A novel measure of sleep based on Google: The case for financial markets

Antonios Siganos

Senior Lecturer in Finance

University of Glasgow

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Adam Smith Business School, Accounting and Finance Subject, Main Building, University of Glasgow, UK, e-mail: Antonios.Siganos@glasgow.ac.uk.

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ABSTRACT

We address in this study the issue of how to proxy sleep and explore sleep's significance for financial markets. We employ daily Google search activity on sleepiness terms (e.g., sleep deprivation) to develop an index and find that a one-day lagged sleepiness index is related negatively to US stock market returns. When investors lack sleep, stock market returns are relatively low. This pattern could be explained by sleep deprivation causing an increased level of investor anxiety and risk aversion. We find that this relation is most pronounced on days with high uncertainty in the market. Sleep is negatively related to stock market returns even after controlling for sentiment. Overall, our results highlight the application of Google Trend in a new field showing that investors' sleep patterns influence their investment decisions.

KEYWORDS: Sleep patterns; Google; stock market returns

JEL CODES: G11; G12

1. Introduction

Sleep influences humans through several neurobiological processes (e.g., Dinges, 1995; Achermann, 2004; Alhola and Polo-Kantola, 2007; Banks and Dinges, 2007; Walker, 2017). The two primary endogenous forces are the circadian and homeostatic processes. The circadian process tells the body when it needs to sleep, and the homeostatic when to be awake. Their interaction by neural systems in the brainstem and basal forebrain determines the sleep/wake pattern. This study addresses the issue of how one could proxy sleep to explore its significance in the field of finance. Only a few studies (Kamstra et al., 2000; Kamstra et al., 2002; Pinegar, 2002; Gregory-Allen et al., 2010; Siganos, 2019) explored the significance of sleep for financial markets all by using the daylight saving time changes. However, they have produced mixed results. Sleep influences everyone, regardless of prior training, occupation, or education (e.g., Walker, 2017), and there is no reason to believe that the significance of sleep may matter any less for participants in financial markets. We develop in this study a novel proxy of sleep based on Google search activity of sleepiness terms (such as sleep deprivation) and explore its relation with stock market returns.

It is clearly a non-trivial matter of how to proxy investor sleep patterns. Only daylight saving time changes have been used to capture investor sleepiness. Daylight saving time changes do indeed offer an external shock to participants' sleep which everyone is susceptible to. Kamstra et al. (2000) conjecture that investors may prefer safer investments following days with sleep abnormalities due to their anxiety and the difficulty to concentrate when solving problems. Based on evidence from psychology and biology (e.g., Spielberger, 1972; Neckelmann et al., 2007; Goldstein et al., 2013), there is a strong relation between a high level of anxiety and lack of sleep. There is also evidence showing that high anxiety makes participants risk-averse (e.g., Maner et al., 2007; Hartley and Phelps, 2012; Charpentier et al., 2017). Investors who are short on sleep are then expected to become risk-averse. They would more likely sell stocks that have experienced gains and also more likely to sell stocks that have experienced losses to reduce any uncertainty on future stock performance. Investors would more likely avoid undertaking purchase transactions. On days that investors are short on sleep, relatively low stock market returns are thus expected.[1] Kamstra et al. (2000) indeed find that sleep deprivation is linked with relatively lower stock market returns by showing that Monday stock market returns tend to be lower following the clock change. However, later studies (Kamstra et al., 2002; Pinegar, 2002; Gregory-Allen et al., 2010; Siganos, 2019) have debated the empirical validity of this relation.

Based on the amount of literature on the importance of sleep, it would be naïve to think that sleep does not impact investor decisions. The lack of a clear empirical relation is likely driven by the difficulty to measure sleep. Daylight saving time changes take place only twice a year, and there is only a one-hour change. So, their impact on our sleep is potentially limited. Beyond the daylight saving time changes, other factors may influence a significant percentage of investors facing sleep abnormalities. As an example, the adoption of new technology has influenced negatively investor sleep patterns in recent years. We develop in this study a proxy of investor sleepiness based on Google search activity. When people have trouble sleeping, they may likely perform a Google search to get informed on this topic. Some of the search terms that may be used are “jet lag” and “sleep apnea”. Google is the dominant search engine globally and according to Statista 79% of citizens with IP addresses located in the US typically use Google to search for information in 2018.[2] There is also plenty of evidence available that citizens follow online sources in the modern world for medical advice, often using Google to get access to relevant medical

[1] Studies in asset pricing literature (e.g., Zahirovic and Okicic, 2016) have previously shown that risk aversion is time varying and that increases in risk aversion are related with relatively low stock returns.
[2] https://www.statista.com/statistics/220534/googles-share-of-search-market-in-selected-countries/

websites (e.g., Sillence et al., 2007; Buhi et al., 2009; Chug et al., 2012). According to the Pew Internet & American Life Project, around 80% of citizens with IP addresses located in the US have searched for information online regarding their health issues.[3] Sleep influences everyone, regardless of prior training, occupation, or education (e.g., Walker, 2017), and there is no reason to believe that professional investors may search in Google any less for information regarding their personal lives in comparison to small investors. It is also unlikely that professional and small investors may exhibit significantly different sleep patterns over time considering similar external factors may influence their sleep such as the development of new technology.

Due to the significance of Google research volume data, an increasing number of academic studies have already employed this database. Da et al. (2011) is the first study that uses Google in the field of finance as a measure of investor attention and shows that search activity on firms' tickers is related to the next period's firm performance. Da et al. (2015) also use Google search activity on terms related to sentiment (e.g., "unemployment", "depression") to develop a sentiment index called the "Fears index". They find that the Fears index is related negatively with contemporaneous stock market returns, supporting the notion that pessimism decreases stock market returns. More recently, Gao et al. (2020) offer further evidence on the significance of sentiment on global stock market returns by extending, amongst others, Da et al.'s (2015) fears index into positive and negative sentiment terms. Google has also been used in several other fields beyond finance such as in the field of terrorism (e.g., Jaspersen and Montibeller, 2020) and economics (e.g., D'Amuri and Marcucci, 2017; Reyes, 2018). Based on the significance of sleep patterns in human decisions and the lack of sufficient empirical support on the significance of sleep

[3] http://www.pewinternet.org/2006/10/29/most-internet-users-start-at-a-search-engine-when-looking-for-health-information-online/

in the field of finance, the relevant application of Google searches for sleep is justified for its potential merit.

We first test the relation of sleep and trading activity in a case study using direct data from a fund manager between October 2015 and January 2017 on his hours of sleep and his investment transactions. In line to an extent with Kamstra et al. (2000), we find direct evidence that the fund manager indeed reduces his amount of trading when lacking sleep by becoming risk-averse. His transactions cannot influence stock returns due to the relatively small size, and for this reason, we develop a sleepiness index based on the daily Google search activity between 2004 and 2018 to test whether sleep influences stock market returns. To offer some validation for Google data, Figure 1 reports Google searches for the term daylight saving time changes in days around the event. We indeed find that the maximum search activity occurs on the day the clocks change, with some increasing activity before the event and decreasing activity after the event.

We apply the developed sleepiness index in the field of finance and find that a one-day lagged Google search activity on sleepiness terms is related negatively to stock market returns. On days that investors are short on sleep, stock markets tend to perform relatively poorly. This relation remains strong in many robustness tests. This pattern could be explained by sleep deprivation causing an increased level of risk aversion as first suggested by Kamstra et al. (2000). Sleep may be related theoretically with the sentiment, but its impact is more widespread such as on participants' attention to detail, their risk-taking, and their cognitive process of information. We find that the main relation holds after controlling for sentiment. Overall, this study develops a new measure of sleep with the assistance of Google Trend and reports that sleep matters for financial markets.

[insert Figure 1 around here]

We contribute to the growing field that explores the significance of web-based technology for financial markets (e.g., Da et al., 2011; McTier et al., 2013; Da et al., 2015; Reyes, 2018; Gao et al., 2020; Fischer and Krauss, 2018). We apply for the first time the Google search activity engine to proxy sleep patterns. We empirically validate the significance of one-day lagged changes in sleepiness with US stock market returns. We also contribute to the field of sleep concerning its significance in financial markets. The developed sleepiness measure has several advantages in comparison to the counterpart daylight saving time changes. First, it is available daily, compared to merely two observations a year, for daylight saving time changes. Second, it is a continuous variable, compared to a dummy used for the counterpart daylight saving time changes. Finally, we find that there is validation that sleep matters with the developed sleepiness index, while daylight saving time changes generate mixed findings, as shown in the data used in this study, and also based on the previous literature (Kamstra et al., 2000; Pinegar, 2002; Gregory-Allen et al., 2010; Siganos, 2019).

The remainder of the paper is structured as follows. Section 2 reports the empirical results of the case study. Section 3 discusses the construction of the sleepiness measure with the use of Google search data. Section 4 reports the main empirical results, and Section 5 concludes this study.

2. Case study

We first use a unique dataset collected for this study only, based on a fund manager's hours of sleep and his transactions to highlight with direct data that sleep can influence an individual's decisions. This section intends to offer anecdotal evidence that sleep matters for investment purposes. The manager is of British nationality, male, over 40 years old. He manages a mutual fund based in the UK of international assets valued at around £1 billion. The manager is the main responsible for stock allocation in the fund and undertakes most of the transactions as identified in the system. The manager self-collected manually the hours of sleep between 8th October 2015 and 31st January 2017. The collection took place daily from Sunday night until Friday morning, and the collection took place only on the days that he was working. He identified the time he awoke based on the alarm clock and that ensures the accuracy of his data collection. However, he began recording his sleep when he decided to go to bed, and a slight overestimation of the daily hours of sleep in comparison to the actual hours of sleep is expected.

Panel A of Table 1 shows the descriptive statistics of the manager's hours of sleep. The manager slept on average 7.7 hours per day, with a median of 7.4 hours. There is significant variation, with the minimum hours of sleep in a day being 5.2, and a maximum of 11.5 hours. The manager also provided us with his stock selections during the sample period. We estimate the number of daily transactions and the absolute sum of daily transactions as a measure of trading intensity. We have the precise timing each order was initiated by the manager. The dataset clarifies the name of the manager who undertook each of the transactions and we focus on his stock selections.

To test whether sleep is related to the number of transactions, the dependent variable is, first, the daily number of transactions, and, second, the logarithmic daily absolute sum invested. The main independent variable is the hours of sleep used as a continuous variable. Panel B of Table 1 shows results on the relation between hours of sleep and the next day's trading intensity. We find that the coefficient on sleep is significantly positive at the 10% level after all relevant controls. One additional hour of sleep is related to 0.77 more transactions and £244,654 higher investment. This relation is thus significant in statistical and economical terms. We thus offer some evidence that the manager hesitates to transact when lacking sleep in line with Kamstra et al.'s (2000) conjecture. In the remaining of the study, we develop the sleepiness measure based on Google and test its relation with the next day's stock market returns.

(Insert Table 1 around here)

3. The construction of the sleepiness index

For the construction of the sleepiness index, we access daily search activity from the Google trend website on terms indicating sleepiness for citizens with IP addresses located in the US. We use Python to get access to these data with the online algorithm, pytrendsdaily.[4] We collect data from January 2004, in line with data available from Google, until June 2018. We download Google search activity for each term separately and we use the scaled results as available from the online logarithm to ensure that data are comparable over time.[5]

A difficulty arose regarding the sleepiness terms that should be used to develop the sleepiness measure. It would not make sense to follow ready lists of sleep-specific terms available from sleep dictionaries. The terms used in these sources are mostly scientific such as "amphetamine sulphate", "rapid eye movement (REM)" or "narcolepsy" and it is thus unlikely that investors would search for such terms online for getting information on their sleep. In a pilot, we access relevant scientific sleep terms as available from the European Sleep Research Society.[6] We indeed find that ten out of the total 35 sleep-related terms, with their names starting with

[4] https://pypi.org/project/pytrendsdaily/

[5] They first download Google search activity for a term in monthly frequency that all values during the sample period can be downloaded at once. They then use these monthly values to scale daily Google searches for the same term.

[6] https://www.esrs.eu/media/glossary-of-sleep-related-terms.html?no_cache=1&tx_mmdictonary_pi1%5Bcapital%5D=A

“alpha”, have no data available on the Google trend website. This result highlights that most people would not normally use scientific sleep terms when searching for information. We instead follow Da et al.’s (2015) methodological approach who published their work in the *Review of Financial Studies* by developing the “Fears Index”. We thus allow the Google algorithm to identify terms that citizens with IP addresses located in the US used most frequently. Google uses autocompletion to suggest searches. Although it is secret the details of how the system works, Google seems to use machine-learning techniques to predict text based on several factors such as the analysis of large scale searches.[7] Since we cannot base on a sleeping dictionary as a starting point, we identify the following primitive terms strongly related to sleep: insomnia, jet lag, lack of sleep, sleep apnea, sleep deprivation, sleep disorders, and sleeping pills. From the options offered from the Google algorithm after searching for each primitive term, we add further relevant terms to our list.

We exclude terms clearly not relevant to sleepiness, such as the popular movie “Sleepless in Seattle”. We include terms such as “sleeping pills for dogs” in our list of terms that indicate citizens potentially experiencing poor sleep due to their dogs’ sleep patterns. We instead exclude the term “sleeping pills for cats,” since the search activity for this term was mostly zero. A significant percentage of search activity in Google for our terms is still zero, close to 50% of the values. To reduce the impact of zeros in the estimation of the sleepiness index we insert zero in the sleepiness index in days that all terms are equal to zero (in seven days). Otherwise, we only consider non-zero Google search values in the daily estimation of the sleepiness index. We estimate the daily average search volume of all terms to construct the sleepiness index. Our final sleepiness index includes 28 terms.[8] Unlike Da et al. (2015), we did not select terms whether are

[7] https://www.quora.com/How-does-Google-suggest-exactly-what-I-want-to-search. Lippi and Torroni (2016) offer a detailed review of available machine-learning techniques.
[8] Insomnia, insomniac, jet lag, jet lag calculator, jet lag cure, jet lag pills, jet lag tips, lack of sleep, lack of sleep headache, list of sleep disorders, sleep apnea, sleep apnea causes, sleep apnea devices, sleep apnea machine, sleep

related to stock market returns to ensure that the relation is not merely driven from data used in this study.[9]

Table 2 offers descriptive statistics for our sleepiness index. Column (1) offers the raw data of the measure that may vary from zero to 100. All searches are assigned a score of 100 for the maximum activity and a score of zero for the day with the minimum search. High search activity of sleepiness terms indicates a relatively high proportion of investors likely experiencing sleep difficulties. On the other hand, low search activity for sleepiness terms indicates a relatively low proportion of investors with sleep disturbances. We find that the average and median search activity of the sleep terms is 27.

As shown in Figure 2, we find that there is a tendency for an increase in search activity for sleepiness terms in recent years. This trend may be related to the development of new technology (e.g., iPhones) and people's increased levels of stress over time.[10] There are many outliers for our sleepiness index and we so winsorize the data at the top and bottom 10%.[11] Column 2 reports the descriptive statistics for the sleepiness index after winsorization. We find that winsorized values have kurtosis closer to 3 and skewness closer to zero. We use the *Sleepiness* variable to validate our measure in the next section, while we use its daily changes Δ*sleepiness* to test the main relation with stock market returns. The descriptive statistics for Δ*sleepiness* are available in column 3. We find that all our variables are stationary as shown from the Augmented Dickey-Fuller test (Dickey and Fuller, 1979). We use in this estimation, one lag with a drift.

apnea mask, sleep apnea mouth guard, sleep apnea surgery, sleep apnea test, sleep apnea treatment, sleep deprivation, sleep deprivation causes, sleep deprivation death, sleep deprivation effects, sleep disorders, sleeping pills, sleeping pills and alcohol, sleeping pills for dogs, sleeping pills names.

[9] In untabulated results, we explore the relation between lagged changes in Google search activity for each sleepiness term and stock market returns. We find that the sign of the main relation is negative in 20 (out of the total 28) of these terms.

[10] http://channel.nationalgeographic.com/sleepless-in-america/.

[11] We report later in this study the main result when winsorizing sleep data at the top and bottom 5%.

[insert Table 2 around here]

[insert Figure 2 around here]

4. Empirical results

4.1 The empirical validation of the sleepiness index

We offer in this section some empirical validation of the developed sleepiness index. Our dependent variable is the sleepiness index in Panels A and B of Table 3. In Panel A our independent variables are the one-day lagged clock changes, and also dummies per day of the week, per month, and year. We find that the parameter coefficient of clock change is significantly positive showing that investors tend to search Google for sleepiness terms the day following daylight saving time changes. This result offers some validity of our sleepiness measurement in comparison to the only other proxy of sleep available.

We find some expected seasonalities in Google search activity (Statista, 2019). We find that in comparison to Monday there is less volume in searching activity for sleepiness terms on Thursday and Friday, while more during the weekend. During the weekend citizens have more time to explore their personal issues online and potentially less time during the end of the working week who may need to finalize all outstanding work commitments. We also find that in comparison to January there is less search activity in Google for sleepiness terms running up to Christmas. As expected we also find that there is more search activity in Google for sleepiness terms in recent years with an increasing percentage of citizens using the internet. Note that less search activity is present during the 2007-2009 period. Citizens are more likely to experience sleep difficulties during the financial crisis period and there should have been stronger rather than lower search activity. This may be a limitation on the developed sleepiness index. Citizens did not explore sleepiness terms during the 2007-2009 period potentially due to their focus on other issues such as their job security. To ensure that our main results later in this study are not driven by seasonality we add day of the week, month, and year fixed effects.

Panel B of Table 3 explores whether macroeconomic variables are related to the developed sleepiness index. We access the daily ADS index[12] that indicates the level of uncertainty in an economy. High ADS values indicate high economic uncertainty. We also access from the Chicago Board Options Exchange returns for S&P500 stock returns that indicate the level of uncertainty in the market (*lnVIX*). These values are collected from WRDS. The number of observations is reduced in this estimation because we have no longer weekend values. We expect that investors face sleep difficulties on days that there is high uncertainty in the economy. We indeed find that both parameter coefficients are significantly positive offering further assurance that our sleepiness index is a good proxy to measure sleep patterns.

Finally, Panel C of Table 3 explores whether sentiment and the sleepiness index are related. We use Facebook's sentiment index (Siganos et al., 2014) that measures the US daily sentiment based on status updates on Facebook. These data are available between September 2007 and March 2012. We find that there is a positive relation that indicates that on days that citizens are relatively happy they tend to search more in Google. In untabulated results, we find that there is no relation between one-day lagged values of sleepiness and sentiment. Although sentiment and sleep are related there are many differences. Sleep is so much more than sentiment since it tends to influence everyone, regardless of prior training, occupation, or education, while this is not the case for the sentiment that influences mostly small investors (e.g., Lemmon and Portniaguina, 2006; Baker and

[12] https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index

Wurgler, 2007). Sleep's impact is also more widespread since it influences participants' attention to detail, risk-taking, and the cognitive process of information (e.g., Walker, 2017).

[insert Table 3 around here]

4.2 One-day lagged sleepiness and stock market returns

We present in this section the main results of this study regarding the relation between one-day lagged changes in the sleepiness index and stock market returns. We explore the applicability of the developed sleepiness index for financial markets. To support the hypothesis developed by Kamstra et al. (2000), we should find a negative relation that would indicate that stock market returns are relatively low when investors are short on sleep.

Table 4 reports the empirical results. The dependent variable is stock market returns (S&P500) as accessed by CRSP and the main independent variable is the one-day lagged changes in sleepiness (Δ sleepiness measure). We do not tabulate all parameter coefficients for space consideration but we add day of the week, month, and year dummies across all estimations to control for seasonality in stock returns. We cluster the standard errors in a month as suggested by Petersen (2009). As expected, we find that the parameter coefficient on Δ*sleepiness* is negative. As shown in column (1) of Table 4 a 1% increase in sleep disturbances is related to a decrease in the next day's stock market returns of 0.14%. This relation is economically significant and is significant at the 1% level.

[insert Table 4 around here]

We also test the significance of the daylight saving time changes on stock market returns with the use of our data to compare directly alternate proxies of sleep. Daylight saving time changes is the only other measure of sleep available in the literature that has though offered mixed results (Kamstra et al., 2000; Kamstra et al., 2002; Pinegar, 2002; Gregory-Allen et al., 2010; Siganos, 2019). As shown in column (2) we find that the parameter coefficient on *clock change* is insignificant highlighting the need to develop a new sleep measure (as we do in this study). This result is actually in line with Kamstra et al. (2010; 2013) who show that the relation has weakened recently, as they argued, potentially due to arbitrageurs' activity after the initial discovery of the pattern in 2000 (i.e. Kamstra et al., 2000).

In column (3) we re-estimate our main regression as shown in column (1) but in this test, we winsorize the sleepiness index at the top and bottom 5% (rather than the top and bottom 10% used earlier). Once again, we find that the parameter coefficient on Δ*sleepiness* remains negative. In column (4) we report results only on Sunday's changes in sleep concerning Monday's stock market returns. Our conclusion remains unchanged within this subsample. It is not then the use of weekend values behind the inability of the daylight saving time changes to influence stock market returns.

In columns (5) and (6) we explore the robustness of the main relation after controlling for macroeconomic variables (ADS Index and VIX) and sentiment (Facebook's sentiment index).[13] Since sentiment data are only available in a relatively short period (between September 2007 and March 2012) we undertake two separate estimations. We find that the parameter coefficient on Δ*sleepiness* remains significantly negative after relevant controls. The relation holds after controlling for macroeconomic conditions and sentiment. As discussed earlier, sleep's relation with stock market returns differs from that of sentiment. In contrast to the sentiment that influences mostly small investors sleep influences everyone. Sleep's impact is also more widespread such as

[13] Note that Siganos et al. (2014) explore the relation between Facebook's sentiment and stock market returns for several international markets. This study explores only the US market.

on participants' attention to detail and the cognitive processing of information (e.g., Lemmon and Portniaguina, 2006; Walker, 2017).

4.3 Endogeneity concerns

There may be some concern of potential reverse causality according to which stock returns may influence sleep patterns. In column (1) of Table 5, we test the contemporaneous relation between stock market returns and sleep and in column (2) whether one-day lagged stock market returns are related to sleep. We find that both relevant parameter coefficients are insignificant showing that there is little, if any, concern that the stock market influences the developed sleepiness index.

We also formally test for endogeneity following an IV procedure. We use as instruments the daily time that the sun rises and sets. We access relevant timings from online sources.[14] We take the sunrises' and sunsets' timings of the mean center of population in the US in 2010 as estimated by the US Census Bureau. This is 37 North latitude and 92 West longitude, Missouri 65793. We expect that the timing of sunsets and sunrises influences bedtime and wake-up patterns. Sunsets and sunrises have not to our knowledge been previously empirically linked with stock market returns.

In the first step, we regress these instruments on changes in sleepiness and estimate the predicted values. In the second step, we regress the predicted changes in sleepiness that arrive from the first stage of the next period's stock market returns. Column (3) reports the first stage results showing that the instruments are related to our sleep patterns. We find that later sunrises and earlier sunsets are related to more sleep disturbances in line with evidence in the literature (e.g., Walch et

[14] http://aa.usno.navy.mil/data/docs/RS_OneYear.php
https://en.wikipedia.org/wiki/Geographic_center_of_the_United_States#/media/File:USCenterPop_Geographic2010.png

al., 2016). This result offers further assurance that our sleepiness index is a good proxy to measure sleep patterns. More importantly, column (4) reports the second stage results showing that variations in sunsets and sunrises influence the effect of the sleepiness measure on stock market returns. Overall, our results seem unlikely to be driven by endogeneity.

[insert Table 5 around here]

4.4 Does this pattern reverse in the days following the initial reaction?

Investors are expected to realize that their response to a lack of sleep may not reflect information about fundamentals. It is then expected that the relation may reverse over the following days to compensate for relevant mispricing. To test this, we add up to five-day lags on the sleepiness variable as a reflection of potential weekly patterns and we estimate the relation between lagged sleepiness and stock market returns.

Table 6 shows the empirical results. As expected, we find evidence of a reversal in this relation. The relevant parameter coefficients are significantly positive when using three- and four-day lagged sleepiness values. These results offer some evidence of later compensation on the initial response.

[insert Table 6 around here]

4.5 When is the relation most pronounced?

We test here the days that the main relation may be most pronounced. To our understanding, Kamstra et al. (2000) conjecture that investors become risk-averse when they are short on sleep. We thus expect that sleepy investors respond more profoundly to the news in days of economic uncertainty. To test this, we interact VIX, which is one of the most well-known measures of economic uncertainty, with Δ*sleepiness*. [15]

The results are shown in Table 7. We find that the parameter coefficient on the interaction variable (Δ *sleepiness{t-1} * LnVIX{t}*) is significantly negative. This result indicates that on days that there is uncertainty in the market, stock market returns experience more pronounced low returns when investors are short on sleep. Investor risk aversion increases on days with uncertainty especially when investors lack sleep. This result offers some empirical validity on the channel behind sleep's impact on financial markets.

[insert Table 7 around here]

5. Conclusion

This study offers an insight into the significance of sleep for financial markets. Existing studies (Kamstra et al., 2000; Kamstra et al., 2002; Pinegar, 2002; Gregory-Allen et al., 2010; Siganos, 2019) previously used the daylight saving time changes to measure sleep disturbances and produced mixed results. We first test the relation of sleep and trading activity in a case study using direct data from a fund manager. In line with Kamstra et al.'s (2000) hypothesis, we find that the fund manager avoids investing the day following a poor night's sleep potentially due to the anxiety and the difficulty to concentrate when solving problems.

We then develop a new measure of sleep based on sleepiness terms (such as sleep deprivation) searched on the Google website. We find a negative relation between the one-day

[15] We acknowledge that VIX has also been used in the literature as a proxy of market risk and investor sentiment (e.g., Smales, 2017), not only as a measure for uncertainty.

lagged sleepiness and US stock market returns, showing that stock market returns are relatively low when investors lack sleep. These results potentially reflect that sleepy investors are risk-averse. This relation becomes most prominent on days that there is high uncertainty in the market. When investors lack sleep, they respond more prominently to the market conditions potentially as a result of the increased risk aversion. Hopefully, the sleep measurement developed in this study may assist with the development of the field.

References

Achermann, P. 2004. “The Two-Process Model of Sleep Regulation Revisited.” *Aviation Space and Environmental Medicine* 75(3): 37-43.

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

Banks, S., and D. Dinges. 2007. “Behavioral and Physiological Consequences of Sleep Restriction.” *Journal of Clinical Sleep Medicine* 3(5): 519-528.

Baker, M., and J. Wurgler. 2007. “Investor Sentiment in the Stock Market.” *Journal of Economic Perspectives* 21(2): 129-151.

Buhi, E., E. Daley, H. Fuhrmann, and S. Smith. 2009. “An Observational Study of How Young People Search for Online Sexual Health Information.” *Journal of American College Health* 58(2): 101-111.

Charpentier, C., J. Aylward, J. Roiser, and O. Robinson. 2017. “Enhanced Risk Aversion, But Not Loss Aversion, in Unmedicated Pathological Anxiety.” *Biological Psychiatry* 81(12): 1014-1022.

Chung, M., R. Oden, B. Joyner, A. Sims, and R. Moon. 2012. “Safe Infant Sleep Recommendations on the Internet: Let’s Google it.” *Journal of Pediatrics* 161(6): 1080-1084.

D’Amuri, F., and J. Marcucci. 2017. “The Predictive Power of Google Searches in Forecasting US Unemployment.” *International Journal of Forecasting* 33(4): 801-816.

Da, Z., J. Engelberg, and P. Gao. 2011. “In Search of Attention.” *Journal of Finance* 66(5): 1361-1499.

Da, Z., J. Engelberg, and P. Gao. 2015. “The Sum of ALL FEARS Investor Sentiment and Asset Prices.” *Review of Financial Studies* 28(1): 1-32.

Dickey, D., and W. Fuller. 1979. “Distribution of Estimators for Time Series Regressions with a Unit Root.” *Journal of the American Statistical Association* 74(June): 427-431.

Dinges, D. 1995. “An Overview of Sleepiness and Accidents.” *Journal of Sleep Research* 4(s2): 4-14.

Fischer, T., and C. Krauss. 2018. “Deep Learning with Long Short-Term Memory Networks for Financial Market Predictions.” *European Journal of Operational Research* 270(2): 654-669.

Gao, Z., H. Ren, and B. Zhang. 2020. “Googling Investor Sentiment Around the World.” *Journal of Financial and Quantitative Analysis* 55(2): 549-580.

Goldstein, A., S. Greer, J. Saletin, A. Harvey, J. Nitschke, and M. Walker. 2013. “Tired and Apprehensive: Anxiety Amplifies the Impact of Sleep Loss on Aversive Brain Anticipation.” Journal of Neuroscience 33(26): 10607-10615.

Gregory-Allen, R., B. Jacobsen, and W. Marquering. 2010. “The Daylight Saving Time Anomaly in Stock Returns: Fact or Fiction?” *Journal of Financial Research* 33(4): 403-427.

Hartley, C., and E. Phelps. 2012. “Anxiety and Decision Making.” *Biological Psychiatry* 72(2): 113-118.

Jaspersen, J., and G. Montibeller. 2020. “On the Learning Patterns and Adaptive Behaviour of Terrorist Organizations.” *European Journal of Operational Research* 282(1): 221-234.

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

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

Kamstra, M., L. Kramer, and M. Levi. 2010. "Effects of Daylight-Saving Time Changes on Stock Market Volatility: A Comment." *Psychological Reports* 107(3): 877-887.

Kamstra, M., L. Kramer, and M. Levi. 2013. "Effects of Daylight-Saving Time Changes on Stock Market Returns and Stock Market Volatility: Rebuttal." *Psychological Reports* 112(1): 89-99.

Lemmon, M., and E. Portniaguina. 2006. "Consumer Confidence and Asset Prices: Some Empirical Evidence." *Review of Financial Studies* 19(4): 1499-1529.

Lippi, M., and P. Torroni. 2016. "Argument Mining: A Machine Learning Perspective." Theory and Applications of Formal Argumentation, Third International Workshop. Springer.

Maner, J., J. Richey, K. Cromer, M. Mallott, C. Lejuez, T. Joiner, and N. Schmidt. 2007. "Dispositional Anxiety and Risk-Avoidant Decision-Making." *Personality and Individual Differences* 42(4): 665-675.

McTier, B., Y. Tse, and J. Wald. 2013. "Do Stock Markets Catch the Flu?" *Journal of Financial and Quantitative Analysis* 48(3): 979-1000.

Neckelmann, D., A. Mykletun, and A. Dahl. 2007. "Chronic Insomnia as a Risk Factor for Developing Anxiety and Depression." *Sleep* 30(7): 873-880.

Petersen, M. 2009. "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches." *Review of Financial Studies* 22(1): 435-480.

Pinegar, M. 2002. "Losing Sleep at the Market: Comment." *American Economic Review* 92(4): 1251-1256.

Reyes, T. 2018. “Limited Attention and M&A Announcements.” *Journal of Empirical Finance* 49(C): 201-222.

Siganos, A., E. Vagenas-Nanos, and P. Verwijmeren. 2014. “Facebook's Daily Sentiment and International Stock Markets.” *Journal of Economic Behavior and Organization* 107(B): 730-743.

Siganos, A. 2019. “The Daylight Saving Time Anomaly in Relation to Firms Targeted for Mergers.” *Journal of Banking and Finance* 105(August): 36-43.

Sillence, E., P. Briggs, P. Harris, and L. Fishwick. 2007. “Going Online for Health Advice: Changes in Usage and Trust Practices over the Last Five Years.” *Interacting with Computers* 19(3): 397-406.

Smales, L. 2017. “The Importance of Fear: Investor Sentiment and Stock Market Returns.” *Applied Economics* 49(34): 3395-3421.

Spielberger, C. 1972. “Anxiety: Current Trends in Theory and Research.” Oxford. England: Academic Press.

Statista 2019. “Online search usage”. https://www.statista.com/study/15884/search-engine-usage-statista-dossier/.

Walch, O., A. Cochran, and D. Forger. 2016. “A Global Quantification of Normal “Sleep” Schedules using Smartphone Data.” *Science Advances* 2(5): 1-6.

Walker, M. 2017. “Why We Sleep.” Penguin Books.

Zahirovic, S., and J. Okicic. 2016. “Effects of Risk Aversion on Securities Portfolio Performance in Underdeveloped Capital Markets: The Case of the Capital Market of Bosnia and Herzegovina.” *Economic Research* 29(1): 343-359.

Table 1. A manager's hours of sleep and his trading intensity: A case study

Panel A: Descriptive statistics

	Hours of sleep	Number of transactions	Absolute amount invested
Mean	7.7	3.0	£457,442
Median	7.4	2.0	£293,111
Minimum	5.2	1.0	£15,064
10%	6.6	1.0	£84,400
90%	9.0	6.0	£878,400
Maximum	11.5	24.0	£8,264,308

Panel B: The relation between hours of sleep and trading intensity

	Number of transactions{t}	Log absolute amount invested{t} (£)
Hours of sleep{t-1}	0.7659*	0.1328*
	(0.062)	(0.059)
N	400	400
Adj. R-sq	0.1642	0.1634

Notes: This table shows the results of a case study. We access a fund manager's hours of sleep and his investment transactions. The figures shown are per day. The number of transactions and the absolute amount invested include the manager's purchases and sales together. N shows the number of observations. P-values are shown in parentheses. The sample period is between 2015 and 2017. * indicates statistical significance at the ten percent level.

Table 2. Descriptive statistics for the developed sleepiness measure based on Google

	Sleepiness (full range) (1)	Sleepiness (2)	Δ sleepiness (3)	S&P500 returns (4)
Average	26.8072	26.7139	-0.0004	0.0003
Median	26.6888	26.6888	-0.0011	0.0007
Minimum	0.0000	20.3639	-0.2596	-0.0904
Maximum	89.0000	33.1505	0.2609	0.1158
Standard deviation	5.3710	4.1339	0.1651	0.0116
Skewness	0.5169	0.0166	0.0090	-0.1263
Kurtosis	8.0270	1.8281	1.8984	15.5152
N	5295	5295	5294	3649
Augmented Dickey Fuller	-35.939***	-33.754***	-79.971***	-34.867***
test statistic	(0.000)	(0.000)	(0.000)	(0.000)

Notes: This table shows the descriptive statistics of the developed sleepiness index and stock market returns. Δ sleepiness is the daily difference in the volume of search activity at Google. N shows the number of observations. The sample period is between 2004 and 2018. MacKinnon's p-values are shown in parentheses. *** indicates statistical significance at the one percent level.

Table 3. The empirical validity of the sleepiness index

Panel A: The significance of daylight saving time changes and seasonality

	Sleepiness{t}		
Clock change{t-1}	1.4656**		
	(0.019)		
Tuesday	-0.0343	2005	1.1349***
	(0.841)		(0.001)
Wednesday	-0.2054	2006	-0.7342**
	(0.238)		(0.022)
Thursday	-0.3619**	2007	-1.6751***
	(0.037)		(0.000)
Friday	-0.6543***	2008	-2.1247***
	(0.000)		(0.000)
Saturday	0.6135***	2009	-0.8440***
	(0.001)		(0.007)
Sunday	1.1346***	2010	-0.3181
	(0.000)		(0.306)
		2011	1.8644***
February	-0.1182		(0.000)
	(0.615)	2012	1.6820***
March	0.9008***		(0.000)
	(0.000)	2013	0.8628***
April	0.4057*		(0.004)
	(0.071)	2014	1.2033***
May	-0.3424		(0.000)
	(0.138)	2015	2.8016***
June	-0.8861***		(0.000)
	(0.000)	2016	2.6522***
July	0.2572		(0.000)
	(0.268)	2017	4.4375***
August	-0.7089***		(0.000)
	(0.002)	2018	5.7853***
September	0.7939***		(0.000)
	(0.001)	Constant	25.8647***
October	0.1904		(0.000)
	(0.423)	N	5295
November	-0.8641***	R-square adjusted	0.2853
	(0.000)		
December	-1.8869***		
	(0.000)		

Panel B: The significance of macroeconomic variables

	Sleepiness{t}
ADS index{t-1}	0.3056***
	(0.008)
LnVIX{t-1}	0.7282***
	(0.005)
Day of the week FEs	Yes
Month FEs	Yes
Year FEs	Yes
Constant	23.5109***
	(0.000)
N	3649
R-square adjusted	0.3125

Panel C: The significance of sleepiness for sentiment

	Sentiment{t}
Sleepiness{t}	0.0408**
	(0.032)
Day of the week FEs	Yes
Month FEs	Yes
Year FEs	Yes
Constant	-0.0373***
	(0.000)
N	1631
R-square adjusted	0.2543

Notes: This table offers results to support empirically the developed sleepiness index. N shows the number of observations. P-values are shown in parentheses. The sample period is between 2004 and 2018. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 4. The relation between one-day lagged sleepiness and stock market returns

	S&P500 returns{t}					
			Winsor Δsleepiness 5%	Sunday's sleep in relation to Monday's returns		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ sleepiness{t-1}	-0.1402***		-0.1099**	-0.8527*	-0.1270**	-0.4025*
	(0.010)		(0.027)	(0.054)	(0.011)	(0.066)
Clock change{t-1}		0.1227				
		(0.553)				
ADS index{t}					-0.1216*	
					(0.092)	
LnVIX{t}					-0.9599***	
					(0.000)	
Sentiment{t-1}						1.5254
						(0.592)
Day of the week FEs	Yes	Yes	Yes	No	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.0547	-0.0625	-0.0546	0.0493	2.5539***	-0.2156
	(0.392)	(0.326)	(0.394)	(0.666)	(0.000)	(0.232)
N	3648	3649	3648	681	3648	1126
R-square adjusted	0.0048	0.0045	0.0047	0.038	0.0351	0.0128

Notes: This table shows the relation between the one-day lagged changes in sleepiness and stock market returns. Our dependent variable is S&P500 stock market returns, while the main independent variable is changes in sleepiness. N shows the number of observations. P-values are shown in parentheses. The sample period is between 2004 and 2018. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 5. Endogeneity concerns

	Δ sleepiness{t}	Δ sleepiness{t}	Δ sleepiness{t-1}		S&P500 returns{t}	
				IV 1st Stage		IV 2nd stage
	(1)	(2)		(3)		(4)
S&P500 returns{t}	-0.0019		Sunrise{t-1}	0.0080***	Δ sleepiness{t-1}	-0.1606***
	(0.440)			(0.000)		(0.000)
S&P500 returns{t-1}		-0.0003	Sunset{t-2}	-0.0004*	Constant	0.0303***
		(0.942)		(0.063)		(0.008)
Day of the week FEs	Yes	Yes	Constant	-0.0968***	N	3648
Month FEs	Yes	Yes		(0.000)	R-square adjusted	0.0004
Year FEs	Yes	Yes	N	3648		
Constant	-0.0519***	0.014	F	8.76***		
	(0.000)	(0.181)		(0.0053)		
N	3649	3649				
R-square adjusted	0.0139	0.0202				

Notes: This table explores whether the relation is the outcome of endogeneity. Columns (3) and (4) report IV results when the instruments are the timings of sunrises and sunsets. N shows the number of observations. P-values are shown in parentheses. The sample period is between 2004 and 2018. *, and *** indicate statistical significance at the ten, and one percent levels, respectively.

Table 6. A reversal in the days following

	S&P500 returns{t}
Δ sleepiness{t-2}	0.1572
	(0.151)
Δ sleepiness{t-3}	0.3399**
	(0.038)
Δ sleepiness{t-4}	0.3156*
	(0.075)
Δ sleepiness{t-5}	0.1231
	(0.293)
Day of the week FEs	Yes
Month FEs	Yes
Year FEs	Yes
Constant	-0.0641
	(0.328)
N	3646
R-square adjusted	0.006

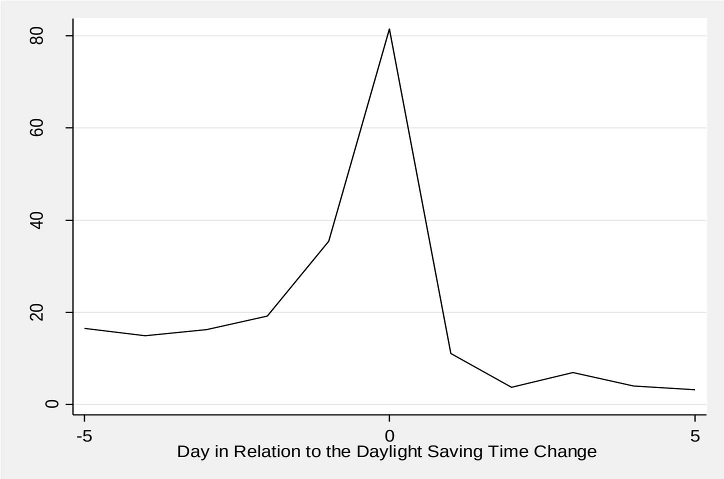
Notes: This table shows that the relation reverses in the days following the initial reaction. N shows the number of observations. P-values are shown in parentheses. The sample period is between 2004 and 2018. *, and ** indicate statistical significance at the ten, and five percent levels, respectively.

Table 7. The magnitude of the relation in association with the level of uncertainty

	S&P500 returns{t}
Δ sleepiness{t-1}	2.5016*
	(0.091)
LnVIX{t}	-0.8646***
	(0.000)
Δ sleepiness{t-1} * LnVIX{t}	-0.9221*
	(0.081)
Day of the week FEs	Yes
Month FEs	Yes
Year FEs	Yes
Constant	2.3060***
	(0.000)
N	3648
R-sq	0.0352

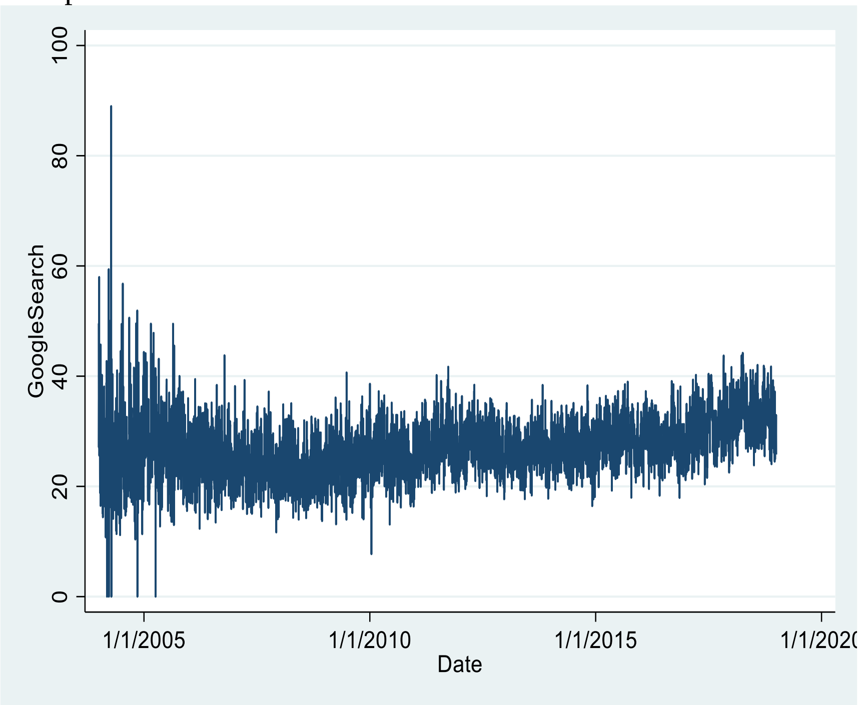
Notes: This table shows that the magnitude of the main relation in association with the level of uncertainty in the market as proxied by LnVIX. N shows the number of observations. P-values are shown in parentheses. The sample period is between 2004 and 2018. *, and *** indicate statistical significance at the ten, and one percent levels, respectively.

Figure 1. Google search activity for the term "Daylight Saving Time Change"



Notes: This figure shows the average daily search activity for the term "Daylight Saving Time Change" around the actual event (Day 0). The sample period is between 2004 and 2018.

Figure 2. The sleepiness index over time



Notes: This figure shows the daily sleepiness level over time (before winsorization). The sample period is between 2004 and 2018.