The Economics of Time: Daylight Savings and Its Effects on Financial Markets

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1 Introduction

1.1 Motivation

Daylight saving time (DST) is a unique environmental factor that has received relatively limited attention in financial market research. Governments' primary objective in implementing DST is to make better use of daylight by shifting an hour of sunlight from the morning to the evening, creating the effect of the day being prolonged. This practice affects the daily lives of millions of people around the world and has various implications for energy consumption, public health, and even psychological well-being. Yet, despite its widespread impact, we find that the potential influence of DST on financial markets has not been explored to a commensurate degree. Prior literature focuses on other environmental and weather factors, such as seasonality and temperature, but DST represents a unique phenomenon that immediately changes the amount of daylight during the typical nine-to-five workday. This sudden shift in daylight hours might have a significant impact on investor sentiment, trading behavior, and information processing, which in turn may influence market returns. By examining the relationship between DST and financial markets in our study, we aim to uncover any empirical evidence supporting a link between daylight hours and market performance, and to contribute to the growing literature on the impact of environmental factors on financial markets.

1.2 Adoption Trends

We should start by providing some context on the widespread adoption of DST. Prior to 1916, no countries had implemented DST. However, during the period from 1916 to 1960, several countries adopted DST, primarily as a response to wartime necessities, such as conserving energy and making better use of daylight. Germany was the first to implement DST in 1916, followed by other European countries, the United States, and Canada.

By the late 1960s, a substantial number of countries had adopted DST, but the practice was far from uniform. For instance, in the United States, the Uniform Time Act of 1966 aimed to standardize DST practices across the nation, but states could still opt-out. By the end of our study period in 2023, all but two states, Hawaii and most of Arizona, observed DST.

In Europe, the adoption of DST became more synchronized after the EU established a common DST schedule in 1981. Prior to this, the start and end dates of DST varied among EU countries. However, since 1996, all EU countries have been required to change their clocks on the same dates.

By 2023, a total of 70 countries had adopted DST, with various start and end dates, while the remaining 125 countries did not observe it. Though we elect to only consider countries that contain cities that are major financial centers in this paper, this global diversity in DST practices, in addition to presenting a control group of countries that is both natural and convenient, also presents an interesting backdrop for investigating the impact of daylight hours on financial markets, allowing for a more nuanced understanding of the phenomenon across different contexts.

1.3 Mechanism

Our empirical model is inspired by the behavioral finance literature, which explores the influence of cognitive and emotional factors on financial market outcomes, such as the work by Barberis, Huang, and Santos (2001)[1]. In this context, we propose that the mechanism through which DST impacts financial market performance is via changes in investor behavior.

The underlying premise is that DST shocks sleep patterns and daily routines of individuals, including investors, causing potential cognitive and emotional effects. Research has shown that even minor disruptions to sleep can have a significant impact on cognitive functions, such as decision-making, risk-taking, and information processing (Harrison and Horne 2000)[2]. As a result, the introduction of DST can alter the behavior of investors, leading to changes in financial market outcomes.

We posit that the immediate effect of DST adoption on financial market performance is due to this initial disruption of sleep patterns and the need for individuals to adjust to the new schedule. This disruption may lead to increased risk-taking behavior, reduced attention to detail, and heightened emotional reactions in the short term, which could influence market performance metrics.

In the longer run, we hypothesize that the effects of DST on financial market performance will evolve as individuals adapt to the new schedule and incorporate the additional daylight into their daily routines, slowly returning to baseline. This adaptation could result in more efficient use of time, potentially leading to better decision-making and improved market performance, leading to a reversal of the immediate effect observed. However, it is also possible that the persistent sleep disruptions caused by DST continue to impact investor behavior and financial market outcomes over time.

Therefore, our proposed mechanism implies that the influence of DST on financial market performance will depend on both changes in sleep patterns and the additional daylight hours. The extent to which these two individual effects impacted investor behavior will be reflected as an overall composite effect on returns. We also anticipate heterogeneity in how DST affects different investors.

2 Prior Literature

We find that the existing literature on the relationship between environmental factors and market performance has primarily focused on the influence of weather conditions and seasonal patterns, such as temperature, sunshine, and precipitation. While these studies provide valuable insights into the relationship between environmental factors and financial markets, they do not directly address the immediate effects of sudden changes, or shocks, in daylight patterns, such as those caused by DST. Our paper aims to build upon and extend this body of research by examining the immediate effects of DST on stock market performance in major financial centers

The early influential papers, such as Hirshleifer and Shumway (2003)[3], explored the relationship between weather conditions, including temperature and sunshine, and stock returns. Their study found evidence of a statistically significant "sunshine effect," where sunny days are associated with higher stock returns, and cloudy or rainy days are linked to lower returns. This research served as the bedrock for later studies further investigating the relationship between specific environmental factors and financial markets. For instance, more recent papers, such as Symeonidis, Daskalakis, and Markellos (2018)[4], have extended the focus to include the impact of weather conditions on stock market volatility. By analyzing the relationship between weather factors (cloudiness, temperature, and precipitation) and volatility measures such as implied volatility indices and realized returns, this study contributes to the understanding of how environmental factors can influence market dynamics and risk (volatility).

A different perspective on the relationship between environmental factors and financial markets is put forth by Kamstra et al. (2003)[5], who examined the role of seasonal affective disorder (SAD) in driving stock market cycles. Their study investigates the influence of daylight duration changes during winter months on stock market returns, while controlling for environmental factors such as cloud cover, precipitation, and temperature. This research highlights the importance of considering psychological factors that may be influenced by changes in daylight patterns. Their work underscores the importance of daylight hours in influencing market trends and naturally paves the way for our investigation into whether a sudden, policy-induced change in daylight could have an even more pronounced effect on market performance.

Indeed, despite these contributions, a notable gap in the literature that remains to be filled is the lack of attention to the immediate effects of sudden changes in daylight patterns, such as those caused by DST, beyond regular seasonal changes. Our study aims to fill this gap by investigating this effect. Another limitation of existing research is the focus on the long-term impact of seasonal patterns and weather conditions, which may not fully capture the causal relationship between daylight patterns and financial market outcomes. Our study overcomes this limitation by using a panel data approach that allows us to estimate the change in the impact of DST over multiple time periods, providing a more precise and complete picture of the treatment effect.

Furthermore, prior studies have predominantly used standard difference-in-differences, static two-way fixed effects, and dynamic two-way fixed effects methods, which may not be suitable for our research question due to the staggered adoption of DST, the potential evolution of treatment effects over time, and difficulties justifying common trends. We elaborate on the insufficiency of these models in Section 3. To remedy this, our paper employs the method proposed by Callaway and Sant'Anna (2021)[6] to address these issues and provide more robust estimates of the causal effects of DST on financial market performance. Thus, our study contributes to the existing body of literature analyzing the relationship between environmental factors and financial markets by focusing on the immediate effects of DST and employing a more suitable empirical methodology. In doing so, we aim to provide valuable insights into understanding the causal relationship between sudden changes in daylight patterns and financial market outcomes.

3 Data

Our dataset includes indices located in numerous countries with and without DST observance. From the countries that do observe DST, we observe the CAC 40 (France), DAX (Germany), FTSE (England), S&P 500, Dow Jones, and NASDAQ (USA). From the countries that do not observe DST, we include the Nikkei 225 (Japan), BSE SENSEX (India), KOSPI (South Korea), and IBOVESPA (Brazil). These indices are reflective of the top 30-500 companies currently traded on the stock market located in the country. We compile historical data from the Wall Street Journal which contains the market open price, the high, the low, and the market close each day going back to 1990. This provides us with ∼8,000 observations for each index, plus or minus depending on the irregularities of gaps in the data due to bank holidays, where markets are not open and numbers are not reported, or other anomalies. Overall, we gathered ∼80,000 observations in total across all indexes for days from 1991 to 2022. Of course, we proceed by removing observations according to the specified size of the event window. For the purposes of the analysis in this paper, we use an event window of $n = 120$ days, capturing four months around each implementation and reversion of DST for each country within each year (or, in the case of reversion, bleeding into the next year by two months). The data from all of these indices are then merged into one large, composite dataset made up of all of the indices under consideration. To compute a lagged measure of market returns for a given country and date, we apply the simple formula:

$$\text{Returns}_{it} = \frac{\text{close}_{it} - \text{close}_{it-1}}{\text{close}_{it-1}}$$

This allowed us to account for changes in the market during non-market hours and also alleviated the worry of dealing with currency exchanges. We source data from the World Bank for macroeconomic indicators at a yearly level of granularity

Figure 1 provide a visualization of a snippet of the stock index data with which we are working. The y-axis is the % returns of the UK's FTSE 100 index in early 2015. The period

Figure 1:

of time spanned by the x-axis is from March 3rd to April 23rd, and the DST implementation which that year occurred on the 29th of March is indicated by the vertical red line. Due to the general volatility of the stock market, it would be incorrect to attempt to attribute any behavior to the right side of the line to DST.

4 Empirical Strategy

4.1 Two-Way Fixed Effects

When examining the effect of DST changes on financial returns over various periods, we encounter a distinct challenge due to the staggered implementation of DST across different regions. Conventional methodologies such as dynamic two-way fixed effects (2WFE) may fall short in adequately addressing our research needs.

Consider our dataset containing market returns from different countries i over a span of years, extending from $-T^*$ to T. Within this time frame, some countries adopt DST (the treatment group) on a recurring basis, while others do not (the control group). Should all regions in our treatment group adopt DST simultaneously at a particular point in time t^*, we might apply a year-by-year difference-in-differences regression methodology. Under the 2WFE approach, the structure of our regression would be

$$Y_{it} = \beta_0 + \beta_1 \cdot DST_{it} + \lambda_i + \gamma_t + \delta \cdot X_{it} + \epsilon_{it}$$

where Y_{it} represents the market returns for country i at time t. DST_{it} is an indicator variable determining whether region i has adopted DST in year t. λ_i and γ_t are the fixed effects for region and time respectively, X_{it} represents a vector of additional covariates, and ϵ_{it} is the error term. Implicit in this model is the assumption that, barring DST implementation, regions adopting DST ($DST_{it} = 1$) and those not ($DST_{it} = 0$) would have followed parallel trends.

Yet, the staggered adoption of DST introduces a subtle layer of complexity. In particular, if we wish to discern how the effects of DST evolve over time, we require a more flexible approach. This is where dynamic two-way fixed effects regression might come in, with the goal of identifying time-varying average treatment effects within event-study time rather than calendar time. Under this framework, the form of our model would be

$$Y_{it} = \lambda i + \sum_{k \in \mathcal{T}} t \cdot \mathbf{1}_{\{k=t\}} + \sum_{p \in \mathcal{T}} \mu_p \cdot \mathbf{1}_{\{t-G_i=l\}} + \nu_{i,t}$$

where λi are unit fixed effects, $\mathcal{T} = \{-T^*, \ldots, T\}$ is our set of event-study time periods, and G_i is the year unit i is treated within our study period. Yet, even this method bears limitations. It necessitates parallel trends which, due to the minutiae of comparing entities as complex and inherently heterogeneous as countries, is a difficult assumption to justify in the absence of the allowance of covariates to account for such potential variations. This is why we turn our attention towards the approach of Callaway and Sant'Anna for our analysis, whose proposed methodology offers a robust way to navigate staggered DST adoption, enables the use of traditional control groups, and importantly, relaxes the stringent parallel trends assumption. We detail the approach and its assumptions in the following section.

4.2 Callaway and Sant'Anna approach

In Callaway and Sant'Anna [6], the authors' parameter of interest can be expressed as:

$$\mathrm{ATT}(g,t) = E\left[Y_t(g) - Y_t(0)\,|\,G_g = 1\right] \quad \text{for} \quad t \in \{1,\ldots,T\}$$

where G_g represents a dummy variable indicating whether a unit i belongs to a group g and the other terms are self-explanatory. In our context, a 'group' refers to a set of units, or countries, that adopt DST at the same time. The ATT is estimated for each group and each point in time, accounting for both the heterogeneous treatment effects and the staggered nature of treatment adoption. This offers a comprehensive, robust way to measure the impacts of DST in event-study time and the differential timing of DST adoption across countries.

In terms of the identification strategy, the approach precludes the use of countries previously treated as a comparison group, an assumption we detail later in this section. The reason for this exclusion is to mitigate potential distortions from their respective treatment dynamics. Instead, the only valid comparison units are those countries that have either not yet adopted DST at a particular moment in time or those that never adopt DST throughout the panel duration. In this case, we focus on the latter, constructing a comparison group comprising units that never undergo the DST transition. The group-time ATTs are then given by:

$$\mathrm{ATT}(g,t) = E\left[\left(\frac{G_g}{E[G_g]} - \frac{\frac{\hat{p}(X)C}{1-\hat{p}C}}{E\left[\frac{\hat{p}(X)C}{1-\hat{p}C}\right]}\right)(Y_t - Y_{g-1})\right]$$

where C is a dummy variable indicating membership in the comparison group. Note that $G_g + C = 1$. The strength of this approach lies in its flexibility and robustness. It allows for unique group-time ATTs to be estimated, reflecting the unique impact of DST adoption for each group and each point in time. Furthermore, by incorporating propensity scores for each group, the method ensures appropriate control for observed covariates. This combination of features leads to a robust estimator for the effects of DST, reflecting the unique circumstances of each group and time period.

However, this approach only ensures unbiased and consistent estimates of each group-time ATT under certain important assumptions. In particular, Callaway and Sant'Anna (CSA) state that there are five crucial assumptions that must be upheld in order to estimate their group-time parameter by the above method:

(1) Data Structure: The CSA approach requires repeated cross-sectional or panel data. Implicit in this assumption then is that our data is i.i.d. In our case, we make use of a rich panel dataset that details DST adoption times as well as their corresponding effects for a variety of entities over an extended time period. Our dataset incorporates both cross-sectional and time-series variations and thus meets this assumption.

(2) Conditional Parallel Trends: This loosening of the standard parallel trends assumption instead requires only that the treated group and either a never-treated or not-yet treated group follow common trends in the absence of treatment after conditioning on some vector of covariates X. In our case, we treat a never-treated group of non DST-observing countries as our control group, so we require parallel trends for that group with respect to our other countries.

We elect to consider a variety macroeconomic factors like GDP, inflation rate, and unemployment rate. Whereas the typical parallel trends assumption was difficult to justify under the knowledge that such factors are so deeply intertwined with market performance, we can reasonably assume that the conditional parallel trends assumption will hold as we posit that much of that variation can be explained by these factors, allowing us to assume that the main driver of differences in market performance will be the adoption or non-adoption of DST.

(3) Irreversibility of Treatment: CSA notes the importance of treatment being irreversible for the robustness of their estimator. That is, for an indicator D representing treatment, that we have:

(a) $D_{i1} = 0$ almost surely

(b) $D_{it-1} = 1 \implies D_{it} = 1 \quad \text{for} \quad t \in \{1, \ldots, T\}$

Intuitively, this assumption can be understood as the idea that units don't "forget" about their experience being treated. However, it presents a notable challenge for our research scenario, as, due to its recurrent nature, DST is indeed a reversible treatment—countries cycle through periods of adoption followed by periods of non-adoption indefinitely. Thus, complying with this assumption requires a slight revision of our estimation strategy.

To abide by this condition, we operationalize the treatment at the annual level and implement the aforementioned event window surrounding the implementation of DST to ensure that, in each yearly subset of our data, the dataset ends before countries are able to revert to an untreated state. This approach circumvents potential recurrences of the treatment in a year-over-year framework while still allowing us to capture the immediate effects of DST adoption.

(4) Common Support: The common support assumption necessitates that there exists a common support domain wherein both the treatment and control groups contain units with approximately equivalent propensity scores. In the context of our investigation, we observe a pool of countries that have either adopted DST or refrained from doing so over the panel's duration. Given the underlying similarities in the economic, demographic, and geographical characteristics among certain treated and untreated countries, i.e the fact that our countries which observe DST are all western countries as opposed to those that do not, we propose the existence of such a common support domain where both groups exhibit comparable propensity scores.

(5) Limited Treatment Anticipation: The final assumption CSA specify is that the anticipatory effect of treatment is minimal (though not necessarily zero). In our context, it is highly reasonable to expect that countries do not significantly anticipate either the implementation or discontinuation of DST within a given year. This is because the adoption or reversion of DST occurs according to a widely-accepted and predetermined schedule, meaning any anticipation of the transition into or out of DST is so expected and deeply ingrained into the operations of societies that observe it that it does not cause significant market behavior distortions. Thus the anticipatory effect on market returns is effectively neutralized as needed.

These are the assumptions explicitly stated as being required by CSA to correctly identify their group-time parameter, hence we may confidently proceed with their approach. However, it is worth noting that SUTVA represents an interesting, attention-warranting consideration in our context. SUTVA prohibits unmodeled spillover effects between entities and methods for causal inference typically depend on it being upheld. In the case of DST and market returns, it would be simply to conceive of a situation where the treatment effect of DST onset felt by one country creates an effect in a different country due to the deep interdependence of global markets.

However, while we concede that SUTVA may not hold for our case in the strictest sense, we argue that this does not diminish our analysis nor invalidate our results. Our reasoning for this is threefold. First, as our objective is to measure the average treatment effect of DST implementation on market performance, though spillover effects might exist, we argue that they are a component of this 'treatment' in a broader sense and thus are part the overall effect that we are intending to measure, meaning that capturing them in our results is in line with our goals. Second, we argue that these spillover effects, if they exist, are likely to be very small due to a variety of reasons. The first is that, though global markets are indeed interconnected, countries themselves have unique policies, market dynamics, and economic structures that can serve to mitigate and buffer against external stimuli. Furthermore, the impact of DST on market returns within a given country is likely to be felt most fully by the country themselves and the effect might be substantially diluted by the time it reaches other countries indirectly. Last, we consider how time zones play into the scenario. Even under the assumption that the onset of DST in one country impacting market returns in that country could in turn effect the market returns in a different country, it is likely that this effect would be significantly damped by the asynchronous opening hours of global financial markets, which would restrict the real-time transmission of market impacts across countries.

Thus, though we acknowledge that there is potential for violations of SUTVA in our framework through the existence of spillover effects, we believe this does not compromise our analysis or results due to their relative smallness. However, we also note that that this is a simplifying assumption, and a more comprehensive consideration of all of the different ways in which spillover effects might manifest and the strength of the mechanisms that exist to limit them might be needed to fully assess the extent of their potential impacts. Nevertheless, we proceed with our application of the CSA approach.

Results

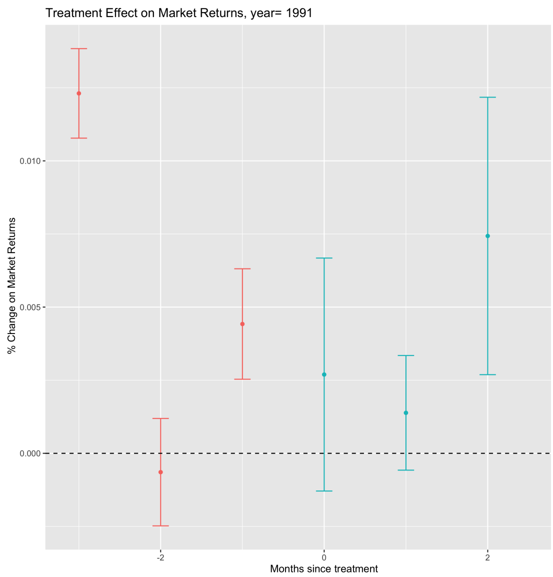

Figure 2: 1991, Spring Forward

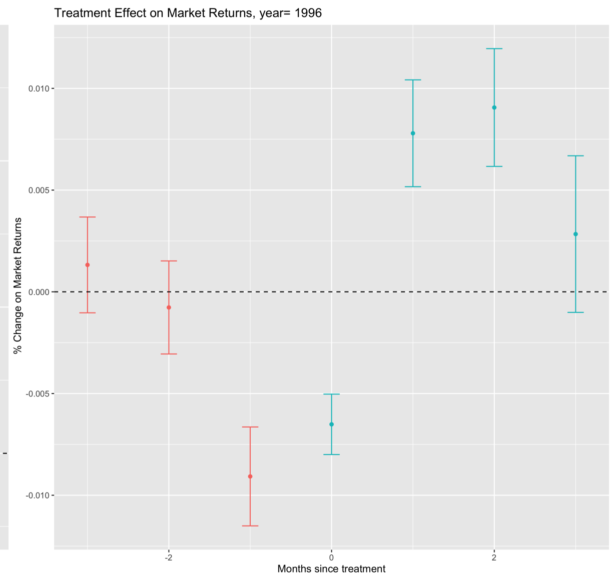

Figure 3: 1996, Spring Forward

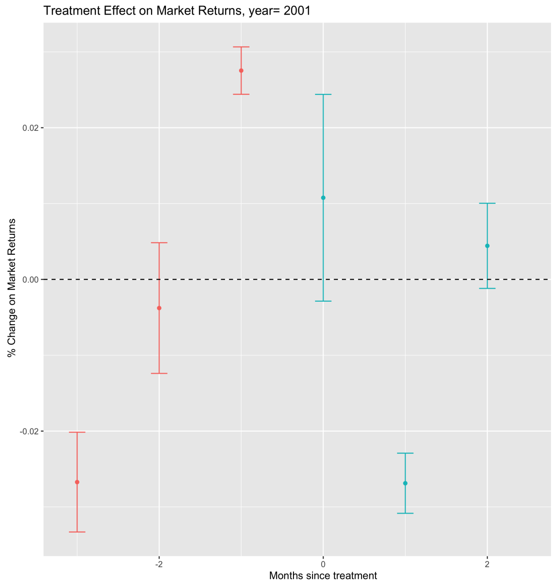

Figure 4: 2001, Spring Forward

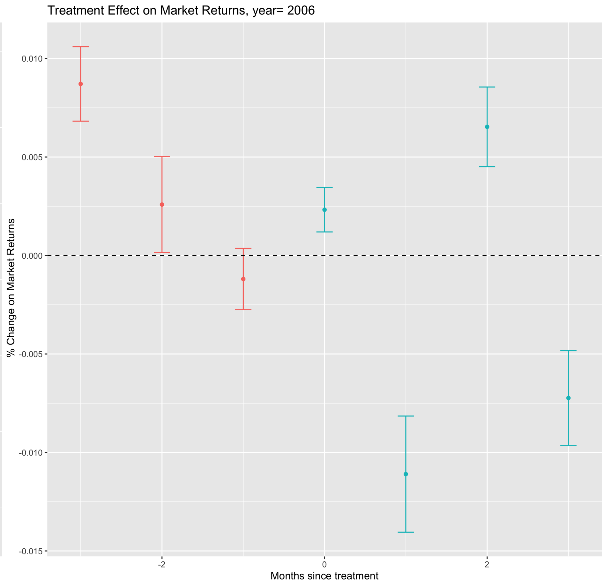

Figure 5: 2006, Spring Forward

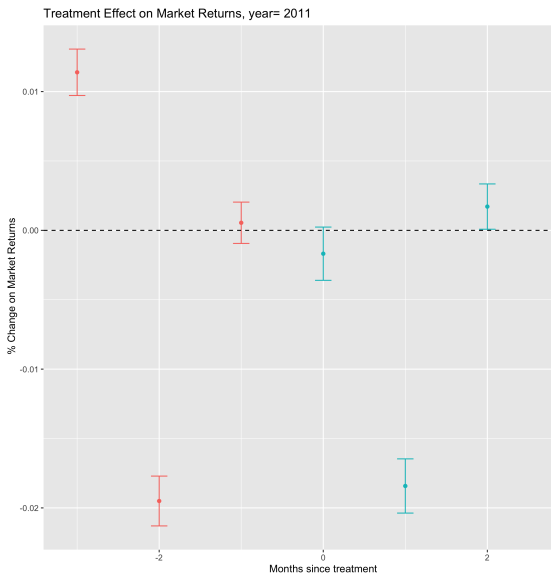

Figure 6: 2011, Spring Forward

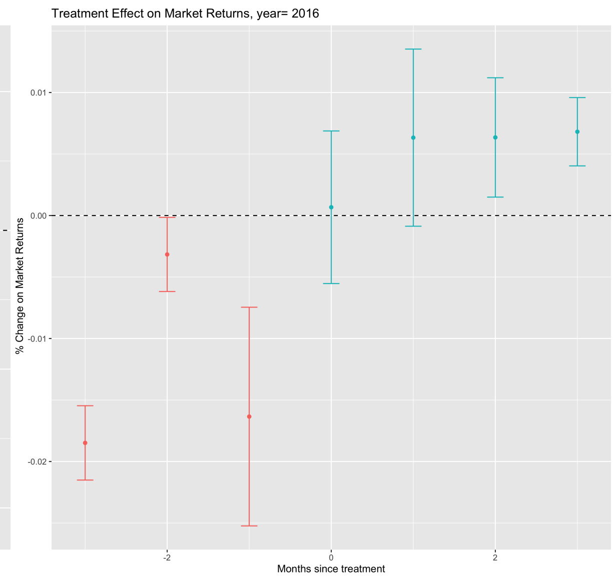

Figure 7: 2016, Spring Forward

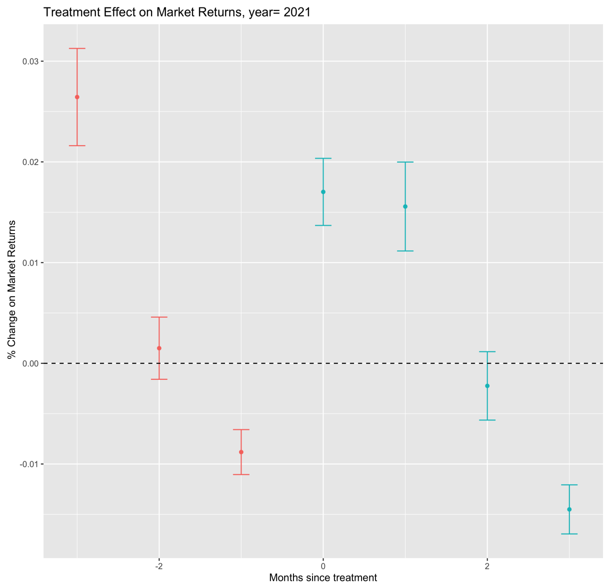

Figure 8: 2021, Spring Forward

We present a small, representative handful of our results to comment on, the remainder of which can be found in the appendix. These plots display the average treatment effect on the treated for three months before and after the DST event takes place. Each month has a dot marking the value of percent change in market returns and the line represents the 95 percent confidence interval. In this context, our plots show the average effect that DST has on the percentage change in market returns for countries that observe DST.

We chose this particular sample of results as they span nearly the entirety of our period of consideration, from the year 1991 to 2022. This would allow use to identify any kind of trend that may emerge in the spring forward plots over the years in order to determine whether or not the effect of DST on the stock market has any time variation across years. However, these plots fail to provide conclusive evidence to declare that the impact of spring forward DST changes in an interesting or significant way over this period.

Figure 3 shows the plot for the spring forward DST effect in the year 1996. The ATT is considered significant on these plots if the confidence interval portrayed by the vertical bars does not include 0. This would make the ATTs for the two months post-treatment significant in Figure 3, but not the final month shown. Also in Figure 3, we can observe that the effect of DST on stock market returns changes over the months following the DST implementation. We see a negative effect of the DST change immediately following DST turning on, and in the following months the ATTs are significant and portray a positive effect on stock market returns.

Figure 4 shows the monthly ATTs for the fall back DST effect in the year 2015. As we can see all but one of the ATTs estimated here are significant, and again the immediate effect attributed to DST removal is strongly positive, while in the later months we see a decline in the effect until we estimate a negative effect.

We measure a quite interesting effect in 2011 shown in Figure 6, where our 95% confidence intervals are considerably smaller on each ATT than they are in other years. This may indicate a lack of significant variation in the stock market returns during that time period.

These results are scattered, but some seem to be in line with the thought behind our mechanism. Springing forward provides us with more sunlight but less sleep, so we would suspect that the effect of additional sunlight would yield positive effects on stock returns while less sleep may yield a negative effect. Over a sufficient time period of a few weeks we may expect that the sleep impact would diminish or vanish entirely as people's sleep cycles would likely have adjusted by then, leaving us with only identifying the effect of additional sunlight. Some of our results reflect this hypothesis (Figure 3), by displaying a negative change in market returns immediately after treatment and then flipping to a positive result in the next three months. Others, like Figure 5, show a positive effect directly after treatment and then flip between negative and positive in the following months. Therefore, it is hard to conclude that our mechanism is accurate given the variety of results. In doing a naive count of all the spring data, we found that out of 33 plots, 9 had a statistically significant negative immediate effect and 14 had a statistically significant positive effect. Out of those 9, 6 plots had an immediate negative effect and then a delayed positive effect.

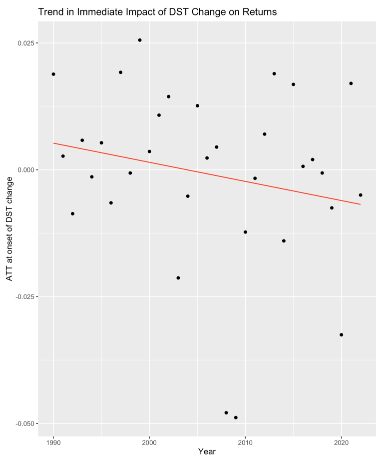

Figure 9: Trend of DST Change

We visualize our results in aggregate in Figure 9. The line of best fit through the data points, each of which represents the ATT of the immediate treatment effect of spring forward

DST in a given year, shows a clear downward trend, and stays close to 0. It is important to note that there are clear outliers on the negative side, namely 2008 and 2009 due to the financial crisis and 2020 due to COVID. This is most likely due to our macroeconomic controls not being frequent enough to account for sudden dips. Upon closer inspection of these years in the appendix, we observe that the markets were highly volatile at this time and change in returns jumped between highly negative and positive numbers in a matter of months.

Unfortunately, the mechanism that we put forward earlier fails to provide an adequate explanation of the downward trend in ATT over the years, as there doesn't seem to be compelling evidence, nor theoretical justification, to suggest that the effect of DST on market returns via more or fewer sunlight hours, or more or fewer hours of sleep, would change over the decades we studied.

Overall, we have identified many instances of a significant average DST effect across our indices, but there are conflicting values of these results. The immediate effect can be both positive and negative. Therefore, it is hard to conclude if DST does contribute to market returns in a meaningful way.

Discussion

Our results are inconclusive regarding whether or not there truly exists a shock effect of DST on stock market returns. While we have statistically significant results in some years, we do not have sufficient evidence to conclude that there is a substantial causal relationship in general between DST and stock market returns.

Our attempt at identifying whether the effect of DST on market returns changes over yielded more fruitful results as we were able to identify a slight downward trend in our immediate ATTs over the years in our data set. There are multiple possibilities as to why this is the case, such as outliers, but there may be other factors at play. One possibility is that financial institutions may be aware of the potential effect of DST on market returns, and aim to exploit this information to profit from it by engaging in forms of arbitrage. This isn't too far-fetched because the "daylight effect" of sunnier weather causing higher market returns is widely widely known. Institutions could then use this information advantage to sell their shares in unison with the bump up and therefore reap the profits and effectively lower the price. If enough institutions are aware of the DST effect and it is working properly, then this could effect market returns.

To conclude, our research fits into the gap exhibited by the broader literature by attempting to identify a novel effect, the shock impact of DST implementation on financial market performance. We build upon existing research by also describing a new psychological mechanism through which DST impacts financial markets. DST does increase sunlight hours, which prior literature has suggested raises market returns, but our described mechanism also accounts for spring forward time causing people to lose sleep which also effects their psychology and therefore the market.

We hope that future research may be able to tackle some of the problems that we faced in carrying out this research. For example, future researchers might look to devise a different means than the one presented in this paper to circumvent CSA's irreversibility of treatment assumption so aggregate ATTs over the entire period of consideration can be more easily calculated. In addition, they might look to figure out how incorporate the known spillover effects of markets, however small they might be, into the model in some capacity so as to ensure that SUTVA truly holds and is not just assumed to hold. Making such changes could lead to more conclusive results on the causal relationship between DST and market returns. We would also encourage future researchers to also study other stock market variables such as trading volume or volatility to determine if there may be an identifiable shock effect of DST on them.

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