to provide casual evidence, which is almost impossible for institutional investors.

Although studies in the psychology and medical fields have shown that sleep plays an important role in cognitive functions, it is not clear whether sleep will have significant impact on retail investors' trading behaviors. On the one hand, retail investors are more likely to suffer from behavioral biases and likely to make mistakes when they have less sleep. Kahneman (2011) show that when individuals lack sufficient sleep, they tend to rely more on intuitive and heuristic decision-making processes than analytical and rational decision-making. Also, individuals are more likely to make suboptimal decisions when they have limited information processing capacity (e.g., Hirshleifer, 2015; Hirshleifer et al., 2019). On the other hand, trading decisions have significant financial consequence, hence investors may overcome potential biases and make rational decision, which is consistent with classic rational agent models in finance and economic literature. Thus, it is an empirical question whether less sleep will lead to worse trading in the stock market.

We examine the effect of sleep on trading performance using detailed transaction-level data of retail investors from a large brokerage account in the 1990s as in Barber and Odean (2000). We draw on the existing literature to establish sunset time as a proxy for sleep of investors. Sleep patterns are influenced by the natural progression of the sun, making the timing of sunset a critical determinant of sleep quality and duration (Roenneberg et al., 2007).[1] We posit that the timing of sunset impacts trading performance through its effect on sleep. Previous research has shown that late sunset time is associated with reduced sleep duration using data from the American Time Use Survey (Gibson and Shrader, 2018; Giuntella and Mazzonna, 2019) and Chinese Health and Retirement Longitudinal Study

[1] In particular, Roenneberg et al. (2007) indicates that the human circadian rhythm is more synchronized with the sun time than social time. Furthermore, Hamermesh et al. (2008) suggests that work schedules do not adjust to sunset time. Social schedules result in morning time constraints for workers, and a later sunset and later bedtime can lead to 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. Moreover, the timing of sunset affects the quality of sleep. It triggers the body's production of melatonin, the hormone involved in regulating the sleep-wake cycle.

(Giuntella et al., 2017).[2] To implement the relationship between sleep and trading performance, we geocode households' locations and calculate their local sunset time. This enables us to examine the extent to which sleep, as proxied by sunset time, affects trading performance among individual investors.

In our study, we measure the quality of retail investors' stock investment decisions based on the future abnormal returns of the stocks bought or sold by the investors. The abnormal returns are calculated based on Fama-French three-factor model, following Barber and Odean (2000)[3]. Additionally, to account for good decisions where an investor sells a stock that generates negative abnormal returns afterward, we multiply the abnormal returns of sold stocks by -1. Thus, if a household buys a stock that generates positive average abnormal returns or sells a stock that generates negative average abnormal returns in the near future, the trading performance measure is positive.

We adopt three empirical strategies to examine the influence of sleep on retail investors' trading performance. First, we utilize a panel regression with household fixed effects to examine the intra-annual changes in the quality of investors' decisions. This approach allows us to focus on the time-series variation in sleep and cognitive ability within individuals. We find a significant negative relationship between sunset time and trading performance. When the sun sets about one hour and twenty minutes (equivalent to one standard deviation of sunset time) later, households tend to trade stocks that generate 0.03% lower daily average abnormal returns in the following ten days. Up to 335 days after the trade, stocks exhibit lower abnormal returns on average as the sun sets later.

[2] Giuntella and Mazzonna (2019) show that being on the late sunset side of the timezone borders leads to a reduction in sleep time by approximately 19 minutes per day. Additionally, Gibson and Shrader, (2018) demonstrate that the daily local sunset variation serves as a valid instrument for sleep, revealing that a one-hour delay in sunset time within a location reduces nighttime sleep by approximately 24 minutes per week.

[3] For robustness, we examine the main analyses with risk-free excess returns. The results using the alternative measure are consistent. See Appendix Table A6.

To establish a causal relationship between sleep and trading performance, we employ our second empirical strategy, a regression discontinuity design (RDD), by utilizing the local discontinuity in sunset time at the time zone borders. Households located on one side of the border experience a different sunset time compared to those on the other side, despite being located in close proximity. A restriction is set on the bandwidth, limiting it to 200km from the time zone borders to mitigate other household-specific factors that could affect trading performance. The RDD result shows that less sleep induces lower trading performance among retail investors. Individuals located on the righthand side of a time zone border, who experience one-hour later sunsets and are therefore more likely to sleep less, suffer from 0.263% lower daily average abnormal return over ten days after stock trading compared to those located across the border.

This effect is further supported by evidence when we examine summer and winter seasons separately. To account for the potential nonlinear effect of the sunset on sleep, we split the sample into summer and winter seasons. The rationale is that a one-hour difference in local sunset time is less likely to disrupt the sleep pattern during the winter season than during the summer, due to the earlier sunset time in winter. Thus, the effect is likely to be more pronounced during the summer season. Indeed, we find evidence supporting this conjecture, which provides additional supportive evidence that the effect of sunset time on investors' trading performance is likely due to sleep.

To complement the RDD analysis, we adopt another empirical strategy using the variation of local sunset time across latitudes. In the northern hemisphere, regions closer to the North Pole experience relatively later local sunset times during the summer season compared to areas nearer to the equator. Conversely, during the winter season, the southern areas observe a later sunset time. If sleep is indeed entrained by sunset time, individuals living in northern areas may exhibit, on average, fewer sleep hours and lower sleep quality during the summer season, potentially leading to a decline in decision making quality. This relationship flips during the winter season. To examine this aspect, we compare the trading performance of households in the top 25% and bottom 25% latitudes in the sample. We find that investors of the northern part of the US exhibit 0.5% lower daily trading performance during the summer season, while there is no distinguishable difference during the winter season. Such a distinct pattern across seasons and latitudes offers further evidence for the impact of sunset time on trading behaviors.

Taking a step further, we study the underlying mechanism through which sleep affects investors' trading decisions. The first potential explanation is that sleep has an impact on investor attention, which affects investor decisions. Research in psychology has explored the impact of sleep on various cognitive functions in complex situations. The findings of this literature suggest that sleep deprivation can harm cognitive abilities such as attention and memory (Alhola and Polo-Kantola, 2007; Hudson et al., 2020; Van Dongen et al., 2003). When people sleep less, the most commonly mentioned feature is that the mental resources they could use are reduced. If it is the case, people would pay less attention to the information available in the stock market.

To test this channel, we look at the earnings announcement days of firms. Following the previous literature, rational investors are expected to incorporate new information into their portfolio holdings. However, if investors suffer from behavioral biases, they might fail to react to important new information. We hypothesize that less sleep induces inattention to new (public) information. In the empirical settings, we examine the propensity to trade a stock in short intervals after its quarterly earnings announcement days. We find that people who live on the earlier sunset side of the time zone border are 4.27% more likely to trade right after the earnings announcement. Merely living on the side with later sunsets reduces the likelihood of trading in response to earnings announcements, which may lead to underperformance.

Next, we examine another potential channel that focuses on the asymmetric risk-preference of sleep-deprived people in psychology literature. In experimental settings, research has found that sleep-deprived subjects are more willing to take risks when considering a gain, but less willing to take risks when considering a loss (Mckenna et al., 2007). We examine the tendency of investors to take tail risk conditioning on stocks' past performance. We hypothesize that less sleep induces more willingness to buy jump stocks and sell crash stocks, if investors trade any. We measure the probability of such asymmetric risk-preference conditional on stock trading. The empirical tests show that being on the late sunset side increases the probability of asymmetric trading by 4.5%, which supports our hypothesis.

Furthermore, we explore several additional potential channels. First, we show that the effect is not due to the trading frequency. The number of trades by two household groups are not statistically different. Second, we do not find evidence that the effect is due to extrapolation since there is no significant relationship between sleep and the propensity for positive feedback trading. Finally, we find that the effect is not likely driven by investor herding since there is no relationship between sleep and herding behavior in the sample.

Our research contributes to the growing literature on the influence of behavioral factors on individual investor decision-making quality in finance. The relationship between sleep and economic decisions has been explored in economics and finance literature by connecting it with the sleep literature in the psychology field. One common setting for testing the effects of changes in sleep is daylight savings time (DST) changes. For instance, in a seminal study, Kamstra et al., (2000) have found negative mean returns in the *aggregate* stock market after daylight saving time (DST) weekends and attribute it to the change in investors' sleep patterns due to the time change.[4] However, the effect of sleep, presented by DST changes, has been controversial (Berument et al., 2011; Gregory-Allen et al., 2010; Pinegar, 2002). This is likely due to limitations in empirical design using DST, which only occurs twice a year, and that the transition out of DST does not necessarily induce a change in sleep patterns (Barnes and Wagner, 2009).

Our paper makes three distinct contributions to the existing literature. First, we adopt a new setting, using the variation in sunset time as an instrument to identify the effect of sleep on trading performance. This allows us to capture a more continuous variation in sleep patterns and better understand the relationship between sleep and stock trading performance. Second, we focus on the effect of sleep of *individual* investors on their trading behaviors, while existing literature focuses on the aggregate stock market. The new setting is important because it allows us to employ RDD to establish a casual effect between sleep and trading performance, which is impossible at the aggregate stock market level. Finally, we provide novel evidence on the economic channels through which sleep affects trading performance.

Our paper also contributes novel evidence to the literature on retail investors. Prior studies show that retail investors' performance can be attributed to gender (Barber and Odean, 2001), age and cognitive ability (Korniotis and Kumar, 2011), and IQ (Grinblatt et al., 2012). Recently, studies find that salience (Frydman and Wang, 2020), trading App (Barber, Huang, Odean, and Schwarz, 2022), and trading hours (deHaan and Glover, 2023) can affect retail investors trading behaviors and trading performance. Our study provides new evidence that the cognitive ability of individuals can vary based on their sleep patterns, which in turn can influence their decision-making capabilities.

[4] Furthermore, studies have found that the spring DST results in sleepiness behind the wheel and more automobile accidents (Smith, 2016), and investors overreact to merger announcements when influenced by sleep imbalance after DST transitions (Siganos, 2019).

The structure of this paper is as follows: section 2 outlines the process of data collection and key measure construction; section 3 presents our empirical results; section 4 provides the results of potential mechanisms; section 5 concludes.

2. Data and Measures

2.1 Individual Investors Data

The primary data used in this study is panel data of stock trades by households spanning six years from 1991 to 1996, provided by a large discount brokerage firm. This individual 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.

To conduct our analysis, 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 obtained 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 the focus of this paper is the active decision-making process of retail investors in the stock market, the final sample is restricted to households that trade common stocks with valid price information. Furthermore, to exploit the discontinuity design of timezones, 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 timezone borders. Considering the timezone borders, we can categorize households into four timezone areas, Pacific, Mountain, Central, and Eastern. Table 1 presents a summary of the final sample, which is divided into these four timezone areas. Panel A of Table 1 shows the number and percentage of households in each timezone area. The Eastern timezone has the largest number of households, accounting for 39.68% of the entire sample, followed by the Pacific timezone with 33.11%. The Mountain timezone has the least number of households, comprising only about 5.76% of the entire sample. Over the six years of the sample, 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 timezone area.

2.2 Distance from Timezone Border Data

The study aims to investigate the impact of sleep on the trading performance of retail investors by leveraging the spatial discontinuity in sunset time at the timezone borders in the US continent. The continent is divided into four different time zones by three timezone borders. To measure the distance from the closest timezone borders in kilometers for each household, we used the ArcGIS program to combine the coordination of each household with the American timezone border shapefile. The spatial discontinuity in sunset time at the timezone borders 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.

The process of assigning distance values to households from the closest timezone borders is as follows. If a household is on the left side of a timezone border, negative values are assigned to the distance from that border. For instance, a household located in the Pacific timezone only has a distance from the PT/MT timezone border, which is a negative value. If a household is located in the Central zone it may have two different distance values; one positive number from MT/CT and the other negative number from CT/ET timezone borders. In this case, we keep the lowest absolute value of distance. This process ensures that the spatial discontinuity cut-off is at 0 in terms of distance measure. Figure 2 visually depicts the sharp discontinuity in average sunset time at the timezone borders, creating a natural experiment where households on either side of the border experience a difference in sunset time. The summary statistics of Distance measure is in Panel A of table 2, which spans from -864.10 to 1510.31.

2.3 Local Sunset Time Data

The aim of our study is to investigate the potential correlation between sleep and the trading performance of retail investors. However, it is difficult to obtain accurate data on an individual's sleep hours and their trades at the same time. To overcome this limitation, we use local sunset time as a proxy for sleep time. This approach is based on the assumption that an individual's natural sleep cycle is entrained by sun time, with exposure to darkness in the evening promoting the onset of sleep. By using local sunset time as a proxy for sleep time, we can capture the impact of sleep on trading performance, as it is expected that individuals in areas with earlier sunsets will have longer sleep periods and potentially better trading performance. Sunset time has previously been used as an instrumental variable for sleep in the literature, as shown by Gibson and Shrader (2018) and Giuntella and Mazzonna (2019).

To identify the location of individual investors, we utilize 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 investor based on the time of sunset in their location.

For each individual investor in the sample, we calculate their daily local sunset time 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 the time when people are typically entrained to begin resting and sleeping.

2.4 Daily Trading Performance Measure

This paper presumes that sleep deprivation lowers investors' cognitive ability; Less sleep hurts the decision-making quality and results in lower trading performance. To measure a retail investor's daily decision quality, we consider the ex-post performance of stocks that the investor trades. We adopt the subsequent risk-adjusted abnormal returns for each stock traded. We first estimate the Fama-French three-factor risk-adjusted expected return by regressing the 250 trading days preceding the day t as follows:

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

where R_{it} is daily return of stock i on day t; 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 Fama-French three-factor model. Once we estimate β_{i1}, β_{i2} and β_{i3}, we calculate the risk-adjusted expected return, $\widehat{R}_{it}$, using respective returns and factors on day t. Following Barber and Odean (2000), we expect that Fama-French three-factor model to be a reasonable model for evaluating the stock performance traded by individual investors since it adjusts the small stock tilt in individual investors' portfolios.

Next, we consider the direction of each trade. If an investor buys (sells) a stock that has positive (negative) future abnormal returns, it is assumed to be a good decision. In contrast, if an investor buys (sells) a stock that has negative (positive) future excess returns, it can be a worse choice. For each executed trading, the retail investor j's trading performance is calculated as Equation 2.

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

where Buy_{ijt} is a dummy variable equaling one (zero) if a household j buys (sells) stock i on day t; 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 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. Considering each household may trade stocks several times a day, we aggregate $StockPerform_{ijt,k}$ into the household-day level, using the weighted average as follows:

$$TradePerform_{jt,k} = \sum_{i} \frac{TQ_{ijt}}{TQ_{jt}} StockPerform_{ijt,k} \tag{3}$$

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 335 trading days so that we can address short-term and long-term performance results. Especially we take 335 trading days, representing 16 months of the average holding period of retail investors (Barber and Odean, 2000). This paper uses $TradePerform_{jt,k}$ as a primary dependent variable, which measures investor j's daily decision consequences. All $TradePerform_{jt,k}$ variables are winsorized at 1% and 99%.

In Panel A of table 2, we present the summary statistics of our primary dependent variables. As expected, our results align with the literature on individual investors, with household stock trading producing negative outcomes on average. Panel B of table 2 provides insight into the correlation between 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 process of retail investors and its consequences.

3. Empirical Results

In this section, we examine the effect of sleep on retail investors' trading performance using three empirical strategies. First, we utilize a OLS setting where various fixed effects are included. Second, we conduct a regression discontinuity design (RDD) to establish a causal link between sleep and trading performance. Finally, we employ a setting where sunset time varies across the latitude to provide further evidence.

3.1 Sleep and Trading Performance: Panel Regression

Our hypothesis is that if sleep and decision-making in the stock market are related, a later sunset time should be negatively correlated with a retail investor's next-day trading performance on average. In order to test this hypothesis, we utilize household-daily level panel data and estimate the correlation coefficients using OLS regression with household fixed effects.

The use of household-level fixed effects allows us to control for household time-invariant factors that may impact trading performance, such as a inherient preference about the stocks (Døskeland and Hvide, 2011; Grinblatt and Keloharju, 2001; Huang, 2019; Huberman, 2001; Seasholes and Zhu, 2010) and trading tendency (Barber and Odean, 2001; Grinblatt et al., 2012; Korniotis and Kumar, 2011).

In addition, to deal with the seasonality in the cross-sectional stock returns, we control the renowned weekend effect (Birru, 2018; French, 1980) and January effect (Keim and Stambaugh, 1986; Rozeff and Kinney, 1976) by adding the day of the week and month fixed effects. We also exclude the transactions made in December in our main estimations assuming that the retail investors show a tax-motivated selling strategy at the end of the year (Odean, 1998) [5]. Thus, by estimating the following equation, we examine the variation in trading performance within households as local sunset time changes.

$$TradePerform_{jt,k} = \alpha + \beta Sunset_{jt-1} + X_t'\delta + \gamma_t + \gamma_j + e_{jt} \tag{4}$$

where $Sunset_{jt-1}$ measures a local sunset time on the day t-1 in household j's location in hours; X_t is a vector of market level variables, including daily CRSP value-weighted index total return and daily VIX level on day t. γ_t represents time fixed effects including the day of week, year, and month; γ_j is a household fixed effect and e_{it} is the error term. In this paper, we hypothesize that later sunset time causes later bedtimes, therefore, lowering the decision quality of the next day. If the hypothesis holds, we should observe a negative coefficient on the sunset time variable, β in Equation (4), indicating that a later sunset time is associated with lower trading performance.

In summary, the results of the panel regression analysis support the hypothesis that a negative relationship exists between sleep and the trading performance of retail investors. Furthermore, this effect is not only statistically significant but also remains robust over extended periods of time.

3.2 Less Sleep causes Worse Trading Performance: RDD

While the panel regression with various fixed effects provides strong evidence on the effect of sleep on trading performance, there are potential endogeneity concerns regarding retail investors' location and related factors, all of which may affect their trading performance. To establish a causal relationship between sleep and trading performance, we

[5] The results are robust to including December trades (See Table A1 in the Internet Appendix).

employ regression discontinuity design (RDD), utilizing the spatial discontinuity in sunset time at the borders of different time zones.

The time zone borders create a natural experiment where households located on one side of the border experience a different sunset time compared to those on the other side, despite being located in close proximity. Spatial proximity is an important criterion in grouping retail investors. Hong et al. (2004) provide evidence of the importance of social interaction with neighbors in stock market participation, suggesting the word-of-mouth information-sharing channel among the community. In addition, the finance literature has shown that the average retail investors tend to trade stocks that are physically close to them (Grinblatt and Keloharju, 2001; Huberman, 2001; Seasholes and Zhu, 2010).

This paper assumes that the households within close distance but across timezone borders are similar and comparable in terms of their stock tradings. About an hour difference in local sunset time across the timezone borders allows us to more precisely isolate the impact of sunset time on trading performance while holding other factors constant. Therefore, the regression discontinuity design provides a more robust and reliable estimate of the effect of sleep on trading performance, enhancing our understanding of the relationship. Our study builds on previous literature by providing additional evidence for the causal relationship between sunset time, sleep, and trading performance of retail investors. To exploit the geographical variation in sunset time at the border, we estimate the following equation.

$$TradePerform_{jt,k} = \alpha + \beta_1 LateSide_j + \beta_2 Distance_j + X_j'\delta + \gamma_t + \gamma_j + e_{jt} \tag{5}$$

where $LateSide_j$ equals one if the household j locates on the right side of the corresponding timezone border, where has the later sunset time by construction. $Distance_j$, a running variable, measures the distance from the household j to the corresponding timezone border in kilometers. Because *LateSide* is a persistent household level variable, including the household fixed effect would subsume it. Therefore, we exploit the available characteristics variables in the data, to minimize the potential confounding factors that could influence trading behavior. To estimate the local discontinuity, the main analysis set 200-kilometer bandwidth on $Distance_j$. X_j includes household characteristics such as age, gender, self-reported knowledge and experience, and linear control for latitude. γ_t contains the trade date fixed effect to compare the tradings on the same day and an indicator for daylight saving time periods to capture the variation due to time changes. γ_j contains state fixed effect and geographical group fixed effects, which is nine categorical groups by three parallel latitude lines and three timezone borders to assure the comparison between households in similar latitude levels. We also include an indicator for financial hubs counties like 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 stock market exchanges may show different trading patterns than the other households. With the Equation (5), we try to identify the relationship between sunset time and individual investors' trading performance. If the later sunset time induces lower trading performance, β_1 will be negative. In addition, positive β_2 will promote the hypothesis since the sunset time and the distance measure have a negative relationship on each side, as represented in Figure 2.

Table 4 presents the results of the RDD test, which estimates the Equation (5), with *TradingPerform10* as the dependent variable. In order to better isolate the impact of sunset time on trading performance, we set a restriction on the bandwidth by limiting it to 200km from the time zone borders.[7] Comparing households nearby helps to exclude other household-specific factors that could affect trading performance. We find a negative coefficient on the *LateSide* variable, indicating being on the late sunset side of the timezone borders negatively affects the trading performance of retail investors, producing 0.263% lower ten days average abnormal returns[9].

Table 5 shows the results of $TradePerform_{jt,k}$ variables with longer performance windows, from 21 to 335 trading days. The coefficients of *LateSide* stay negative and significant. Comparing two households that are similar in terms of age, gender, knowledge, and experience but located on different sides of the timezone border, the household lives in later side trade stocks producing 0.183 % lower daily average abnormal returns over the next 335 days. Therefore, we argue that the effect of disturbed sleep exists and is economically significant.

The discontinuity at the timezone border is depicted well in Figure 3. Panel A of figure 3 shows the scatter plot and the fitted lines with 95% confidence intervals between the mean residuals obtained from a regression of $TradePerform_{jt,10}$ on the set of controls and fixed effects in the Equation (5) except $LateSdie_j$ and $Distance_j$. There is a sharp discontinuity at 0 which indicates the timezone border. Panel B of figure 3 represents similar results using $TradePerform_{jt,335}$.

Our study provides evidence that individuals living on the right-hand side of the time zone border tend to experience later sunsets and are more likely to get less sleep, which ultimately leads to worse trading performance compared to those living on the left-hand side of the time zone border. This finding supports the hypothesis that sleep is a crucial

[7] The results are robust to using different bandwidths (See Table A2 in the Internet Appendix). The sign of coefficients is negative and stable with different bandwidths. Overall, the significance reduces as the bandwidth increases and this aligns with the idea of local discontinuity.

[9] The results stay similar when using equal-weighted version of trade performance (See Table A4 in the Internet Appendix).

determinant of individual investors' trading performance, consistent with prior research showing that sleep deprivation affects cognitive functions, including attention, decision making, and risk-taking abilities.

We further hypothesize that local sunset times impact sleep in a nonlinear fashion. For example, a one-hour difference in local sunset time, shifting from 8 p.m. to 9 p.m., is likely to have a more adverse effect on sleep than a shift from 5 p.m. to 6 p.m. This is because the later shift does not allow sufficient dark hours before bedtime. In this context, we examine the nonlinear impact of sleep on trading performance. According to our hypothesis, this effect should be more pronounced during the summer season when the sunset time is later (April to September) than during the winter season (October to March).

In Table 6, we divide the trade sample into two seasons, labeled as summer and winter. We estimate the Equation (5) for each subsample, with results presented in columns (2) and (3), respectively. The findings support our hypothesis. The impact of sleep is more pronounced during the summer. Summer season in column (2) shows 0.291% lower daily average abnormal return over the next 10 days, contributing significantly to the overall effect. This demonstrates that local sunset times influence sleep patterns in a nonlinear manner, which in turn affects trading performance.

In sum, by leveraging the variation in sunset time across longitude, resulting from time zone differences, this quasi-experimental approach provides further evidence supporting the negative causal relationship between sleep and trading performance among retail investors.

3.3 Trading Performance across Latitudes and Seasons

Although the regression discontinuity design allows us to extract the effect of sleep, we lose a number of observations in the analysis because of the property of local discontinuity.

Since we look at the households near the timezone borders, households located on the west and east coasts are excluded, where the most of population live in the congruous United States. Also, dividing samples into earlier and later local sunset times along the timezone borders naturally coincides with dividing the sample into locations with different distance to the major stock markets, which makes it hard to identify the effect of sleep with the spatial discontinuity design.

Therefore, we adopt an additional empirical approach using a different feature of solar system settings. Local sunset times vary not only across the longitude but also across the latitude. In the contiguous United States, the northern areas observe a later sunset in the summer season than the southern areas. In contrast, during the winter season, the southern areas observe a later sunset time.

We can take two major cities, Buffalo, New York, and Miami, Florida as an example. Both cities are in the Eastern timezone and located in similar longitude, -78.8784 and -80.1918, respectively. However, their latitude coordinates are far enough, 42.8864 and 25.7617, respectively. Figure 4 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 1st, Buffalo observes sunset at 20.97 (8:58 p.m.) and Miami does at 20.27 (8:16 p.m.). On January 2$^{\text{nd}}$, 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 US.

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

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 the Equation (5), such as characteristics control variables and fixed effects. If less sleep, measured by later sunset time, negatively influence the trading decision and trading results, β will be negative during the summer season (April, May, June, July, and August) and positive during the winter season (October, November, December, January, and February).[10]

The regression estimates of Equation (6) are presented in Table 7. The coefficient of $NorthernPart_j$ in the regression captures the comparison between the average $TradePerform_{jt,10}$ of the top 25% latitudes and the bottom 25% latitudes[11]. Notably, the analysis takes into account the influence of seasonal variations. In column (2) of Table 7, during the summer season, we observe that the stocks traded in the northern part of the United States exhibit 0.5% significantly lower daily performance compared to those in the southern part. However, in column (3), an intriguing reversal occurs, with the coefficient of $NorthernPart$ now being positive. This reversal aligns with the expectation that the northern part experiences earlier local sunset times during the winter season. The finding suggests that the timing of sunset may impact trading performance, with different effects observed in different seasons.

Of particular interest is the fact that the difference in trading performance between the northern and southern parts of the United States is only statistically significant during the summer season but not during the winter season. This implies that the relationship between sunset time and trading performance may be nonlinear, depending on the duration of dark hours between sunset time and bedtime. This nonlinear effect can be attributed to the onset of melatonin production, a hormone that aids sleep. The Centers for Disease Control and Prevention (CDC) reports that melatonin production typically begins around

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

[11] For the results using $TradePerform_{jt,335}$ is in the appendix Table A5. The results are weaker but similar to Table 7.

two hours before an individual's usual bedtime. Therefore, as long as the dark hours between sunset time and bedtime exceed two hours, the differences in sunset time may not significantly impact sleep patterns and, consequently, trading performance.

In summary, the regression results highlight the seasonal variations in the relationship between sunset time and trading performance. The northern part of the United States demonstrates differing performance outcomes compared to the southern part, depending on the season. These findings underscore the potential nonlinear impact of sunset time on sleep patterns and suggest that differences in trading performance can be influenced by bedtime.

4. Mechanisms

In this section, we focus to mechanism tests to uncover the underlying channels through which sleep influences trading performance. We explore four potential explanations: 1) investor attention; 2) trading activeness; 3) asymmetric risk-preference, 4) positive feedback; 5) herding.

4.1 Investor Attention

To address the impact of sleep on trading decisions, our study investigates the mechanisms through which sleep influences these choices. A primary factor under consideration is attention, particularly its reduction as a well-documented consequence of impaired sleep in neuroscience and psychology. The literature predominantly focuses on sustained attention, which refers to the ability to maintain stable, focused attention over a period. Especially, this type of attention is typically measured using performance tasks that require responses to target signals (Hudson et al., 2020; Warm et al., 2008). In financial market settings, reduced sleep could lead to decreased attention to new information available in the market, impacting trading decisions.

Following established finance literature on attention (DellaVigna and Pollet, 2009; Hirshleifer et al., 2009; Hirshleifer and Sheng, 2022), we utilize quarterly earnings announcement 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 scenarios requiring prompt attention to news, we exclude earnings announcements made on days when the market is closed.

The finance theory suggests that rational investors should adjust their portfolio holdings in response to new information. Conversely, investors with limited rationality might fail to respond adequately to new information. In our empirical analysis, we assess the likelihood of trading a stock shortly after its quarterly earnings announcement. We posit that lower sleep levels result in decreased attention, causing individuals in areas with later sunset times to trade less around earnings announcements compared to those in areas with earlier sunsets. To explore this hypothesis, we employ a linear probability regression model.

$$EAtrading_{jt} = \alpha + \boldsymbol{\beta_1} LateSide_j + \beta_2 Distance_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt} \qquad (7)$$

where $EAtrading_{jt}$ is a binary indicator representing the trading activity of household j on day t in relation to recent quarterly earnings. $EAtrading_{jt}$ takes value 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 typically rare[12]. 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 the earnings announcements literature, we cluster the standard errors at both zip-code and day levels.

Table 8 displays the estimates of Equation (7) under various specifications. Focusing on the 0 to 2 days prior to the earnings announcements, individuals residing on the earlier sunset side of the time zone border are more inclined to trade stocks based on new information. This trend becomes statistically significant when household characteristics are included in the analysis. As highlighted in column (3), merely living on the side with later sunsets reduces the likelihood of trading in response to earnings announcements by 4.27%. This negative association is maintained even when the analysis is refined to exclude trading on the day of the earnings announcements, thus conservatively defining attention to new information in column (4). Beyond this period, as indicated in Column (5), the effect becomes insignificant, supporting the idea that people who sleep better quickly and sufficiently react to earnings news.

Next, we extend our analysis of the attention mechanism to include a comparison between the northern and southern parts of the US. To do this, we estimate Equation 6 with the dependent variable $EAtrading_{jt}$, which takes value 1 if household j trade at least one stock on day t which has announced its quarterly earnings one or two days prior. This part of our study compares households located in the top 25% and bottom 25% of latitudes

[12] Table A7 in the Internet Appendix shows the estimation of the equation 6 using the entire sample. The results are consistent with Table 8.

across two distinct seasons. Specifically, we define the summer season as comprising earnings announcements in July and August, and the winter season as those in January and February. This definition is based on the observation that most earnings announcements are typically concentrated, and during April, May, October, and November, the local sunset times in the northern and southern regions are relatively similar. We anticipate that the magnitude of the effect in this latitude-based comparison will be greater than that observed in our previous local discontinuity analysis, owing to the larger variations enabled by broader geographical comparison.

Table 9 presents the results of the latitude comparison. In line with our hypothesis and previous findings across different latitudes, the data reveals a distinct pattern that households in the northern area react 14.2% less to earnings announcements in July and August compared to their southern counterparts. Conversely, during the winter season, northern households show a 0.819% higher reaction to earnings announcements than those in the south and this difference is not statistically significant.

4.2 Asymmetric Risk-Preference

Next, we focus on the asymmetric risk-preference of sleep-deprived people in psychology literature. The list of psychology and neurology literature (Kuhnen and Knutson, 2005; Mckenna et al., 2007; Venkatraman et al., 2007) has been interested in risk preference and they often distinguish risk-seeking and risk-aversion depending on the frames (gains or losses). Based on the idea, we examine whether sleep changes stock trading behavior that can be explained by the risk preference. Specifically,

We look at the previous month's return distribution to determine what risk information investors get. We adopt the frequency measure of return crashes and jumps from Chang et al. (2022) and Hutton et al. (2009). $Crash_{it}$ and $Jump_{it}$ are determined based on the number of the firm i's previous month returns respect to day t that exceed approximately 2.33 standard deviations below or above its mean values, respectively. 2.33 standard deviation is chosen to generate a frequency of 1% in the normal distribution. Then we construct an indicator $bJsC_{jt}$ to track the asymmetric trading behavior of households; willingness to buy stock experiencing extreme positive return and to sell off stock experiencing extreme negative return. The indicator $bJsC_{jt}$ equals one on a given day if a household j either buys a jump stock or sells crash stock, and zero otherwise.

The results of estimating Equation 7 with $bJsC_{jt}$ as a new dependent variable are in Table 10. According to our hypothesis, we anticipate that the coefficient β_1 would be positive saying that people living on the later sunset side are more likely to buy jump stocks and sell crash stocks when they trade. In table 10, the coefficient of $LateSide_j$ is positive and significant at least at 90% level. The level of significance increases as we include more characteristic variables. In this analysis, we restrict the sample to have all characteristics. In column (5), on average, being on the less sleep side induces 4.5% higher chance to react to jump and crash stocks on a given day.

We also apply the variation of local sunset time across the latitude. In table 11, we estimate the Equation 6 with the dependent variable $bJsC_{jt}$. Column (3) in table 11 indicates that when northern part of the US sleeps well during the winter season, they less exhibit the asymmetric trading behavior compared to the southern part of the US who has relatively late local sunset time during the winter.

4.3 Trading Activeness

A potential concern with using trading activity around earnings announcements as a measure of attention is that it could be confounded by the overall trading activeness of households. Specifically, sleep might influence trading performance not only by affecting investors' attention but also by altering their overall trading activeness. Frequent trading among retail investors leads to adverse investment outcomes (Barber and Odean, 2000). Also, trading hours may contribute to differences in trading frequency. deHaan and Glover (2023) present the link between stock market accessibility and the outcomes of retail investors' stock trading. Consequently, the variability in trading activity cannot be disregarded, especially considering the discontinuities at timezone borders, where shifts in trading hours occur.To address this concern, we conducted an additional test to determine whether the frequency of trading significantly differs between households residing on opposite sides of time zone borders.

We perform the local regression discontinuity analysis with the dependent variable, $ln(Trade_j)$, natural logarithm of the number of total trades over the six years of sample period of household j.

Table 12 provides evidence that trading activeness does not serve as the dominant mechanism through which sleep affects trading performance. As shown in Panel B, the estimates of the *LateSide* coefficients are not statistically significant, even after controlling for other household characteristics. This lack of significance leads us to conclude that trading activeness is not the primary mechanism through which sleep influences trading behavior. Instead, it suggests that attention is a dominating pathway.

4.4 Positive Feedback

Another potential mechanism for the effects of sleep is over-extrapolation. The detrimental impact of inadequate sleep on mental resource capacity implies that individuals with poorer sleep quality may be more inclined to rely on heuristics in decision-making. Given its well-documented presence in the finance literature, extrapolation could be a key mechanism through which sleep exerts its influence. To investigate its role, we utilize positive feedback trading as a proxy for extrapolation among retail investors, with a specific focus on short-term positive feedback trading. This emphasis is due to the frequent short-term reversals in daily returns, which often result in negative trading outcomes. By adopting this approach, we aim to examine if reduced sleep quality influences trading performance through over-extrapolation.

To define winners and losers, we adopt the 11-quantile strategy from Hirshleifer and Sheng (2022), ensuring that winners are associated with positive values. We categorize daily raw returns into 11 quantiles: the bottom 5 quantiles are assigned to negative returns, the 6^{th} quantile to zero returns, and the top 5 quantiles to positive returns. We then measure $PosFeedback_{jt}$ that equals 1 if household j either buys stocks in the top 3 quantiles of the previous day's return distribution or sells stocks in the bottom 3 quantiles out of the 11-quantile distribution on day t. Consequently, $PosFeedback_{jt}$ measures household j's the propensity to short-term positive feedback trading on day t.

Table 13 presents the results of a local regression discontinuity design with $PosFeedback_{jt}$ as the dependent variable, keeping other variables consistent with equation (5). From Column (1) to (4), we incrementally include various household characteristics in our analysis. However, we do not find a statistically significant causal relationship between sleep and the propensity for positive feedback trading. Therefore, we conclude that extrapolation is not a dominant mechanism of the sleep effect.

4.5 Investor Herding

Herding behavior among retail investors is a well-documented phenomenon in the stock market. To quantify each household's propensity to engage in herding, we adapt the fund herding measure from Jiang and Verardo (2018) to suit the household and daily level context. We aim to assess each household's sensitivity to the trading activities of others. This is achieved by estimating the following equation:

$$Trade_{ijt} = a_{jt} + \boldsymbol{b_{jt}} Others_{it} + d_{1it} Mom_{it-1} + d_{2jt} MC_{it-1} + d_{3jt} BM_{it} + e_{ijt} \qquad (8)$$

where $Trade_{ijt}$ is the sum of stock i's quantities that household j trades on day t. Especially we assign positive value to buying trading quantity and assign negative to selling trading quantity. And $Others_{it}$ represents the sum of stock i's quantities that traded on day t by all household except the focal household j. We also incorporate stock characteristics from the CRSP and Compustat databases into our analysis. The variable Mom_{it-1} denotes the daily return of stock i on the previous day, MC_{it-1} indicates the market capitalization of stock i on the previous day, and BM_{it} is the book-to-market ratio of stock i for the month in which day t falls. We use the coefficient b_{jt} as a measure of sensitivity to the trading direction of other retail investors. This approach allows us to assess the extent to which individual trading is influenced by the other retail investors.

The results in Table 14 do not support the idea that herding is the main mechanism of sleep. We gradually include the household characteristics in the regression from column (1) to (4), but we could not reject the null hypothesis that there is no causal relationship between sleep and herding behavior. Consequently, we conclude that herding does not constitute a dominant mechanism in the relationship between sleep quality and trading performance.

5. Conclusion

This study investigates the relationship between sleep and individual investors' trading performance. Building upon previous research concerning the entrainment of the human circadian clock to the sun, we adopt local sunset time as a proxy for individual sleep to overcome data limitations.

The findings consistently support the hypothesis that sleep significantly impacts individual investors' trading performance. The previous day's sunset time predicts the outcomes of the next day's stock trading decisions, with later sunset times correlating with lower trading performance on average. This relationship remains significant when analyzing a longer window of up to 335 days.

Furthermore, employing a regression discontinuity design at time zone borders provides compelling evidence of a causal link between sleep and trading performance among retail investors. Investors residing on the right-hand side of a time zone border, experiencing later sunsets and, consequently, potentially obtaining less sleep, exhibit inferior trading performance compared to their counterparts across the border. The effect of sleep on trading performance is also evident across latitudes and seasons. Specifically, households in the northern part of the US tend to trade stocks with lower average abnormal returns during the summer, whereas no such effect is observed during the winter, aligning with variations in local sunset times.

To examine economic mechanisms, we examine several channels. We find that attention and the asymmetric risk-preference channel as a dominant mechanism of the sleep effect. One hour increment in local sunset time induces the probability of making prompt reaction to earnings announcement drops by 4.27%. The latitudes comparison across seasons shows a larger effect size, 14.2% low probability of reaction among late sunset areas. Also, sleep affects the willingness to buy jump stocks and to sell crash stocks. Being on the later sunset side causes 4.5% more chances to trade jump and crash stocks asymmetrically on a day. We do not find supporting evidence for other channels, such as trading activeness, positive feedback, and investor herding.

The research contributes to the literature on the influence of sleep in the financial market. By establishing the link between sleep patterns and the decision quality and outcomes of retail investors, this study suggests that sleep is a promising candidate for plausible explanations for retail investor behavior in the stock market.

The findings underscore the significance of sleep as a fundamental physiological and biological feature of human beings in the context of financial decision-making. The implications of these findings can extend beyond retail investors to include institutional investors and financial professionals who may also be affected by sleep deprivation. Considering the notorious long working hours of the financial industry, it would be important to understand how professional money managers are affected by sleep. Understanding the potential influence of sleep on financial decision-making can inform investment strategies and decision-making practices across various market participants.

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Figure 1: Distribution of households and Timezone 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 timezone borders dividing the time zones.

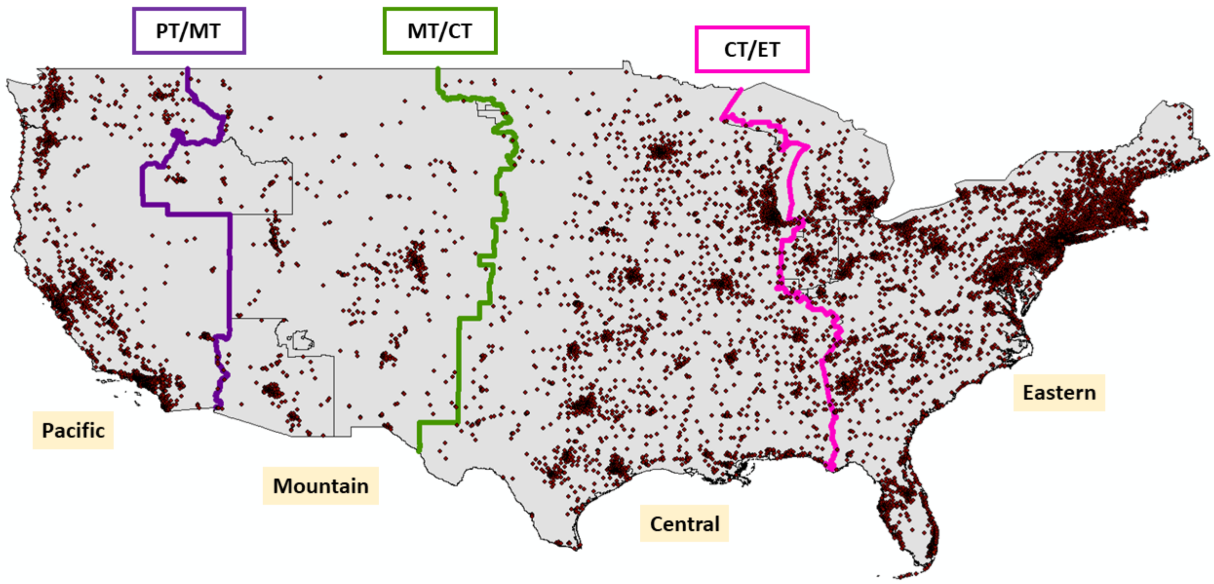

Figure 2: Local sunset discontinuity at time zone borders

Average local sunset time refers the average of each zip code's daily local sunset time over 6 years of the main sample (from 1991 to 1996). Daily local sunset time is computed using the information on the latitude and longitude of zip codes' centroid in the main sample. Distance to the timezone border indicates each household's location relative to its closest timezone border, which makes time zone borders have the value 0.

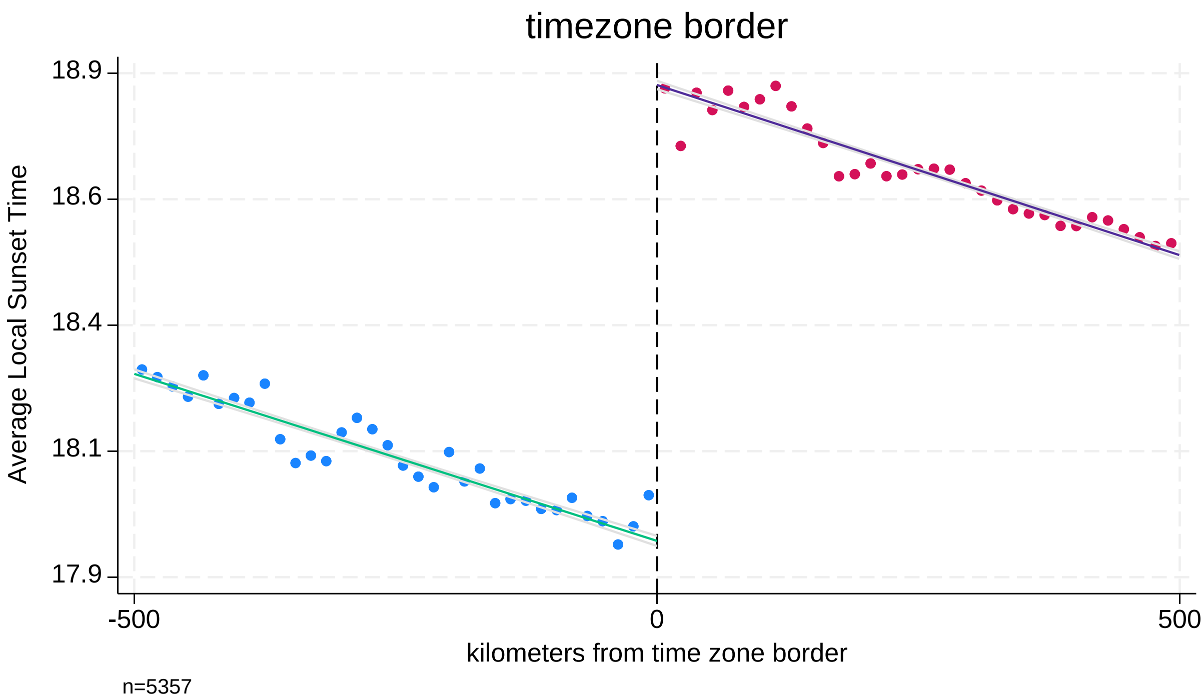

Figure 3: Trade Performance discontinuity at time zone borders

This figure illustrates the discontinuity in trade performance relative to distance from timezone borders. Points represent the mean residuals obtained from a regression of trade performance on all variables in equation 5 except $LateSide_j$ and $Distance_j$ to depict the discontinuity of trade performance along the distance to timezone borders. Panel A uses mean residuals of trade performance over 10 days after each trade, and Panel B uses mean residuals of trade performance over 335 days after each trade. The residuals are categorized into bins determined by Stata's cmogram command. Each panel displays linear fitted lines for both sides of the timezone border, encompassed by 95% confidence intervals.

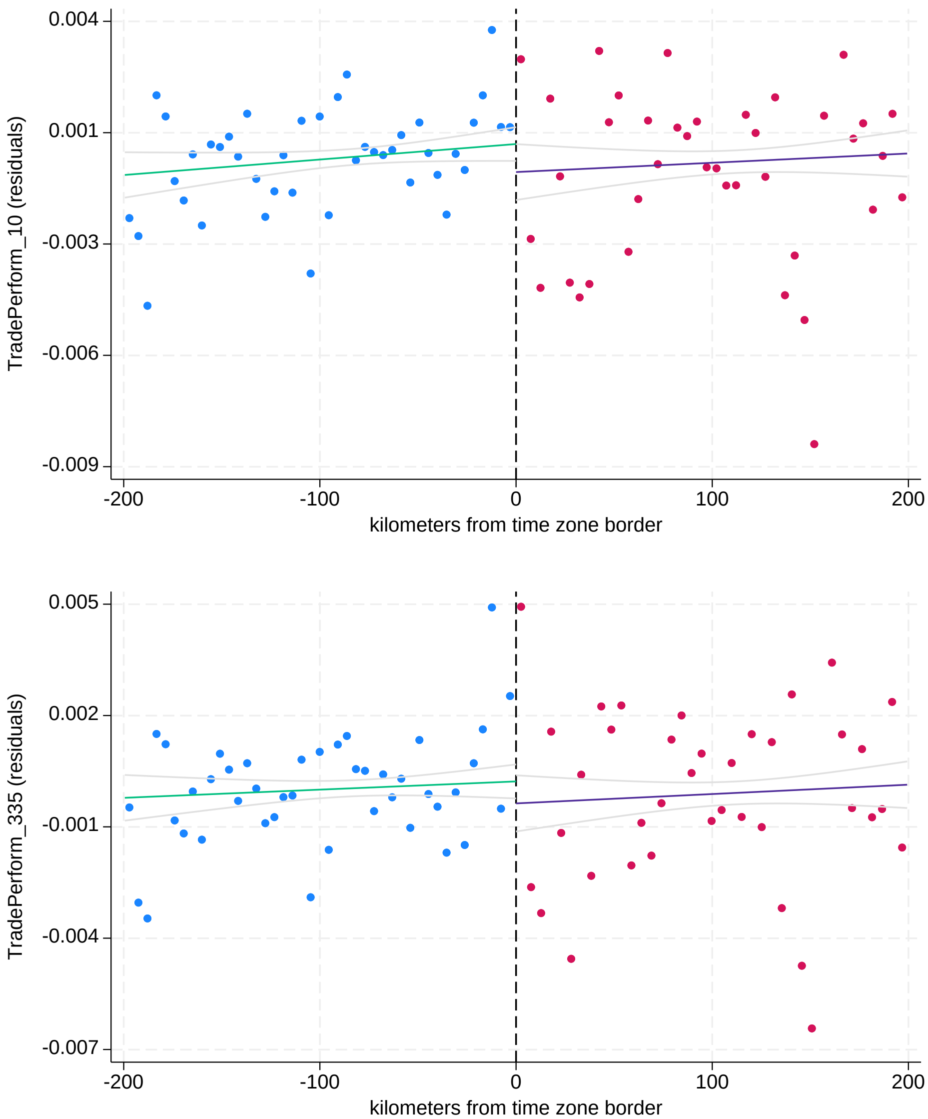

Figure 4: Sunset variation across Latitudes: Northern vs. Southern

This figure illustrates the variation in local sunset time over a year, 1994, of two location; 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 longitude but have large difference in latitudes, i.e., Buffalo is located in the northern area and Miami in the southern. This difference in latitude creates two intersects in the local sunset time over a year, in March and September.

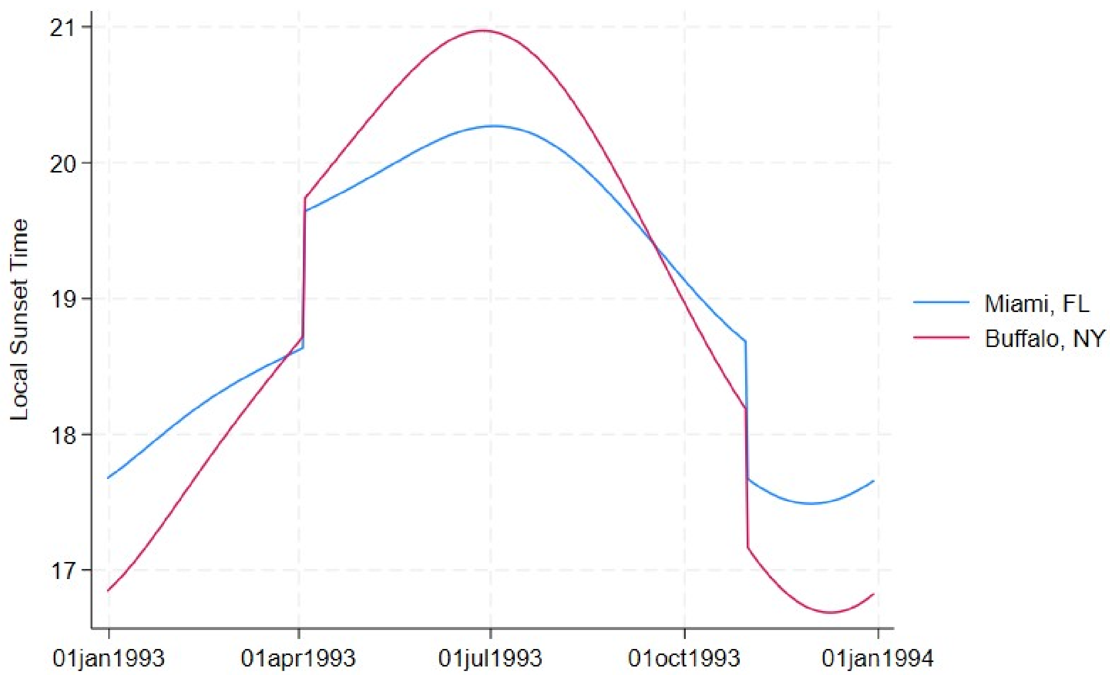

Table 1: Sample Distribution by Time zone

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) Pacific	(2) Mountain	(3) Central	(4) Eastern	(5) 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) Pacific	(2) Mountain	(3) Central	(4) Eastern	(5) 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	7,560	4,650	7,417	8,542	9,722
average trade volume	695.7412	639.9132	610.7390	621.5754	644.7330
	[1648.112]	[1874.374]	[1473.311]	[1682.365]	[1639.64]
average trade price	30.4073	30.5936	29.6375	30.2711	30.1974
	[93.7780]	[85.0294]	[92.7624]	[95.7191]	[93.9197]

Table 2: Variables 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. Distance 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. $TradePerform_k$ 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	1.3704	15.74	21.94
Distance (in kilometers)	180.56	625.2351	-864.10	1510.31
$TradePerform_{10}$	-0.0019	0.0188	-0.0453	0.0453
$TradePerform_{335}$	-0.0018	0.0162	-0.0234	0.0234
market return	0.0006	0.0065	-0.0341	0.0331
VIX	14.9090	2.9528	9.31	36.20

Panel B: Correlation between Main Variables

	Sunset	$TradePerform_{10}$	$TradePerform_{335}$	market return
$TradePerform_{10}$	-0.0141***			
$TradePerform_{335}$	-0.0177***	0.8757***		
market return	-0.0368***	-0.0306**	0.0351***	
VIX	-0.0872***	-0.0367***	-0.0345***	-0.1210***

Table 3: Trading Performance and Sunset Time

This table presents the results from estimating equation 4. The dependent variable $TradePerform_k$ is calculated by equation 3 over the different k-day windows from 10 days to 335 days after trading. The k-day window used is at the top of each column. Sunset is the local sunset time of each household on day t-1, measured in hours. Mktret and VIX are CRSP daily value-weighted market return and daily VIX, respectively. All regressions include the day of the week, year, and month fixed effects. We incorporate fixed effects for households and for counties observing daylight saving time. We restrict the household to having at least 10 transactions over 6 years. Transactions in December are excluded. Standard errors are clustered at the household level. t statistics in parentheses. Significance indicated by * p $<$ 0.10, ** p $<$ 0.05, and *** p $<$ 0.01.

$$TradePerform_{jt,k} = \alpha + \beta Sunset_{jt-1} + X_t'\delta + \gamma_t + \gamma_j + e_{it}$$

	(1) $k = 10$	(2) $k = 21$	(3) $k = 63$	(4) $k = 125$	(5) $k = 250$	(6) $k = 335$
Sunset	-0.000300***	-0.000241***	-0.000234***	-0.000215***	-0.000209***	-0.000304***
	(-3.58)	(-3.05)	(-3.09)	(-2.89)	(-2.85)	(-4.07)
Mktret	0.0676***	0.0700***	0.0670***	0.0671***	0.0660***	0.0605***
	(12.72)	(13.46)	(13.17)	(13.28)	(13.27)	(12.27)
VIX	-0.000059***	-0.000041***	-0.000072***	-0.000072***	-0.000077***	-0.000074***
	(-4.26)	(-3.09)	(-5.59)	(-5.69)	(-6.17)	(-5.95)
FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.0334	0.0369	0.0396	0.0405	0.0403	0.0408
Obs.	661,224	659,600	652,872	643,336	623,521	591,295

Table 4: Local discontinuity at time zone borders

This table presents the results from estimating equation 5. The dependent variable for each estimation is indicated at the top of each column. $TradePerform_{10}$ is calculated by equation 3 over the 10-day windows. $LateSide$ is an indicator if a household is located on the right side of the relevant timezone where the household observes a later local sunset time than one across the timezone border. $Distance$, a running variable, measures the distance from the household j to the corresponding timezone border in kilometers. To estimate the local discontinuity, we set bandwidths on $Distance$ to be from -200km to 200km when timezone borders are set to 0 as cutoffs. From columns (2) to (5) we gradually include household characteristics such as age, gender, self-reported knowledge, and experience. and linear control for latitude. All columns contain trade date fixed effect, state fixed effect, linear control for the latitudes, and geographical group fixed effects which is nine categorical groups by three parallel latitude lines and three timezone borders to assure the comparison between households in 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) and an indicator for daylight saving time periods. We restrict the household to having at least 10 transactions over 6 years. Transactions in December are excluded. Standard errors are clustered at the zip-code level. t statistics in parentheses. Significance indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

$$TradePerform_{jt,k} = \alpha + \beta_1 LateSide_j + \beta_2 Distance_j + X_j'\delta + \gamma_t + \gamma_j + e_{it}$$

	(1)	(2)	(3)	(4)	(5)
			$TradePerform_{10}$		
LateSide	-0.000705	-0.00105	-0.00109	-0.00270**	-0.00263**
	(-1.16)	(-1.51)	(-1.56)	(-2.52)	(-2.40)
Distance	0.00000417	0.00000370	0.00000386	0.00000906*	0.00000915*
	(1.56)	(1.25)	(1.32)	(1.89)	(1.85)
Age		-0.0000210***	-0.0000214***	-0.0000311***	-0.0000312***
		(-2.76)	(-2.80)	(-2.73)	(-2.65)
Female			-0.000654*	-0.000932*	-0.00105**
			(-1.87)	(-1.89)	(-2.06)
Knowledge: Good				-0.000639*	-0.00155**
				(-1.77)	(-2.38)
Limited				-0.000965**	-0.00189**
				(-2.39)	(-2.38)
None				-0.000438	-0.000686
				(-0.71)	(-0.65)
Experience: Good					0.000945
					(1.57)
Limited					0.00103
					(1.35)
None					-0.000968
					(-1.00)
Tradedate FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Latitude Control	Yes	Yes	Yes	Yes	Yes
Financial Hubs	Yes	Yes	Yes	Yes	Yes
bandwidth	200km	200km	200km	200km	200km
Adj. R^2	0.0165	0.0169	0.0171	0.0196	0.0200
Obs.	91639	75629	74956	35781	34187

Table 5: Local discontinuity at time zone borders over extended periods

This table presents the results from estimating equation 5. The dependent variable for each estimation is indicated at the top of each column. $TradePerform_k$ is calculated by equation 3 over the different k-day windows. LateSide is an indicator if a household is located on the right side of the relevant timezone where the household observes a later local sunset time than one across the timezone border. $Distance$ is the running variable that 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. We set bandwidths on $Distance$ to be from -200km to 200km when timezone borders are set to 0 as cutoffs. We control household characteristics, such as experience, knowledge, gender, and age. All columns contain trade date fixed effect, state fixed effect, linear control for the latitudes, and geographical group fixed effects. We also include an indicator for financial hubs and an indicator for daylight saving time periods. We restrict the household to having at least 10 transactions over 6 years. Transactions in December are excluded. Standard errors are clustered at the zip-code level. t statistics in parentheses. Significance indicated by * p < 0.10, ** p < 0.05, and *** p < 0.01.

$$TradePerform_{jt,k} = \alpha + \beta_1 LateSide_j + \beta_2 Distance_j + X_j'\delta + \gamma_t + \gamma_j + e_{it}$$

	(1) $k = 21$	(2) $k = 63$	(3) $k = 125$	(4) $k = 250$	(5) $k = 335$
LateSide	-0.00243**	-0.00225**	-0.00228**	-0.00200*	-0.00183*
	(-2.23)	(-2.04)	(-2.08)	(-1.83)	(-1.66)
Distance	0.00000816	0.00000725	0.00000704	0.00000527	0.00000545
	(1.64)	(1.44)	(1.42)	(1.08)	(1.12)
Age	-0.0000312***	-0.0000282**	-0.0000278**	-0.0000247**	-0.0000266**
	(-2.71)	(-2.51)	(-2.46)	(-2.23)	(-2.44)
Female	-0.00100**	-0.000847	-0.000699	-0.000550	-0.000579
	(-2.00)	(-1.57)	(-1.34)	(-1.05)	(-1.17)
Knowledge: Good	-0.00156**	-0.00168***	-0.00146**	-0.00147**	-0.00136**
	(-2.50)	(-2.65)	(-2.35)	(-2.41)	(-2.28)
Limited	-0.00193**	-0.00205***	-0.00177**	-0.00175**	-0.00157**
	(-2.50)	(-2.60)	(-2.29)	(-2.28)	(-2.09)
None	-0.000816	-0.000991	-0.000751	-0.000934	-0.000872
	(-0.86)	(-0.97)	(-0.78)	(-0.96)	(-0.90)
Experience: Good	0.00116**	0.00140**	0.00126**	0.00128**	0.00108**
	(2.03)	(2.42)	(2.24)	(2.31)	(2.03)
Limited	0.00120	0.00143*	0.00118	0.00132*	0.00112
	(1.63)	(1.94)	(1.64)	(1.85)	(1.59)
None	-0.000856	-0.000311	-0.000559	-0.000472	-0.000885
	(-0.94)	(-0.34)	(-0.62)	(-0.53)	(-1.00)
Tradedate FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Latitude Control	Yes	Yes	Yes	Yes	Yes
Financial Hubs	Yes	Yes	Yes	Yes	Yes
bandwidth	200km	200km	200km	200km	200km
Adj.R^2	0.0209	0.0227	0.0231	0.0230	0.0214
Obs.	34110	33763	33251	32201	30326

Table 6: Nonlinearity in the effect of Sleep on Trading Performance

This table presents the results from estimating equation 5. The dependent variable for each estimation is indicated at the top of each column. $TradePerform_{jt,10}$ is calculated by equation 3 over 10-day window. *LateSide* is an indicator if a household is located on the right side of the relevant timezone where the household observes a later local sunset time than one across the timezone border. *Distance* is the running variable. It 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. Bandwidths are from -200km to 200km when timezone borders are set to 0 as cutoffs. 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. We control household characteristics, such as experience, knowledge, gender, and age. All columns contain trade date fixed effect, state fixed effect, linear control for the latitudes, and geographical group fixed effects, which is nine categorical groups by three parallel latitude lines and three timezone borders to assure the comparison between households in similar latitude levels. We also include an indicator for financial hubs counties and an indicator for daylight saving time periods. We restrict the household to having at least 10 transactions over 6 years. Transactions in December are excluded. Standard errors are clustered at the zip-code level. t statistics in parentheses. Significance indicated by * p < 0.10, ** p < 0.05, and *** p < 0.01.

$$TradePerform_{jt,10} = \alpha + \beta_1 LateSide_j + \beta_2 Distance_j + X_j'\delta + \gamma_t + \gamma_j + e_{it}$$

	(1) Entire	(2) Summer Season	(3) Winter Season
LateSide	-0.00263**	-0.00291**	-0.00226
	(-2.40)	(-2.13)	(-1.55)
Distance	0.00000915*	0.0000113*	0.00000658
	(1.85)	(1.91)	(1.07)
age	-0.0000312***	-0.0000318**	-0.0000297*
	(-2.65)	(-2.18)	(-1.95)
Female	-0.00105**	-0.000978	-0.00109
	(-2.06)	(-1.50)	(-1.58)
Knowledge: Good	-0.00155**	-0.00120	-0.00194**
	(-2.38)	(-1.51)	(-2.09)
Limited	-0.00189**	-0.000633	-0.00324***
	(-2.38)	(-0.69)	(-3.01)
None	-0.000686	-0.000623	-0.000759
	(-0.65)	(-0.50)	(-0.55)
Experience: Good	0.000945	0.000633	0.00130
	(1.57)	(0.86)	(1.51)
Limited	0.00103	-0.000116	0.00226**
	(1.35)	(-0.13)	(2.19)
None	-0.000968	-0.000701	-0.00120
	(-1.00)	(-0.52)	(-0.85)
Tradedate FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Latitude Control	Yes	Yes	Yes
Financial Hubs	Yes	Yes	Yes
bandwidth	200km	200km	200km
Adj.R^2	0.0200	0.0171	0.0233
Obs.	34,187	17,846	16,341

Table 7: Northern vs. Southern depending on Sunset Seasonality

This table presents the results from estimating equation 6. The dependent variable $TradePerform_{jt,10}$ is calculated by equation 3 over 10-day window. *NorthernPart* equals one if a household is located 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, January, and February. We control household characteristics, such as experience, knowledge, gender, and age. We include trade-date fixed effects and state fixed effects. Longitude control includes linear control for the longitude and categorical groups dividing each timezone into three parts by two vertical longitude lines. We also include an indicator for financial hubs counties and an indicator for daylight saving time periods. We restrict the household to having at least 10 transactions over 6 years. Households in Financial hubs are also excluded. Transactions in December are excluded. Standard errors are clustered at the zip-code level. t statistics in parentheses. Significance indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

$$TradePerform_{jt,k} = \alpha + \beta NorthernPart_j + X_j'\delta + \gamma_t + \gamma_j + e_{it}$$

	(1) Entire	(2) Summer Season	(3) Winter Season
Northern Part	-0.00348**	-0.00500***	-0.00194
	(-2.12)	(-3.24)	(-0.88)
Age	-0.0000163**	-0.0000209**	-0.0000104
	(-2.46)	(-2.45)	(-1.26)
Female	-0.000232	-0.000141	-0.000329
	(-0.81)	(-0.38)	(-0.88)
Knowledge: Good	-0.000575	-0.000815**	-0.000305
	(-1.64)	(-1.98)	(-0.60)
Limited	-0.000319	-0.000313	-0.000377
	(-0.74)	(-0.62)	(-0.65)
None	-0.000279	-0.000763	0.000200
	(-0.54)	(-1.24)	(0.29)
Experience: Good	0.0000181	0.0000370	0.00000190
	(0.06)	(0.10)	(0.00)
Limited	-0.0000143	-0.0000396	0.0000565
	(-0.04)	(-0.09)	(0.10)
None	-0.000518	-0.000192	-0.000809
	(-0.79)	(-0.24)	(-0.92)
Tradedate FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Longitude Control	Yes	Yes	Yes
Financial Hubs	Yes	Yes	Yes
Adj. R^2	0.0169	0.0167	0.0168
Obs.	98,720	52,793	45,927

Table 8: Mechanism-Investor Attention

This table presents the results from estimating equation 7. 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 few days prior. At the top of each column, the numbers in brackets represent the number of days between the quarterly earnings announcement and the trade. For this analysis, we exclude the trading in March, June, September, and December, when the earnings announcements are typically rare. *LateSide* is an indicator if a household is located on the right side of the relevant timezone where the household observes a later local sunset time than one across the timezone border. *Distance* is the running variable. It 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. Bandwidths are from -200km to 200km when timezone borders are set to 0 as cutoffs. We control household characteristics, such as experience, knowledge, gender, and age. We include trade-date fixed effects and state fixed effects. All columns contain trade date fixed effect, state fixed effect, linear control for the latitudes, and geographical group fixed effects, which is nine categorical groups by three parallel latitude lines and three timezone borders to assure the comparison between households in similar latitude levels. We also include an indicator for financial hubs counties and an indicator for daylight saving time periods. We restrict the household to having at least 10 transactions over 6 years. Transactions in December are excluded. Standard errors are clustered at the zip-code and day level. t statistics in parentheses. Significance indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

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

	(1) [0, 2]	(2) [0, 2]	(3) [0, 2]	(4) [1, 2]	(5) [3, 5]
LateSide	-0.0135	-0.0290**	-0.0427**	-0.0412**	-0.0287
	(-1.00)	(-1.98)	(-2.15)	(-2.16)	(-1.52)
Distance	0.0000464	0.000104*	0.000110	0.0000883	0.000115
	(0.93)	(1.92)	(1.33)	(1.15)	(1.61)
Age		-0.00000325	-0.000256	-0.000249	-0.000000564
		(-0.02)	(-1.15)	(-1.19)	(-0.00)
Female		0.00413	0.00745	0.00888	-0.00112
		(0.61)	(0.77)	(0.92)	(-0.13)
Knowledge: Good			-0.0295**	-0.0225*	-0.0132
			(-2.45)	(-1.94)	(-1.15)
Limited			-0.0198	-0.0169	-0.00151
			(-1.38)	(-1.20)	(-0.12)
None			-0.0110	-0.00680	0.00849
			(-0.54)	(-0.36)	(0.51)
Experience: Good			0.0273***	0.0206**	0.0149
			(2.62)	(1.96)	(1.35)
Limited			0.0168	0.0159	0.00747
			(1.28)	(1.22)	(0.61)
None			-0.0148	-0.00852	-0.00109
			(-0.80)	(-0.47)	(-0.06)
Tradedate FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Latitude Control	Yes	Yes	Yes	Yes	Yes
Financial Hubs	Yes	Yes	Yes	Yes	Yes
bandwidth	200km	200km	200km	200km	200km
Adj.R^2	0.0547	0.0555	0.0646	0.0468	0.0462
Obs.	72,681	59,501	26,908	26,908	26,908

Table 9: Attention Mechanism tests across Latitudes

This table presents the results from estimating equation 6 with the dependent variable $EAtrading_{jt}$. $EAtrading_{jt}$ takes value 1 if household j trade at least one stock on day t which has announced its quarterly earnings one or two days prior. *NorthernPart* equals one if a household is located in the top 25% latitude and zero if in the bottom 25%. Column (1) shows the result of the entire sample in July, August, January, and February. Column (2) only includes the Summer season; July and August. Column (3) includes the Winter season; January and February. We control household characteristics, such as experience, knowledge, gender, and age. We include trade-date fixed effects and state fixed effects. Longitude control includes linear control for the longitude and categorical groups dividing each timezone into three parts by two vertical longitude lines. We also include an indicator for financial hubs counties and an indicator for daylight saving time periods. We restrict the household to having at least 10 transactions over 6 years. Households in Financial hubs are also excluded. Transactions in December are excluded. Standard errors are clustered at the zip-code and day level. t statistics in parentheses. Significance indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

$$EAtrading_{jt[1,2]} = \alpha + \boldsymbol{\beta} NorthernPart_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

	(1)	(2)	(3)
	Entire	Summer Season	Winter Season
Northern Part	-0.0592**	-0.142***	0.00819
	(-2.37)	(-4.63)	(0.20)
Age	0.0000310	0.0000393	0.0000207
	(0.20)	(0.20)	(0.10)
Female	0.00410	0.00591	0.00222
	(0.58)	(0.60)	(0.23)
Knowledge: Good	-0.0154	-0.00651	-0.0237*
	(-1.56)	(-0.52)	(-1.83)
Limited	-0.00734	0.00404	-0.0181
	(-0.62)	(0.27)	(-1.20)
None	-0.0231*	-0.00528	-0.0383**
	(-1.83)	(-0.34)	(-2.34)
Experience: Good	0.00863	0.00419	0.0127
	(1.12)	(0.41)	(1.18)
Limited	0.00113	-0.000713	0.00333
	(0.11)	(-0.05)	(0.26)
None	-0.0127	-0.0195	-0.00729
	(-1.07)	(-1.21)	(-0.43)
Tradedate FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Longitude Control	Yes	Yes	Yes
Financial Hubs	Yes	Yes	Yes
Adj.R^2	0.0436	0.0572	0.0317
Obs.	47,188	22,152	25,035

Table 10: Asymmetric Risk Preference as a Mechanism

This table presents the results from estimating equation 7 with the dependent variable, $bJsC_{jt}$. $bJsC_{jt}$ is an indicator variable that equals one on a given day if a household j either buys a 'jump' stock or sells a 'crash' stock, and zero otherwise. Crash and Jump stocks are determined based on the number of the firm i's previous month returns respect to day t that exceed approximately 2.33 standard deviations below or above its mean values, respectively, where 2.33 standard deviation is chosen to generate a frequency of 1% in the normal distribution. ***LateSide*** is an indicator if a household is located on the right side of the relevant timezone where the household observes a later local sunset time than one across the timezone border. ***Distance***, a running variable, measures the distance from the household j to the corresponding timezone border in kilometers. To estimate the local discontinuity, the main analysis set 200-kilometer bandwidth on *Distance*. From columns (2) to (5) we gradually include household characteristics such as age, gender, self-reported knowledge, and experience and linear control for latitude. *We restrict the sample to have all characteristics variables.* All columns contain trade date fixed effect, state fixed effect, linear control for the latitudes, and geographical group fixed effects which is nine categorical groups by three parallel latitude lines and three timezone borders to assure the comparison between households in similar latitude levels. We also include an indicator for financial hubs counties and an indicator for daylight saving time periods. We restrict the household to having at least 10 transactions over 6 years. Transactions in December are excluded. Standard errors are clustered at the zip-code level. t statistics in parentheses. Significance indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

$$bJsC_{jt} = \alpha + \boldsymbol{\beta_1} LateSide_j + \beta_2 Distance_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

	(1)	(2)	(3) $bJsC_{jt}$	(4)	(5)
LateSide	0.0433*	0.0438**	0.0446**	0.0439**	0.0450**
	(1.94)	(1.97)	(2.01)	(1.97)	(2.04)
Distance	-0.0000548	-0.0000645	-0.0000619	-0.0000599	-0.0000598
	(-0.55)	(-0.65)	(-0.62)	(-0.59)	(-0.61)
Age		-0.000608**	-0.000623**	-0.000635**	-0.000641**
		(-2.40)	(-2.47)	(-2.53)	(-2.53)
Female			0.00769	0.00777	0.00745
			(0.68)	(0.69)	(0.71)
Knowledge: Good				0.00308	0.0246*
				(0.40)	(1.74)
Limited				-0.00251	0.0332*
				(-0.29)	(1.74)
None				-0.00376	0.0105
				(-0.29)	(0.57)
Experience: Good					-0.0225*
					(-1.71)
Limited					-0.0412**
					(-2.27)
None					-0.0105
					(-0.46)
Tradedate FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Latitude Control	Yes	Yes	Yes	Yes	Yes
Financial Hubs	Yes	Yes	Yes	Yes	Yes
bandwidth	200km	200km	200km	200km	200km
Adj.R^2	0.00844	0.00872	0.00872	0.00867	0.00893
Obs.	36,626	36,626	36,626	36,626	36,626

Table 11: Asymmetric Risk Preference as a Mechanism-Seasons

This table presents the results from estimating equation 6 with the dependent variable, $bJsC_{jt}$. $bJsC_{jt}$ is an indicator variable that equals one on a given day if a household j either buys a 'jump' stock or sells a 'crash' stock, and zero otherwise. Crash and Jump stocks are determined based on the number of the firm i's previous month returns respect to day t that exceed approximately 2.33 standard deviations below or above its mean values, respectively, where 2.33 standard deviation is chosen to generate a frequency of 1% in the normal distribution. *NorthernPart* equals one if a household is located 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, January, and February. We control household characteristics, such as experience, knowledge, gender, and age. We include trade-date fixed effects and state fixed effects. Longitude control includes linear control for the longitude and categorical groups dividing each timezone into three parts by two vertical longitude lines. We also include an indicator for financial hubs counties and an indicator for daylight saving time periods. We restrict the household to having at least 10 transactions over 6 years. Households in Financial hubs are also excluded. Transactions in December are excluded. Standard errors are clustered at the zip-code level. t statistics in parentheses. Significance indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

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

	(1) Entire	(2) Summer Season	(3) Winter Season
Northern Part	-0.0706**	-0.00397	-0.141***
	(-2.21)	(-0.07)	(-4.88)
Age	-0.000296**	-0.000371**	-0.000220
	(-2.07)	(-2.09)	(-1.24)
Female	-0.0105	-0.0192***	-0.000266
	(-1.64)	(-2.65)	(-0.03)
Knowledge: Good	-0.000516	0.00408	-0.00525
	(-0.06)	(0.40)	(-0.47)
Limited	0.0155	0.0169	0.0148
	(1.41)	(1.38)	(1.00)
None	-0.00254	0.00121	-0.00637
	(-0.23)	(0.09)	(-0.45)
Experience: Good	-0.00608	-0.00483	-0.00784
	(-0.77)	(-0.52)	(-0.78)
Limited	-0.0227**	-0.0251**	-0.0205
	(-2.25)	(-2.22)	(-1.52)
None	-0.0165	-0.0187	-0.0154
	(-1.50)	(-1.34)	(-0.96)
Tradedate FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Longitude Control	Yes	Yes	Yes
Financial Hubs	Yes	Yes	Yes
Adj.R^2	0.00722	0.00846	0.00607
Obs.	106,382	56,989	49,393

Table 12: Trading Activeness is not a Mechanism

Panel A shows the descriptive statistics of the number of total trade over the six years of sample period and natural logarithm of it, $ln(Trade_j)$, by households that location is identified in the contiguous United States. Panel B presents the regression estimates of equation 7 with the dependent variable $ln(Trade_j)$. *LateSide* is an indicator if a household is located on the right side of the relevant timezone where the household observes a later local sunset time than one across the timezone border. *Distance* is the running variable. It 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. Bandwidths are from -200km to 200km when timezone borders are set to 0 as cutoffs. From column (1) to (5), we gradually include controls for household characteristics, such as age, gender, knowledge, and experience. We include trade-date fixed effects and state fixed effects. Latitude control includes linear control for the latitudes and categorical groups by the three parallel latitude lines and three timezone borders. We also include an indicator for financial hubs counties and an indicator for daylight saving time periods. We restrict the household to having at least 10 transactions over 6 years. Transactions in December are excluded. Standard errors are clustered at the zip-code level. t statistics in parentheses. Significance indicated by * p < 0.10, ** p < 0.05, and *** p < 0.01.

$$\ln(Trade_j) = \alpha + \boldsymbol{\beta_1} LateSide_j + \beta_2 Distance_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

Panel A: Summary Statistics of the Number of Trading by Household					
Variable	Obs.	Mean	Std. Dev.	Min	Max
Number of total trades	41,131	29.22	68.008	1	3559
$\ln(Trade_j)$	41,131	2.407	1.373	0	8.177

Panel B: Local Regression Discontinuity analysis of the Number of Trading					
	(1)	(2)	(3)	(4)	(5)
			$\ln(Trade_j)$		
LateSide	-0.0133	-0.201	-0.189	-0.263	-0.273
	(-0.10)	(-1.43)	(-1.35)	(-1.14)	(-1.17)
Distance	-0.000563	-0.000144	-0.0000933	-0.000517	-0.000414
	(-1.02)	(-0.24)	(-0.16)	(-0.53)	(-0.42)
Age		0.00446***	0.00449***	0.00631**	0.00732***
		(2.86)	(2.88)	(2.38)	(2.67)
Female			0.115	0.172	0.141
			(1.61)	(1.41)	(1.14)
Knowledge: Good				-0.292**	0.0626
				(-2.52)	(0.31)
Limited				-0.628***	0.258
				(-5.30)	(1.13)
None				-0.639***	0.0847
				(-4.13)	(0.34)
Experience: Good					-0.369*
					(-1.96)
Limited					-0.998***
					(-4.72)
None					-0.703***
					(-2.80)
State FE	Yes	Yes	Yes	Yes	Yes
Latitude Control	Yes	Yes	Yes	Yes	Yes
Financial Hubs	Yes	Yes	Yes	Yes	Yes
bandwidth	200km	200km	200km	200km	200km
Adj.R^2	0.00205	0.00344	0.00402	0.0414	0.0611
Obs.	5,691	4,770	4,739	1,795	1,688

Table 13: Positive Feedback Trading is not a Mechanism

This table presents the regression estimates of equation 5 with the dependent variable $PosFeedback_{jt}$. $PosFeedback_{jt}$ has a value 1 if either a household j buys stocks in the top 3 previous day return quintile or sells stocks in the bottom 3 previous day return quintile out of 11 quintile distribution on day t. *LateSide* is an indicator if a household is located on the right side of the relevant timezone where the household observes a later local sunset time than one across the timezone border. *Distance* is the running variable. It 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. Bandwidths are from -200km to 200km when timezone borders are set to 0 as cutoffs. From column (1) to (5), we gradually include controls for household characteristics, such as age, gender, knowledge, and experience. We include trade-date fixed effects and state fixed effects. Latitude control includes linear control for the latitudes and categorical groups by the three parallel latitude lines and three timezone borders. We also include an indicator for financial hubs counties and an indicator for daylight saving time periods. We restrict the household to having at least 10 transactions over 6 years. Transactions in December are excluded. Standard errors are clustered at the zip-code level. t statistics in parentheses. Significance indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

$$PosFeedback_{jt} = \alpha + \boldsymbol{\beta_1} LateSide_j + \beta_2 Distance_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

	(1)	(2)	(3)	(4)	(5)
			$PosFeedback_{jt}$		
LateSide	-0.0400	-0.0335	-0.0318	-0.0229	-0.0219
	(-1.22)	(-1.09)	(-1.03)	(-0.55)	(-0.52)
Distance	0.000115	0.000130	0.000141	-0.0000979	-0.000108
	(0.90)	(0.95)	(1.03)	(-0.65)	(-0.69)
Age		0.000435	0.000429	0.000656	0.000713
		(1.22)	(1.19)	(1.28)	(1.38)
Female			0.0159	0.0289	0.0321*
			(1.14)	(1.42)	(1.67)
Knowledge: Good				-0.000947	-0.00482
				(-0.06)	(-0.22)
Limited				0.00619	0.0268
				(0.35)	(0.82)
None				-0.0140	-0.0141
				(-0.62)	(-0.51)
Experience: Good					0.00614
					(0.30)
Limited					-0.0314
					(-1.08)
None					0.00494
					(0.17)
State FE	Yes	Yes	Yes	Yes	Yes
Latitude Control	Yes	Yes	Yes	Yes	Yes
Financial Hubs	Yes	Yes	Yes	Yes	Yes
bandwidth	200km	200km	200km	200km	200km
Adj.R^2	0.0132	0.0137	0.0138	0.0176	0.0179
Obs.	98,534	81,334	80,609	38,290	36,572

Table 14: Herding is not a Mechanism

This table presents the regression estimates of equation (5) with the dependent variable b_{jt}. The dependent variable b_{jt} is a regression coefficient of the equation (8), where $Trade_{ijt}$ is the sum of stock i's quantities that household j trades on day t after we assign positive value to buying trading quantity and assign negative to selling trading quantity. And $Others_{it}$ is the sum of stock i's quantities that traded on day t by all household except the focal household j. Mom_{it-1} denotes the daily return of stock i on the previous day, MC_{it-1} indicates the market capitalization of stock i on the previous day, and BM_{it} is the book-to-market ratio of stock i for the month in which day t falls. We exclude the December tradings when obtaining the coefficient b_{jt}. *LateSide* is an indicator if a household is located on the right side of the relevant timezone where the household observes a later local sunset time than one across the timezone border. *Distance* is the running variable. It 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. Bandwidths are from -200km to 200km when timezone borders are set to 0 as cutoffs. From column (1) to (5), we gradually include controls for household characteristics, such as age, gender, knowledge, and experience. We include trade-date fixed effects and state fixed effects. Latitude control includes linear control for the latitudes and categorical groups by the three parallel latitude lines and three timezone borders. We also include an indicator for financial hubs counties and an indicator for daylight saving time observing counties. We restrict the household to having at least 10 transactions over 6. Standard errors are clustered at the zip-code level. t statistics in parentheses. Significance indicated by * p < 0.10, ** p < 0.05, and *** p < 0.01.

$$Trade_{ijt} = a_{jt} + \boldsymbol{b_{jt}} Others_{it} + d_{1it} Mom_{it-1} + d_{2jt} MC_{it-1} + d_{3jt} BM_{it-1} + e_{ijt}$$
$$\boldsymbol{b_{jt}} = \alpha + \boldsymbol{\beta_1} LateSide_j + \beta_2 Distance_j + X_j'\delta + \gamma_t + \gamma_j + \varepsilon_{jt}$$

	(1)	(2)	(3)	(4)	(5)
			b_{jt}		
LateSide	-0.0832	-0.113	-0.112	-0.0681	-0.0722
	(-0.63)	(-0.93)	(-0.92)	(-0.97)	(-0.96)
Distance	0.000239	0.000140	0.000130	0.000193	0.000189
	(0.62)	(0.39)	(0.36)	(0.51)	(0.47)
Age		-0.00127	-0.00130	0.00226	0.00225
		(-0.60)	(-0.61)	(1.18)	(1.11)
Female			0.0974**	0.0345	0.0388
			(2.04)	(1.05)	(1.10)
Knowledge: Good				-0.0999*	-0.0643
				(-1.87)	(-1.29)
Limited				-0.0676	-0.0402
				(-0.92)	(-0.66)
None				-0.0967*	-0.0842
				(-1.66)	(-1.34)
Experience: Good					-0.0421
					(-1.41)
Limited					-0.0294
					(-0.57)
None					-0.0704
					(-0.95)
State FE	Yes	Yes	Yes	Yes	Yes
Latitude Control	Yes	Yes	Yes	Yes	Yes
Financial Hubs	Yes	Yes	Yes	Yes	Yes
bandwidth	200km	200km	200km	200km	200km
Adj.R^2	-0.00265	-0.00339	-0.00350	-0.0246	-0.0293
Obs.	3,132	2,611	2,594	1,119	1,058

Internet Appendix for

“Trading in Twilight: Sleep and Retail Investors’ Stock Investment Performance”

This appendix includes additional tables used in the paper:

- Table A1: Trading Performance and Sunset Time including December
- Table A2: Local discontinuity at time zone borders with various Bandwidths
- Table A3: Local Regression Discontinuity with the characteristic-available sample
- Table A4: Local discontinuity of Equal-Weighted Trade Performance
- Table A5: Loger Effect of Sleep over Northern vs. Southern
- Table A6: Trading Performance measured with Excess Return
- Table A7: Mechanism-Investor Attention including the entire sample

Table A1: Trading Performance and Sunset Time including December

This table presents the results from estimating equation 4. The dependent variable for each estimation is indicated at the top of each column. $TradePerform_k$ is calculated by equation 3 over the different k-day windows from 10 days to 335 days after trading. Sunset is the local sunset time of each household on day t-1, measured in hours. Mktret and VIX are CRSP daily value-weighted market return and daily VIX, respectively. All regressions include the day of the week, year, and month fixed effects. We incorporate fixed effects for households and for counties observing daylight saving time. We restrict the household to having at least 10 transactions over 6 years. Standard errors are clustered at the household level. t statistics in parentheses. Significance indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

$$TradePerform_{jt,k} = \alpha + \beta Sunset_{jt-1} + X_t^{'}\delta + \gamma_t + \gamma_j + e_{it}$$

	(1) $k = 10$	(2) $k = 21$	(3) $k = 63$	(4) $k = 125$	(5) $k = 250$	(6) $k = 335$
Sunset	-0.000210**	-0.000140*	-0.000128*	-0.000106	-0.000107	-0.000182**
	(-2.57)	(-1.81)	(-1.74)	(-1.46)	(-1.49)	(-2.50)
Mktret	0.0732***	0.0756***	0.0725***	0.0726***	0.0706***	0.0650***
	(14.06)	(14.89)	(14.59)	(14.68)	(14.53)	(13.49)
VIX	-0.0000677***	-0.0000497***	-0.0000784***	-0.0000786***	-0.0000842***	-0.0000818***
	(-5.10)	(-3.91)	(-6.36)	(-6.47)	(-7.00)	(-6.89)
FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.0320	0.0354	0.0380	0.0390	0.0391	0.0394
Obs.	714,688	712,888	705,659	695,102	673,746	640,453

Table A2: Local discontinuity at time zone borders with various Bandwidths

This table presents the results from estimating equation 5 with different bandwidth settings. The dependent variable $TradePerform_{10}$ is calculated by equation 3 over the 10-day windows. $LateSide$ is an indicator if a household is located on the right side of the relevant timezone where the household observes a later local sunset time than one across the timezone border. $Distance$, a running variable, measures the distance from the household j to the corresponding timezone border in kilometers. From columns (1) to (5) we gradually increase the bandwidth, the distance from the corresponding timezone border, from 100km to 500km. Household characteristics such as age, gender, self-reported knowledge and experience and linear control for latitude of household location are included. All columns contain trade date fixed effect, state fixed effect, linear control for the latitudes, and geographical group fixed effects which is nine categorical groups by three parallel latitude lines and three timezone borders to assure the comparison between households in similar latitude levels. We also include an indicator for financial hubs and an indicator for daylight saving times periods. We restrict the household to having at least 10 transactions over 6 years and an indicator for daylight saving time periods. Transactions in December are excluded. Standard errors are clustered at the zip-code level. t statistics in parentheses. Significance indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

$$TradePerform_{jt,k} = \alpha + \beta_1 LateSide_j + \beta_2 Distance_j + X_j'\delta + \gamma_t + \gamma_j + e_{it}$$

	(1)	(2)	(3)	(4)	(5)
			$TradePerform_{10}$		
LateSide	-0.00382***	-0.00263**	-0.00198**	-0.00123*	-0.00124*
	(-2.92)	(-2.40)	(-2.39)	(-1.76)	(-1.77)
Distance	0.0000135	0.00000915*	0.00000356	0.000000822	0.000000818
	(1.36)	(1.85)	(1.54)	(0.61)	(0.62)
age	-0.0000133	-0.0000312***	-0.0000292***	-0.0000299***	-0.0000300***
	(-0.94)	(-2.65)	(-3.51)	(-4.38)	(-4.40)
Female	-0.000845	-0.00105**	-0.000277	-0.000315	-0.000316
	(-1.32)	(-2.06)	(-0.69)	(-0.99)	(-0.99)
Knowledge: Good	-0.00222***	-0.00155**	-0.00133**	-0.00103**	-0.00103**
	(-2.61)	(-2.38)	(-2.58)	(-2.40)	(-2.40)
Limited	-0.00241**	-0.00189**	-0.00114*	-0.000810*	-0.000809*
	(-2.52)	(-2.38)	(-1.89)	(-1.71)	(-1.71)
None	-0.00101	-0.000686	-0.00104	-0.000927*	-0.000927*
	(-0.79)	(-0.65)	(-1.43)	(-1.68)	(-1.67)
Experience: Good	0.00174**	0.000945	0.000573	0.000255	0.000255
	(2.18)	(1.57)	(1.19)	(0.63)	(0.63)
Limited	0.00163*	0.00103	0.000336	0.000127	0.000125
	(1.84)	(1.35)	(0.60)	(0.28)	(0.28)
None	-0.000590	-0.000968	-0.000272	0.000333	0.000333
	(-0.55)	(-1.00)	(-0.33)	(0.52)	(0.52)
Tradedate FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Latitude Control	Yes	Yes	Yes	Yes	Yes
Financial Hubs	Yes	Yes	Yes	Yes	Yes
bandwidth	100km	200km	300km	400km	500km
Adj.R^2	0.0192	0.0200	0.0190	0.0167	0.0167
Obs.	21,602	34,187	63,424	93,738	93,808

Table A3: Regression Discontinuity with the characteristic-available sample

This table presents the results from estimating equation 5 with households whose characteristics are available. The dependent variable for each estimation is indicated at the top of each column. $TradePerform_{10}$ is calculated by equation 3 over the 10-day windows. $LateSide$ is an indicator if a household is located on the right side of the relevant timezone where the household observes a later local sunset time than one across the timezone border. $Distance$, a running variable, measures the distance from the household j to the corresponding timezone border in kilometers. To estimate the local discontinuity, the main analysis set 200-kilometer bandwidth on $Distance$. From columns (2) to (5) we gradually include household characteristics such as age, gender, self-reported knowledge, and experience and linear control for latitude. All columns contain trade date fixed effect, state fixed effect, linear control for the latitudes, and geographical group fixed effects which is nine categorical groups by three parallel latitude lines and three timezone borders to assure the comparison between households in 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) and an indicator for daylight saving time periods. We restrict the household to having at least 10 transactions over 6 years. Transactions in December are excluded. Standard errors are clustered at the zip-code level. t statistics in parentheses. Significance indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

$$TradePerform_{jt,10} = \alpha + \beta_1 LateSide_j + \beta_2 Distance_j + X_j^{'}\delta + \gamma_t + \gamma_j + e_{it}$$

	(1)	(2)	(3)	(4)	(5)
			$TradePerform_{10}$		
LateSide	-0.00252**	-0.00250**	-0.00239**	-0.00258**	-0.00263**
	(-2.28)	(-2.28)	(-2.20)	(-2.35)	(-2.40)
Distance	0.00000878*	0.00000826*	0.00000860*	0.00000894*	0.00000915*
	(1.75)	(1.66)	(1.75)	(1.80)	(1.85)
age		-0.0000305**	-0.0000326***	-0.0000323***	-0.0000312***
		(-2.57)	(-2.75)	(-2.73)	(-2.65)
Female			-0.00108**	-0.00107**	-0.00105**
			(-2.02)	(-2.06)	(-2.06)
Knowledge: Good				-0.000675*	-0.00155**
				(-1.84)	(-2.38)
Limited				-0.00100**	-0.00189**
				(-2.43)	(-2.38)
None				-0.000734	-0.000686
				(-0.88)	(-0.65)
Experience: Good					0.000945
					(1.57)
Limited					0.00103
					(1.35)
None					-0.000968
					(-1.00)
Tradedate FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Latitude Control	Yes	Yes	Yes	Yes	Yes
Financial Hubs	Yes	Yes	Yes	Yes	Yes
bandwidth	200km	200km	200km	200km	200km
Adj.R^2	0.0191	0.0194	0.0196	0.0198	0.0200
Obs.	34,187	34,187	34,187	34,187	34,187

Table A4: Local discontinuity of Equal-Weighted Trade Performance

This table presents the results from estimating equation 5. The dependent variable for each estimation is indicated at the top of each column. $TradePerform_{10}$ is calculated, by modifying equation 3 to be equal-weighted, over the 10-day windows. $LateSide$ is an indicator if a household is located on the right side of the relevant timezone where the household observes a later local sunset time than one across the timezone border. $Distance$, a running variable, measures the distance from the household j to the corresponding timezone border in kilometers. To estimate the local discontinuity, we set bandwidths on $Distance$ to be from -200km to 200km when timezone borders are set to 0 as cutoffs. From columns (2) to (5) we gradually include household characteristics such as age, gender, self-reported knowledge, and experience. and linear control for latitude. All columns contain trade date fixed effect, state fixed effect, linear control for the latitudes, and geographical group fixed effects which is nine categorical groups by three parallel latitude lines and three timezone borders to assure the comparison between households in 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) and an indicator for daylight saving time periods. We restrict the household to having at least 10 transactions over 6 years. Transactions in December are excluded. Standard errors are clustered at the zip-code level. t statistics in parentheses. Significance indicated by * p < 0.10, ** p < 0.05, and *** p < 0.01.

$$TradePerform_{jt,k} = \alpha + \beta_1 LateSide_j + \beta_2 Distance_j + X_j^{'}\delta + \gamma_t + \gamma_j + e_{it}$$

	(1)	(2)	(3)	(4)	(5)
			$TradePerform_{jt,10}$		
LateSide	-0.000695	-0.000986	-0.00102	-0.00268**	-0.00259**
	(-1.11)	(-1.37)	(-1.41)	(-2.49)	(-2.37)
Distance	0.00000414	0.00000354	0.00000374	0.00000914*	0.00000917*
	(1.52)	(1.17)	(1.25)	(1.92)	(1.88)
age		-0.0000223***	-0.0000229***	-0.0000335***	-0.0000338***
		(-2.92)	(-2.97)	(-2.95)	(-2.88)
Female			-0.000694**	-0.000909*	-0.00102**
			(-1.97)	(-1.82)	(-1.98)
Knowledge: Good				-0.000608*	-0.00163**
				(-1.67)	(-2.47)
Limited				-0.000881**	-0.00195**
				(-2.16)	(-2.42)
None				-0.000388	-0.000789
				(-0.63)	(-0.75)
Experience: Good					0.00106*
					(1.74)
Limited					0.00118
					(1.54)
None					-0.000825
					(-0.85)
Tradedate FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Latitude Control	Yes	Yes	Yes	Yes	Yes
Financial Hubs	Yes	Yes	Yes	Yes	Yes
bandwidth	200km	200km	200km	200km	200km
Adj.R^2	0.0167	0.0171	0.0172	0.0202	0.0207
Obs.	91,639	75,629	74,956	35,781	34,187

Table A5: Loger Effect of Sleep over Northern vs. Southern

This table presents the results from estimating equation 6. The dependent variable $TradePerform_{jt,335}$ is calculated by equation 3 over 335-day window. $NorthernPart$ equals one if a household is located 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, January, and February. We control household characteristics, such as experience, knowledge, gender, and age. We include trade-date fixed effects and state fixed effects. Longitude control includes linear control for the longitude and categorical groups dividing each timezone into three parts by two vertical longitude lines. We also include an indicator for financial hubs counties and an indicator for daylight saving time periods. We restrict the household to having at least 10 transactions over 6 years. Households in Financial hubs are also excluded. Transactions in December are excluded. Standard errors are clustered at the zip-code level. t statistics in parentheses. Significance indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

$$TradePerform_{jt,335} = \alpha + \beta NorthernPart_j + X_j^{'}\delta + \gamma_t + \gamma_j + e_{it}$$

	(1) Entire	(2) Summer Season	(3) Winter Season
Northern Part	-0.00142	-0.00346***	0.00121
	(-1.22)	(-2.90)	(0.51)
age	-0.0000128**	-0.0000177**	-0.00000653
	(-2.02)	(-2.22)	(-0.83)
Female	-0.000208	-0.000115	-0.000330
	(-0.77)	(-0.35)	(-0.92)
Knowledge: Good	-0.000750**	-0.00110***	-0.000311
	(-2.21)	(-2.76)	(-0.65)
Limited	-0.000650	-0.000928**	-0.000331
	(-1.64)	(-1.97)	(-0.63)
None	-0.000387	-0.00101*	0.000321
	(-0.83)	(-1.68)	(0.56)
Experience: Good	0.000211	0.000461	-0.0000998
	(0.66)	(1.23)	(-0.23)
Limited	0.000354	0.000563	0.000116
	(0.95)	(1.29)	(0.23)
None	-0.000132	0.000276	-0.000589
	(-0.24)	(0.38)	(-0.81)
Tradedate FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Longitude Control	Yes	Yes	Yes
Financial Hubs	Yes	Yes	Yes
Adj.R^2	0.0206	0.0194	0.0220
Obs.	87,495	48,905	38,590

Table A6: Trading Performance measured with Excess Return

This table presents the results from estimating equations 4 and 5. The dependent variable $TradePerform_k$ in this table is calculated by equation 3 using excess return, $R_{it} - R_{ft}$, instead of Fama-French three-factor abnormal return where R_{ft} is the one-month Treasury bill rate. Panel A shows equation 4 estimation with the same specifications as Table 3. The k-day window used is at the top of each column. Standard errors are clustered at the household level. t statistics in parentheses. Panel B presents the results from estimating equation 5 with the same specifications as Table 4. Standard errors are clustered at the zip-code level. t statistics in parentheses. Significance indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Panel A: $TradePerform_{jt,k} = \alpha + \beta Sunset_{jt-1} + X_t'\delta + \gamma_t + \gamma_j + e_{it}$

	(1)	(2)	(3)	(4)	(5)	(6)
	$k = 10$	$k = 21$	$k = 63$	$k = 125$	$k = 250$	$k = 335$
Sunset	-0.000173**	-0.000177**	-0.000207***	-0.000148**	-0.000156**	-0.000248***
	(-2.24)	(-2.40)	(-2.93)	(-2.11)	(-2.27)	(-3.53)
mktret	0.0640***	0.0667***	0.0619***	0.0623***	0.0617***	0.0566***
	(12.90)	(13.98)	(13.02)	(13.05)	(13.12)	(12.12)
VIX	-0.0000273**	-0.0000114	-0.0000638***	-0.0000638***	-0.0000698***	-0.0000632***
	(-2.26)	(-1.02)	(-5.60)	(-5.42)	(-5.96)	(-5.43)
FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.0328	0.0366	0.0391	0.0401	0.0401	0.0405
Obs.	690,864	689,214	682,384	672,641	652,193	618,300

Panel B: $TradePerform_{jt,10} = \alpha + \beta_1 LateSide_j + \beta_2 Distance_j + X_j'\delta + \gamma_t + \gamma_j + e_{it}$

	(1)	(2)	(3)	(4)	(5)
LateSide	-0.000619	-0.000888	-0.000924	-0.00256**	-0.00250**
	(-1.05)	(-1.32)	(-1.37)	(-2.47)	(-2.35)
Distance	0.00000363	0.00000290	0.00000307	0.00000943**	0.00000942*
	(1.42)	(1.02)	(1.09)	(2.03)	(1.95)
age		-0.0000176**	-0.0000181**	-0.0000289***	-0.0000303***
		(-2.39)	(-2.43)	(-2.60)	(-2.66)
Female			-0.000605*	-0.000889*	-0.00101**
			(-1.84)	(-1.93)	(-2.12)
Knowledge: Good				-0.000681*	-0.00120*
				(-1.90)	(-1.79)
Limited				-0.00102**	-0.00141*
				(-2.57)	(-1.78)
None				-0.000790	-0.000727
				(-1.26)	(-0.66)
Experience: Good					0.000524
					(0.84)
Limited					0.000435
					(0.56)
None					-0.00144
					(-1.48)
FEs	Yes	Yes	Yes	Yes	Yes
bandwidth	200km	200km	200km	200km	200km
Adj.R^2	0.0165	0.0164	0.0165	0.0185	0.0188
Obs.	95,454	78,766	78,065	37,222	35,525

Table A7: Mechanism-Investor Attention including the entire sample

This table presents the results from estimating equation 7. 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 few days prior. At the top of each column, the numbers in brackets represent the number of days between the quarterly earnings announcement and the trade. For robustness check, we include the entire trading, except December. *LateSide* is an indicator if a household is located on the right side of the relevant timezone where the household observes a later local sunset time than one across the timezone border. *Distance* is the running variable. It 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. Bandwidths are from -200km to 200km when timezone borders are set to 0 as cutoffs. We control household characteristics, such as experience, knowledge, gender, and age. We include trade-date fixed effects and state fixed effects. All columns contain trade date fixed effect, state fixed effect, linear control for the latitudes, and geographical group fixed effects, which is nine categorical groups by three parallel latitude lines and three timezone borders to assure the comparison between households in similar latitude levels. We also include an indicator for financial hubs counties and an indicator for daylight saving time periods. We restrict the household to having at least 10 transactions over 6 years. Standard errors are clustered at the zip-code and day level. t statistics in parentheses. Significance indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

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

	(1) [0, 2]	(2) [0, 2]	(3) [0, 2]	(4) [1, 2]	(5) [3, 5]
LateSide	-0.0138	-0.0266*	-0.0368**	-0.0336*	-0.0197
	(-1.07)	(-1.87)	(-2.07)	(-1.93)	(-1.14)
Distance	0.0000391	0.0000884*	0.0000758	0.0000571	0.0000894
	(0.89)	(1.77)	(1.08)	(0.86)	(1.43)
age		0.00000936	-0.000175	-0.000189	-0.000134
		(0.06)	(-0.90)	(-1.02)	(-0.74)
Female		0.00570	0.0144*	0.0147*	0.00350
		(0.99)	(1.69)	(1.75)	(0.45)
Knowledge: Good			-0.0256**	-0.0202*	-0.0137
			(-2.13)	(-1.77)	(-1.27)
Limited			-0.0103	-0.00933	0.000487
			(-0.74)	(-0.70)	(0.04)
None			-0.00508	-0.00448	0.00746
			(-0.29)	(-0.27)	(0.48)
Experience: Good			0.0211*	0.0167	0.0132
			(1.95)	(1.60)	(1.30)
Limited			0.00899	0.00959	0.00311
			(0.70)	(0.77)	(0.28)
None			-0.0195	-0.0116	-0.00574
			(-1.16)	(-0.71)	(-0.36)
Tradedate FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Latitude Control	Yes	Yes	Yes	Yes	Yes
Financial Hubs	Yes	Yes	Yes	Yes	Yes
bandwidth	200km	200km	200km	200km	200km
Adj.R^2	0.0592	0.0590	0.0685	0.0483	0.0458
Obs.	98,534	80,609	36,572	36,572	36,572