Productivity losses in the transition to Daylight Saving Time: Evidence from hourly GitHub activity

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September 2024

forthcoming, *Journal of Economic Behavior & Organization*

Abstract

Using data on GitHub users around the world, we estimate the effects of transitions to Daylight Saving Time on worker activity. In daily activity, transitions appear short lived—there is evidence of two days of declines before activity returns to baseline levels. However, hourly analysis reveals a transition to Daylight Saving Time that is much longer—losses appear in the early working hours of work days into a second week following the initiation of Daylight Saving Time.

Keywords: daylight saving time; productivity; sleep; time use
JEL: J24; J22

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1 Introduction

Motivated by potential energy savings, Daylight Saving Time (DST) was introduced in 1916 and widely adopted by many Western countries soon after. The shifting forward of the clock increased the availability of natural light in the evenings—at the time, this lessened the need for the carbon filaments and kerosene associated with indoor lighting (Nordhaus, 1997). Today, the consensus opinion with respect to energy consumption is that any savings associated with DST are likely small (Kotchen and Grant, 2011; Belzer et al., 2008)—they are on the order of plus-or-minus one percent. The merits of continuing these twice-yearly adjustments to the clocks of 1.6 billion people across 75 countries are therefore important contributors to the continuing debate, even as countries abandon the practice.[1] Most recently, the United States (US) Senate unanimously passed the Sunshine Protection Act in 2021, which would have the United States likewise abandoning the practice.[2]

While the Sunshine Protection Act remains in the US House of Representatives, of note is the House Energy and Commerce Committee's interest in learning of the productivity effects of time changes prior to holding a vote. Our analysis contributes directly to the debate, then, and with immediate implication for policy. To that end, we document significant declines in worker activity following DST, with patterns that suggest a weeks-long period of transition through which workers are adjusting to the shifting of time relative to the cycle of daylight and darkness.

To measure the potential declines in activity induced by DST we exploit publicly available activity data from GitHub, a popular cloud based version-control platform used by collabora-

[1] China first abandoned the practice in 1991, and several other countries following that path in the mid-to-late 2000s. Other countries discontinuing DST include Pakistan (2009), Russia (2010), Azerbaijan (2015), and Brazil (2019).

[2] This national-level action follows several state-level initiates that similarly moved toward the permanent adoption of DST. For example, Oregon (2019) and Washington (2019) have passed such legislation, and California's Proposition 7 (2018) was approved by over 60 percent of voters.

tive programmers. Observations include detailed information regarding changes to a project's codebase—including what was changed and who made the change—providing a direct measurement of labor activity. Of particular value, though, is that we observe GitHub user activity in second-level precision. This level of granularity makes GitHub a natural laboratory to consider the effects of DST. In our analysis, we consider activity aggregated to both the daily and hourly levels across cities that experience the Spring transitions to DST differently—those that experience it earlier than others, experience it later than others, or do not experience it at all.

In daily activity we find significant declines on the order of one or two days. While such declines are presumably associated with significant economic costs, this alone suggests that the productivity losses are relatively short-lived. However, in hourly activity we find much longer periods of transition. In particular, in the two weeks following transitions to DST we find significant declines in worker activity in early work hours, between 8am and 10am. That daily measures of productivity evidence significant declines for such a short period of time suggests that the slow morning hours in the data are made up for with increases in activity elsewhere in the work day. However, increases in activity tend not to cluster in particular hours of the day. Rather, the data are consistent with workers recovering from morning productivity declines without a common strategy for dealing with the transition. In the end, it is clear from an hourly analysis that the belief in "one or two days of decline" likely fails to capture the full economic, personal, or potential social costs induced by DST.

One of the primary mechanisms highlighted by the literature to explain the productivity declines around DST changes is the sleep deprivation experienced by workers—and there is an established relationship between sleep and outcomes. For example, (Gibson and Shrader, 2018) use variation in sunset times (e.g., due to time-zone differences) to suggest that more natural light reduces sleep and earnings. (Giuntella and Mazzonna, 2019) also suggests that natural light is correlated with health outcomes that are related to circadian rhythm and percapita income. (Costa-Font et al., 2024a) suggests that weekly sleep is positively correlated with employment and weekly earnings. Among miners working in the United States, the one-hour time change induced by DST has been associated with decreases in sleep on the order of 40 minutes (Barnes and Wagner, 2009), making sleep loss a contending mechanism in explaining reductions in activity around DST.

Circadian rhythms—that is, the processes that synchronize and regulate the body's sleep-wake cycle around the 24-hour day—are resilient to adjustments to sleep-wake cycles, and the transition to a modified cycle of daylight and darkness is not immediate (Kantermann et al., 2007). Thus, that we find long-lasting disruptions to activity are consistent with this resilience. This is also consistent with laboratory results suggest that transitions to DST are measured in days (Monk and Aplin, 1980; Czeisler et al., 1999), and associated with immediate losses of sleep that do not typically return to normal for roughly seven days (Kantermann et al., 2007; Lahti et al., 2006). Workplace safety (Barnes and Wagner, 2009; Lahti et al., 2011), road safety (Smith, 2016; Bünnings and Schiele, 2021), and student performance (Gaski and Sagarin, 2011) have all been shown to decline following DST. Google searches for entertainment-related keywords and phrases in US cities that experience DST (i.e., those other than in Arizona and Hawaii) are differentially higher on the Monday that immediately follows DST transitions than on the Monday prior to DST (Wagner et al., 2012). This has been interpreted as DST-induced increases in "cyberloafing" and suggests that declines in workplace productivity can result from DST. However, to our knowledge, documenting worker activity around DST transitions has thus far been absent in the literature.[3]

While high-frequency observations of activity available on GitHub make for a rare oppor-

[3] Somewhat more removed from the research question, DST has also been associated with lower well-being and general life satisfaction (Kountouris and Remoundou, 2014; Kuehnle and Wunder, 2016), increases in myocardial infarction (Toro, Tigre, and Sampaio, 2015), reductions in crime (Doleac and Sanders, 2015), and increases in suicide (Berk et al., 2008). DST has been associated with movements in financial markets, though the evidence is mixed. For example, Kamstra, Kramer, and Levi (2000) suggests that there are negative financial returns following DST weekends, while Gregory-Allen et al. (2010) finds no evidence of a Daylight Saving Time anomaly.

tunity to learn about such behavior, GitHub users are not representative of the labor force of any country, and certainly not of the world. However, with roughly 83 million users currently, GitHub does account for a large and growing sector of the global labor market. It is also arguable that our sample is representative of a much-larger group of similarly skilled workers who work across industry, government, academic, and policy environments. In many work environments, for example, similarly skilled individuals are working in proprietary tasks that preclude their formal participation in a public code-sharing environment, and in others we would find still more consumers of the public offerings of active GitHub users. In this way, it is reasonable to infer that the effects we identify extend naturally to a larger group of workers.

In Section 2 we describe the data we rely on in our analysis and provide the necessary context for the interpretation of GitHub user data as we consider whether there is evidence of a causal relationship between DST and worker activity. In Section 3 we discuss our methodology and report event-study analyses at both the daily and hourly level. We summarize and offer concluding remarks in Section 4.

2 Data

2.1 Sample selection

GitHub is a popular cloud based version-control and code-hosting platform. Widely adopted by software developers, engineers, and scientific coders for hosting and maintaining collaborative projects, GitHub is a web based extension to the most popular distributed version control system, Git.[4] With a reported userbase of over 83 million, GitHub is the largest platform of its kind.

Consistent with its origin as a tool for collaboration with excellent version control, the pri-

[4] Of the 80,000 respondents in the 2021 Stack Overflow Annual Developer Survey, over 90 percent reported using Git.

mary feature of GitHub is the facilitation of code updates across multiple collaborative users. In essence, it provides broad access and version control to a remote copy of a project and all of its files, and as progress is made to a project hosted on the platform, contributions are tracked across time and contributor, which generates a record of labor activity metadata.

For the purpose of this study, we collect GitHub activity around the DST episodes from 2013 through 2019.[5] To reflect "active" users we restrict each year's sample to those we observe activity for in each month of that year. To limit the potential presence of "bot" activity, we discard all observations originating from accounts that ever have more than 30 events in one hour or 150 in one day (McDermott and Hansen, 2021). Following these restrictions, the total number of unique users in the sample is 174,505. Having matched each event in the raw data to the location identified in the user's profile at the time of the event, we aggregate event counts to the city-by-day level (or city-by-hour level) and restrict the sample to the 50 most-active cities in the Northern Hemisphere. These cities are reported in Table A2. As expected, the geographic distribution of these workers reflects major cities known for their robust presence in the tech industry. Our geographic restriction to the 50 most-active cities implies coverage of roughly 42 percent (174,505) of all active GitHub users with observable geographic location during the sample period (414,416). GitHub user activity also falls off precipitously. For example, the total activity of the 50 most-active cities represents 82.8 percent of the total activity of the 100 most-active cities. (All results are robust to the inclusion of activity originating in the 100 most-active cities.) Our econometric models will consider three weeks before and after DST transitions. Thus, for "never-treated" cities we include all observations in the window of three weeks before the earliest treatment and three weeks after the latest treatment.

[5] We draw our sample from two third-party sources (GH Archive and GHTorrent) that have organized the event data from GitHub's public timeline for the purpose of being more accessible to researchers. Our analysis therefore does not include any activity on private repositories. For example, a business producing proprietary software, or a team of data scientists performing analysis on valuable or sensitive data, would host their repositories privately and would not be observed on the public timeline.

2.2 Outcomes

All activity on GitHub is recorded as an "event," and categorized as one of 13 types (see Table A1). In some way, they are each potential measures of incremental productivity on shared projects. However, given the inability to distinguish the relative productivities of event types, broadly, we will consider all events, and then separately consider the 46.6 percent of events that are classified as "pushes." Push events are uploaded changes of a local file to the remote copy, which are likely stronger signals of productivity. For example, this analysis will exclude "pull requests," which represent contributors' requests to merge the code changes of others into their remote copy. In the end, we find comparable patterns in activity around transitions to DST in both measures.

2.3 Treatment

While many countries practice DST, there is variation across cities in both the practice of DST and in the timing of DST. Across the 50 cities in our sample, two important sources of treatment variation exist. In North America, clocks transition to DST on the second Sunday of March.[6] In the European Union, clocks transition on the last Sunday of March. Both of these will contribute to identifying the effect of DST on GitHub activity—given the staggered timing of treatment, they each act as a control for the other, and can each be compared to the "never-treated" cities. We follow Sun and Abraham (2021) in the estimation of treatment effects.[7]

In Figure 1 we plot patterns of GitHub events around DST transitions. In Panel A we show daily events in the three weeks before and after DST and aggregate across sample years, separating users by whether they are in North America, in the EU, or in locations that do not experience

[6] The exceptions to this in the 2013–2019 period are Hawaii, parts of Arizona, Puerto Rico, US territories in the Pacific Islands, Saskatchewan, and the Yukon. None of these are among the 50 most-active cities, and are therefore not in our sample.

[7] In supplementary material (Figure A2) we produce estimates separately for users in North American and European Union cities with users in "never-treated" cities as controls—results are robust to this distinction.

DST. A large portion of GitHub activity originates in recognizable technology centers, many of which are located in the United States. Thus, activity in North America is higher across the sample period. This is also evident in Panel B, where we plot hourly events. As a general rule, activity is also higher during traditional working hours of 9am to 5pm, Monday through Friday—a dip in activity during traditional lunch hours is also apparent.

3 Results

To identify the effect of Daylight Saving Time on activity we employ an event-study design. We first consider specifications at the daily level, followed by similarly constructed models at the hourly level. Daily estimates provide insight into the size and duration of any level-decreases in labor activity associated with DST. Hourly estimates, on the other hand, can speak to within-day variation in user activity—this will prove important to understanding the full extent to which transitions to DST are disruptive to productivity, inducing a substitution of activity across hours of the day. In both environments, however, we are interested in identifying the potential changes in activity around the initiation of DST in treatment locations—their dynamics, in particular. In related literatures that assess impacts of DST transitions on outcomes, much of the identifying variation arrises across time. For example, control groups often consist of only parts of Arizona and Hawaii. In such cases, treatment is often captured by estimating a regression discontinuity in time (RDiT) (Bünnings and Schiele, 2021; Doleac and Sanders, 2015; Smith, 2016; Toro et al., 2015). Given the worldwide nature of GitHub, however, there is considerable cross-sectional variation available to us in estimating the change in activity induced by treatment—our modeling will include both variation in the timing of treatment among those who experience DST and and a “never treated” group where GitHub activity should be unperturbed by DST.

3.1 Day-level analysis

In estimating the effect of DST on daily activity we estimate

$$\begin{aligned}\ln(\text{Events}_{cyd}) \;=\; \alpha \;+\; \sum_{d=-21}^{-2} \beta_d \;+\; \sum_{d=0}^{21} \beta_d \, \text{DST}_{cyd} \;+\; \psi_c \;+& \\ \lambda_y \;+\; \delta_d \;+\; X_{cyd} \;+\; u_{cyd} \;,&\end{aligned} \tag{1}$$

where $\ln(\text{Events}_{cyd})$ is the log number of events in city c in year y on day d. With the day immediately before DST as the excluded category, this allows for the estimated $\hat{\beta}_d$ to be interpreted as percentage differences relative to the day before DST. In estimating (1) we also include city fixed effects (ψ_c) to absorb any level differences in average events across cities, day-of-year (δ_d) fixed effects to absorb differences over time and work-week seasonality, and year fixed effects (λ_y) to absorb any average difference in activity across years in our sample. In X_{cyd} we also include controls for day-of-the-week and for national holidays, capturing variation in activity that should not be attributed to DST when likely due to holidays that coincide with Sunday transitions.[8] Errors are captured in u_{cyd}. Given the staggered timing of DST, we follow Sun and Abraham (2021), though the qualitative results do not vary with this consideration.

In Figure 2 we report estimates of (1) for a pooled model (i.e., across all days). However, patterns in Figure 1 suggest that day-of-week effects may vary by city—some cities exhibit more or less weekend activity, for example. We are inclined, then, to allow day-of-week effects to vary by city. This is empirically challenging, however, as DST falls on Sundays, which precludes the estimation of separate day-of-week effects by city. To allow for the same flexibility, then, we estimate separate models for each day of the week, which we report in Panel B. (Stratifying the sample in this way allows the city fixed effect to absorb any city-specific day-of-week effects.) For ease of interpretation, we present each of the seven models together in Panel B.

[8] As Easter coincides with treatment in the European Union in 2013 and in 2016, we also differentiate Easter from other holidays. For example, Presidents' Day falls within the three-week sample in six out of the seven years of the US cities. (In 2016, President's Day is 27 days prior to DST.)

With each model using the same day in the week prior as the omitted category, the results are interpreted as percentage differences relative to the same day (e.g., Monday, Tuesday) the week before the initiation of DST.

In the end, in daily measures of activity we find a short-lived decline associated with DST. It is only the first Sunday of DST itself and the Monday following DST for which we can distinguish activity from baseline levels. That said, these effects are economically meaningful, suggesting reductions in the number of events on the public GitHub timeline on the order of 10.6 percent on the Sunday ($p < 0.001$, $\sigma = 0.11$) and 5.4 percent on the Monday following treatment ($p = 0.033$, $\sigma = 0.06$).[9,10] While longer-lasting effects are statistically indistinguishable from zero, we note a distinct "Sunday effect" in the data following DST, which we interpret as a response to the extra hour of daylight that is coincident with DST inducing more of a weekend out of users in treated cities relative to those in control cities. In terms of the hours of typical activity, these DST-induced decreases on Sunday and Monday correspond to the equivalent of losing 91.5 minutes of average Sunday activity and 35.9 minutes of average Monday activity.[11]

In Figure 3 we restrict our sample in two ways, each having the potential to inform how we interpret the systematic relationship between DST and GitHub activity. In Panel A we consider events that occur between 9am and 5pm—these are the most active hours of the day, accounting for 58.8 percent of activity. Under this restriction we find a similar pattern—a 14.5-percent reduction in the number of events on Sunday ($p < 0.001$, $\sigma = 0.16$) and 7.1-percent reduction on the Monday following treatment ($p = 0.058$). In Panel B we restrict observations to only

[9] To ensure this result is not merely reflecting the mechanical loss of one hour on treated Sundays, we impute the activity of this missing hour by adding the number of events that occurred during the same hour in the same city in the same year on the Sunday immediately prior to DST. Without this imputation, which induces a mechanical decline in treated Sundays, the measurable impact for the first treated Sunday is a reduction in activity by 12.0 percent (instead of 10.6 percent).

[10] Results are robust to dropping all Easter Sundays from the sample.

[11] As another point of comparison, we also note that when controlling for city, year, and day of week, GitHub activity is 60.93-percent lower on Christmas day, suggesting that the estimated declines we find on Sunday and Monday correspond to roughly 17.36- and 8.84-percent of the declines experienced on this widely celebrated international holiday.

"pushes."[12] Again, we find similar patterns in the number of events—declines of 13.3 percent on Sunday ($p < 0.001$, $\sigma = 0.14$) and 5.2 percent on the Monday following treatment ($p = 0.020$, $\sigma = 0.06$).[13]

3.2 Hour-level analysis

To formally model *hourly* GitHub events around transitions to DST we estimate

$$\begin{aligned} \ln(\text{Events}_{cydh}) \;=\; \alpha \;+\; \sum_{d=-21}^{-2} \beta_d \,\text{DST}_{cydh} \;+\; \sum_{d=0}^{21} \beta_{dh} \,\text{DST}_{cydh} \;+\; \psi_c \;+ \\ \lambda_y \;+\; \delta_d \;+\; \sigma_h \;+\; X_{cyd} \;+\; u_{cydh} \;, \end{aligned} \tag{2}$$

with $\ln(\text{Events}_{cydh})$ now defined at the city-by-year-by-day-by-hour (h). In daily activity, DST always falling on Sundays prohibited the estimating of separate day-of-week effects by city. To flexibly fit hour effects in (2) we model each hour of the day separately for each day of the week.[14]

In Panel A of Figure 4 we present six plots, each corresponding to an hour of the day between 7am and 12pm—each plot then allows for the across-time comparison of relative productivities in the same hour of the day. (For example, in the 9am panel, point estimates inform the question "What happens to productivity between 9:00am and 9:59am each day, before and

[12] Recall that "pushes" are among all events in the earlier analysis, but arguably represent the type of event type that we would think is most representative of productivity as they encompass all changes uploaded to a remote copy.

[13] In Appendix Figure A6 we report results of the same models applied to all other event types recorded by GitHub. Recall that the event most clearly interpretable with productivity is likely "pushes," which are uploaded changes of a local file to the remote copy. However, across all thirteen categories (pushes, and the additional 12 reported in Figure A6) we see similar directional responses to the DST transition. We interpret this as evidence against an appeal to a type of work simply being displaced for other types of work. That said, this inference should also be conditioned, as we do not have evidence of work activity outside of the GitHub environment, which may or may not change.

[14] In supplemental material (Figure A1) we demonstrate the patterns in activity visually, focussing on one week before and after DST transitions. In Panel A we plot weekly mean event counts separately for each group (i.e., cities in North America, in the EU, and those never treated) across each hour of the day. In Panel B we plot the difference in means, subtracting hourly averages by treatment status separately for pre- and post-treatment period. In Panel C we plot the "second difference" in means, subtracting the post-treatment differences by pre-treatment differences (again, separately by group). This suggests declines in GitHub activity in the traditional morning work hours.

after DST?") Unlike daily estimates of the spring transition to DST, which identify one to two days of significant decreases in activity, the analysis of hourly data reveals longer-lived declines in activity following DST—this is particularly evident in the traditional morning work hours. Relative to baseline activity, the initiation of DST induces significant declines in the 8am, 9am, and 10am hours even into a second week. (Declines in the 8am hour are distinguishable from zero for 11 days, in the 9am hour for 11 days, and in the 10am hour for 8 days.)

In magnitude, these estimated declines are between 32.0 and 46.8 percent in the 11 days following treatment. While there are no significant increases in activity elsewhere in the day, the overall patterns of daily activity are consistent with users adopting a variety of strategies to cope with the transition.[15] Specifically identifying off of DST, (Costa-Font et al., 2024b) suggests that DST increases the feeling of being pressed for time, corroborating the idea that if workers are less productive in the morning the may try to "catch up" the rest of the day.

We suggest that the differences evident in other hours of the day (i.e., outside of the morning hours), and the lack of significance in single hours, in particular, may reflect individual heterogeneity in how people best respond to the morning decline. To the extent the shock to productivity targets morning hours more precisely (where we identify significant departures from baseline) but the response is diffuse, we may not detect specific hourly estimates of the rebound. That said, we cannot rule out that worker responses are offsetting the morning declines, generally, to the extent that we are compelled to see the hourly estimates in the context offered earlier, in the day-level analysis. That is, overall productivity declines are on the order of two days, consistent with enough "offsetting" increases in activity in the afternoons, leaving overall productivity unchanged.

In Panel B of Figure 4 we report estimates of the same models, but on the fall return to standard time. Of note, activity *increases* in the early work hours on the Sunday of the return

[15] In Appendix Figure A3 we present the daily estimates for the return to standard time. In figures A4 and A5 we present the full 24-panel plots for spring and fall, each corresponding to an hour of the day.

to standard time—this increase is evident into the 10am hour on the Mondays following the fall transition. While these estimated effects do not persist in the same way as is evident with the loss of an hour of sleep in the spring, we interpret the absence of decreases in activity in the fall return to standard time as suggestive of sleep as a mechanism in explaining the spring results. For example, this is suggestive of more than merely a confusion or dissonance resulting from the change in calendar time, regardless of direction—this, we imagine, would result in decreased activity whether the hour was lost (spring) or gained (fall). This is also consistent with Jin and Ziebarth (2020), which finds that returns to standard time have been associated with increases in sleep.[16]

To synthesize the variation in hourly estimates and better understand the nature of users' transitions to DST, in Figure 5 we consider whether there are discernible patterns in the spring point estimates from the hourly analysis. Separately for each week, we ask whether the point estimates of all 24 hourly models (in Figure A4) exhibit any seasonality across hours of the day. On the left of Figure 5, then, we re-align those same point estimates to instead represent the 168 hours in each week leading into and out of DST. On the right, we then present the hourly variation that is identifiable in that week (i.e., one estimated parameter for each hour of the day), omitting 4am as the reference category. This context makes clear that the "shape" of what is normal variation in hourly activity changes with the arrival of DST. While no systematic patterns exists across hour of the day in the weeks prior to DST, with DST's arrival the systematic declines in activity in the morning work hours are again evident. Immediately following DST, magnitudes of the decline are greatest in the 9am hour, with a 30.5-percent reduction. Further, this pattern attenuates in the second and third weeks following DST, as workers arguably recover from the disruption to time. Reductions remain largest at 9am but reduce in magnitude to 11.0-percent and 6.8-percent in the second and third week following DST.

[16] Interestingly, Jin and Ziebarth (2020) also documents reductions in hospital admissions for cardiovascular diseases and other health issues.

In considering how reasonable it is to extend to a larger group of workers, we note that to the extent GitHub workers are more time-flexible than average workers, being able to shift their workload more flexibly than may be typical, these measured responses may overestimate the effects in the wider population. That said, even in occupations where shifting the timing of work is more costly, leaving workers less apt to respond, the quality or efficiency of work may still be depressed. For example, (Wagner et al., 2012) suggests that cyberloafing increases with Daylight Saving Time, and (Costa-Font et al., 2024a) suggests that workers are less likely to report being a thorough worker when they experience less sleep. In general, we suggest caution with respect to external validity.

4 Conclusion

Even though Daylight Saving Time changes the social clocks of over one billion people each year, concerns over the associated economic and social welfare implications continue to be debated. By considering active users of a popular cloud based version-control platform, we exploit variation in the application of DST across technology centers around the world to estimate the productivity implications of shifting clock time this way.

At the daily level, we find significant level declines in the recorded activity of GitHub users who experience DST—on the Sunday of DST itself, and the Monday immediately following the transition to DST. While this suggests that the productivity declines are over quickly, there are two ways that the data support the belief that the transition is more costly to productivity. First, we find persistent "Sunday effects" in treated cities—while daily activity returns to baseline following two-day declines, GitHub activity is persistently lower on Sundays. Second, hourly analysis reveals much-longer-lasting disruptions—morning declines are evident for upwards of two weeks following the initiation of DST.

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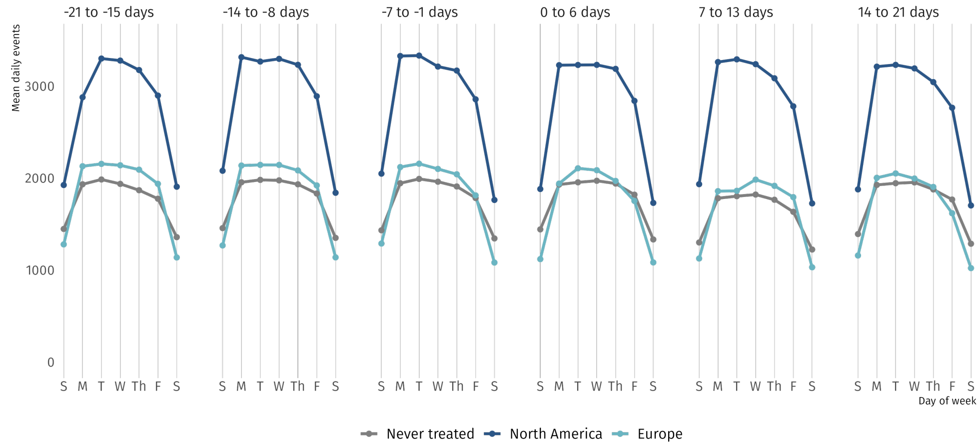
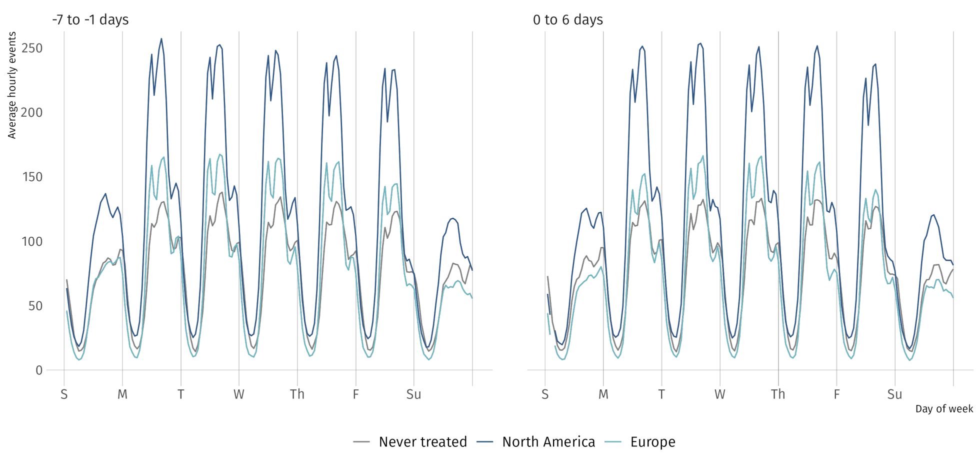
Wagner, D. T., C. M. Barnes, V. K. G. Lim, and D. L. Ferris (2012). Lost sleep and cyberloafing: Evidence from the laboratory and a Daylight Saving Time quasi-experiment. *Journal of Applied psychology 97*(5), 1068–76.

Figure 1: Mean number of GitHub events, by treatment status

A: Total events per day, ±3 weeks to DST



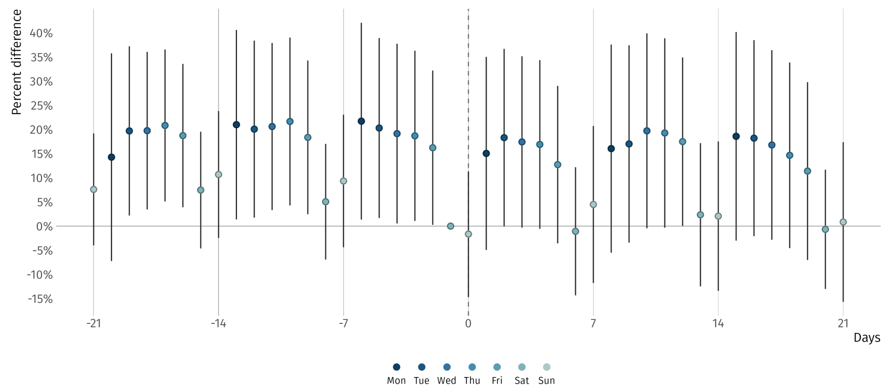
B: Total events per hour, ±1 weeks to DST



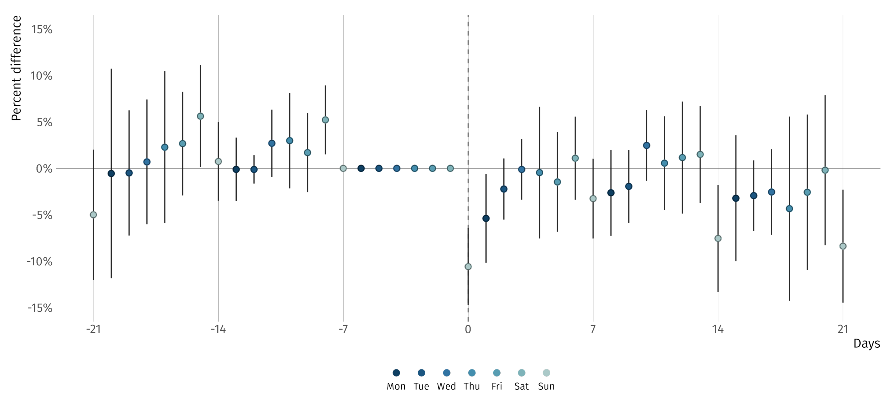
Notes: The sample includes the observations of the total number of GitHub events in the 50 most-active cities, three weeks before and after DST (n = 16,394, representing 174,505 unique users). In Panel A we report day-level means. In Panel B we report hourly means (averaged across days) in the week before and after DST. North America includes the treated cities in the United States and Canada. Europe includes the treated cities in the European Union. See Table A3 for specific dates associated with DST. (In the "-21 to -15" cell of Panel A, the lower level of activity on Monday in North America is attributable to President's day.)

Figure 2: Does DST induce a change in the total number of daily GitHub events?

A: Pooled model (across day of week) normalized
to the Saturday prior to treatment



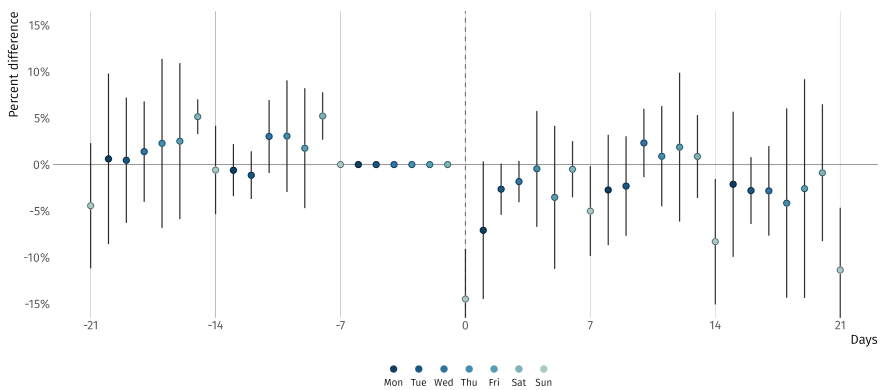
B: Separate models (by day of week), with events
normalized to the week prior to treatment



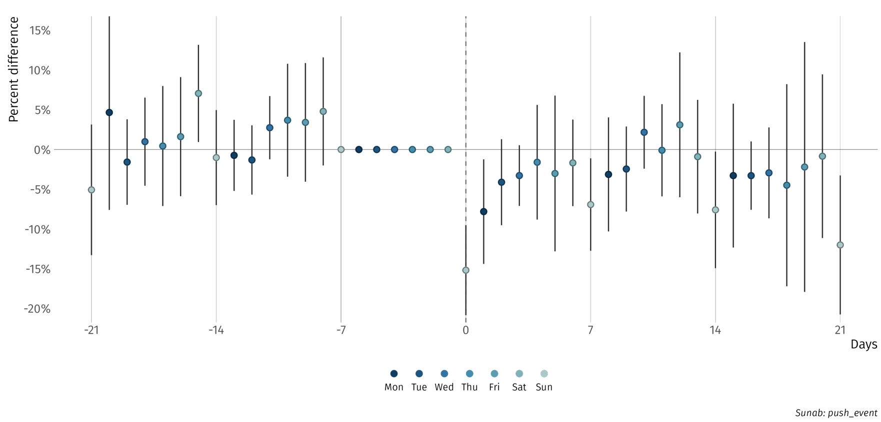
Notes: The sample includes the observations of the total (logged) number of GitHub events three weeks before and after DST, for the 50 most-active cities (representing 16,394 city-day observations of 174,505 unique users). In Panel A we estimate one pooled model of all days, with the Saturday prior to treatment as the omitted category. We estimate city, day-of-week, day-of-year, year, and holiday fixed effects. As day-of-week effects vary by city (e.g., some cities exhibit more or less weekend activity), we are inclined to allow day-of-week effects to vary by city. However, as treatment always falls on a Sunday we cannot estimate separate day-of-week effects by city. In Panel B we therefore estimate seven separate models (i.e., one model for each day of the week) where the city fixed effect then implicitly absorbs any day-of-week differences.

Figure 3: Do we see different responses within working hours, or if we restrict events to "pushes" only?

A: Total events during work hours (9a-7p)



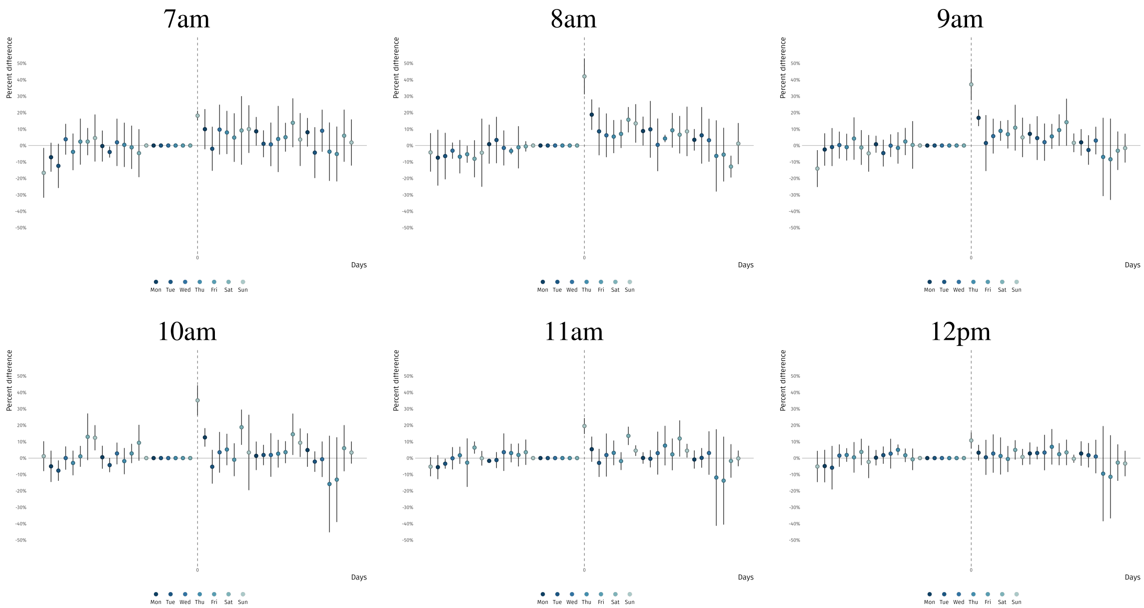
B: Pushes only (all hours)



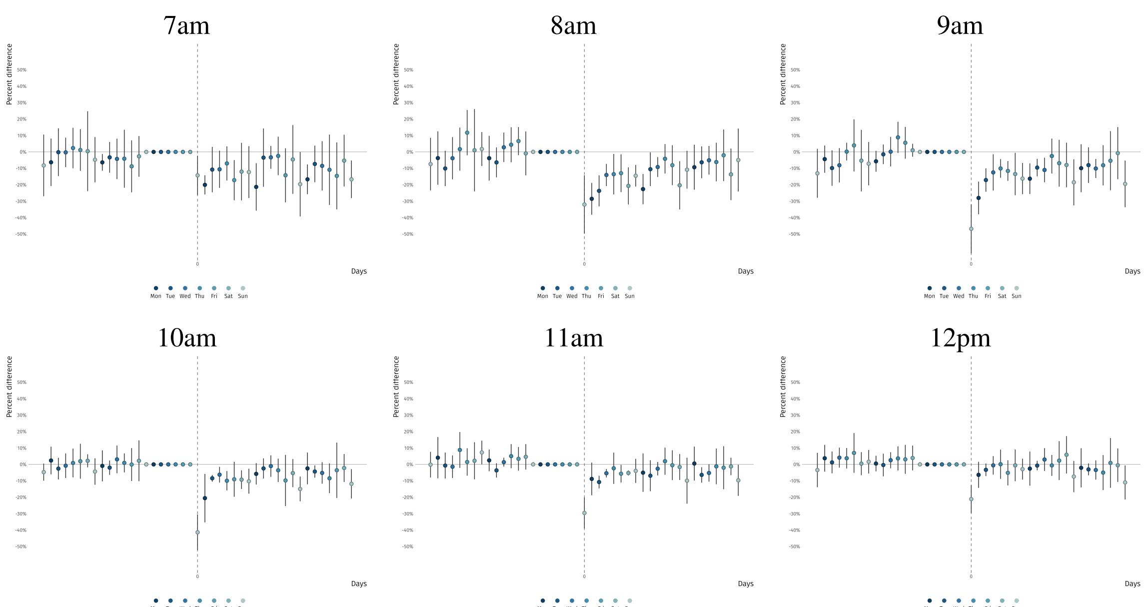
Notes: The sample includes the observations of the total (logged) number of GitHub events three weeks before and after DST, for the 50 most-active cities (representing 16,394 city-day observations of 174,505 unique users). In both panels we estimate seven separate models (i.e., one model for each day of the week). In Panel A we model the (logged) total number of GitHub events that fall within the hours of 9am to 7pm. In Panel B we model the (logged) number of pushes.

Figure 4: Hour-specific estimates of the effect of DST and return to standard time on GitHub events

A: The reduction in morning activity induced by DST



B: The return to standard time

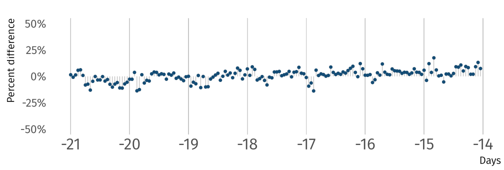


Notes: In both panels, the sample includes the observations of the total (logged) number of GitHub events three weeks before and after the transitions to DST and the return to standard time. In Panel A this represents 393,162 city-hour observations of 174,505 unique users. In Panel B, this represents 378,672 city-hour observations of 174,505 unique users. In both, we estimate 168 separate models (i.e., one model for each hour of the week) where the city fixed effect then implicitly absorbs any hour-of-week differences.

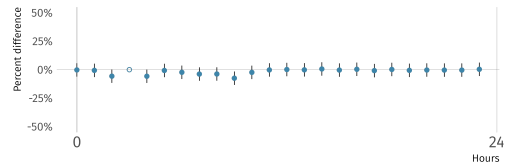
Figure 5: Does the pattern of hourly events change around DST?

A: -21 to -15 days to DST

(i) Hour-specific estimates

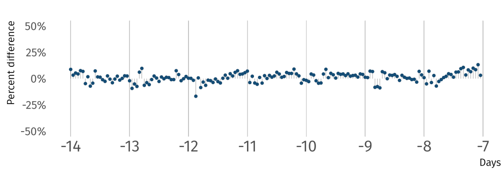


(ii) Average activity by hour

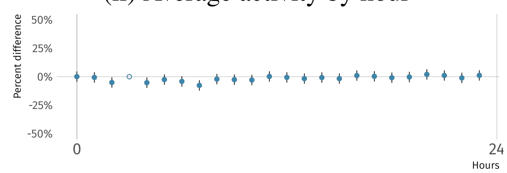


B: -14 to -8 days to DST

(i) Hour-specific estimates

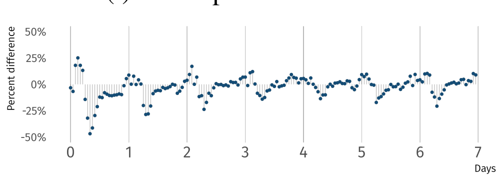


(ii) Average activity by hour

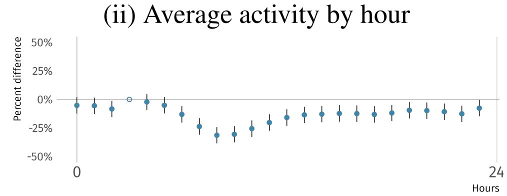


C: 0 to 6 days from DST

(i) Hour-specific estimates

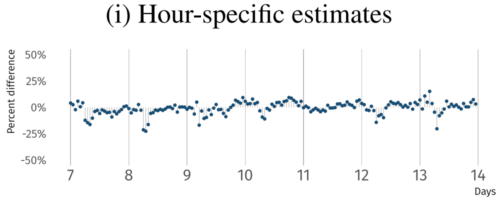


(ii) Average activity by hour

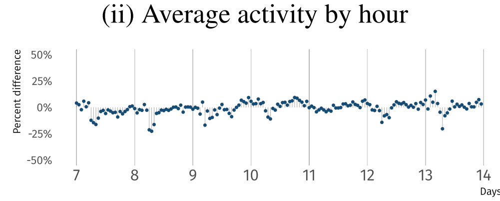


D: 7 to 13 days from DST

(i) Hour-specific estimates

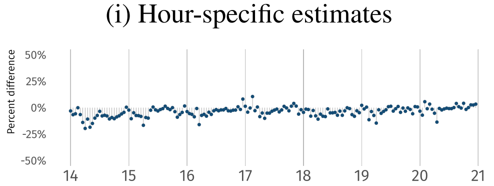


(ii) Average activity by hour

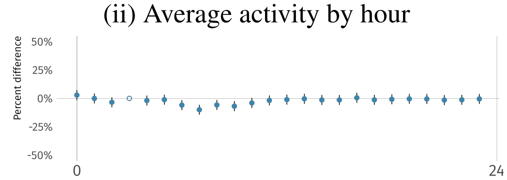


E: 14 to 20 days from DST

(i) Hour-specific estimates



(ii) Average activity by hour



Notes: Point estimates in Column (i) are taken from corresponding hours in Figure A4, and sorted by hour of the week. Point estimates in Column (ii) are estimates of the average hourly activity in the corresponding week, sorted by hour of the day.

Appendix

Table A1: GitHub events with proportional breakdowns

Name	Description	Proportion
Push	One or more commits are pushed to a repository branch or tag	0.466
Issue comment	Activity related to an issue or pull request comment	0.112
Create	A Git branch or tag is created	0.108
Watch	When someone stars a repository	0.086
Pull request	Activity related to pull requests	0.078
Issues	Activity related to issues	0.051
Pull request review comment	Activity related to pull request review comments in the pull request's unified diff	0.034
Delete	A Git branch or tag is deleted	0.027
Fork	A user forks a repository	0.021
Gollum	When a wiki page is created for a repository	0.008
Release	Activity related to a release	0.004
Member	Activity related to repository collaborators	0.003
Public	When a private repository is made public	0.001

Notes: The sample includes observations of all GitHub events in the 50 most-active cities between 2013–2019. The proportional breakdown is of all evens three weeks before and after DST (representing 16,394 city-day observations of 174,505 unique users).

Table A2: 50 most-active GitHub cities (ranked by total events) in the Northern Hemisphere in 2013–2019

Rank	City	Events	Pushes	Early / Late / Never DST
1	San Francisco	26,220,671	11,464,699	Early
2	London	19,511,879	8,840,797	Late
3	New York	18,571,890	9,123,456	Early
4	Seattle	16,706,522	7,232,050	Early
5	Paris	10,261,588	4,729,269	Late
6	Berlin	9,999,729	4,087,816	Late
7	Tokyo	9,889,374	4,539,373	Never
8	Boston	9,405,851	4,396,030	Early
9	Los Angeles	7,365,915	3,474,078	Early
10	Moscow	6,312,342	3,006,135	Never
11	Toronto	6,174,122	2,934,192	Early
12	Chicago	5,960,846	2,946,564	Early
13	Austin	5,834,262	2,738,333	Early
14	Portland	5,793,351	2,712,860	Early
15	Bengaluru	5,359,385	2,542,372	Never
16	Washington	4,941,728	2,398,345	Early
17	Amsterdam	4,295,359	1,986,714	Late
18	Vancouver	4,219,302	1,948,889	Early
19	Montreal	3,983,904	1,876,482	Early
20	Denver	3,782,576	1,766,305	Early
21	Stockholm	3,782,445	1,810,495	Late
22	Munich	3,444,518	1,520,287	Late
23	Seoul	3,434,359	1,774,131	Never
24	Madrid	3,375,069	1,532,040	Late
25	Kyiv	3,373,661	1,665,148	Late
26	Atlanta	3,135,574	1,608,506	Early
27	Philadelphia	2,880,876	1,373,885	Early
28	Zurich	2,877,658	1,282,288	Late
29	San Diego	2,853,542	1,477,020	Early
30	Delhi	2,604,071	1,185,269	Never
31	Hamburg	2,536,831	1,161,703	Late
32	Prague	2,483,811	1,095,295	Late
33	Pittsburgh	2,359,704	1,269,121	Early
34	Raleigh	2,313,654	991,554	Early
35	Oslo	2,295,868	1,092,017	Late
36	Warsaw	2,258,030	1,064,295	Late
37	Saint Petersburg	2,170,095	968,918	Never
38	Minneapolis	2,051,118	971,689	Early
39	Copenhagen	2,029,562	914,542	Late
40	Cambridge	2,012,722	969,881	Late
41	Helsinki	1,995,306	1,000,439	Late
42	Dallas	1,972,359	960,276	Early
43	Phoenix	1,845,819	869,805	Never
44	Barcelona	1,841,706	905,971	Late
45	Dublin	1,821,963	924,427	Late
46	Tulsa	1,798,579	772,251	Early
47	Ottawa	1,724,724	794,807	Early
48	Cologne	1,677,009	752,390	Late
49	Lyon	1,600,373	733,745	Late
50	Budapest	1,579,333	790,950	Late

Table A3: Daylight Saving Time across treated locations, 2013–2019

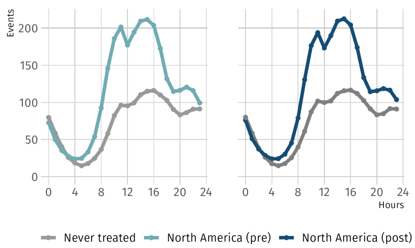
Year	North America	European Union
2013	March 10	March 31
2014	March 9	March 30
2015	March 8	March 29
2016	March 13	March 27
2017	March 12	March 26
2018	March 11	March 25
2019	March 10	March 31

Figure A1: Constructing hourly difference-in-differences estimates

A: Mean counts of total events by treatment status, DST ± 1 week

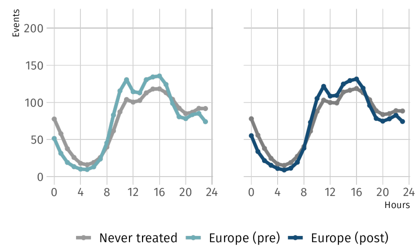
(i) North America and the never treated

Pre Post



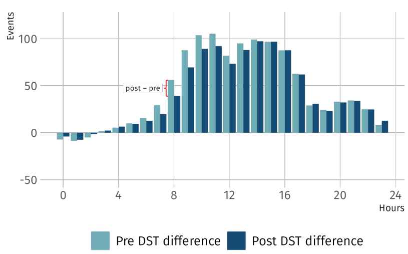
(ii) EU and the never treated

Pre Post

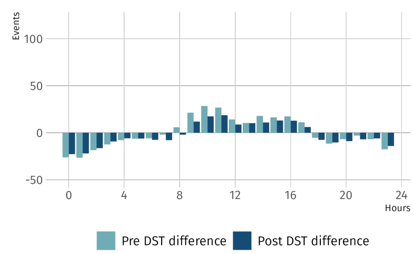


B: Post- and pre-DST differences in total number of events ("treatment – control")

(i) North America



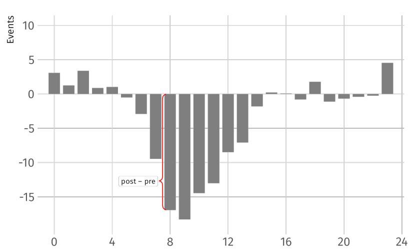
(ii) European Union



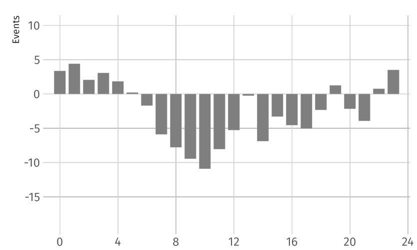
C: Difference in differences

(Post-DST "treatment – control" – Pre-DST "treatment – control")

(i) North America



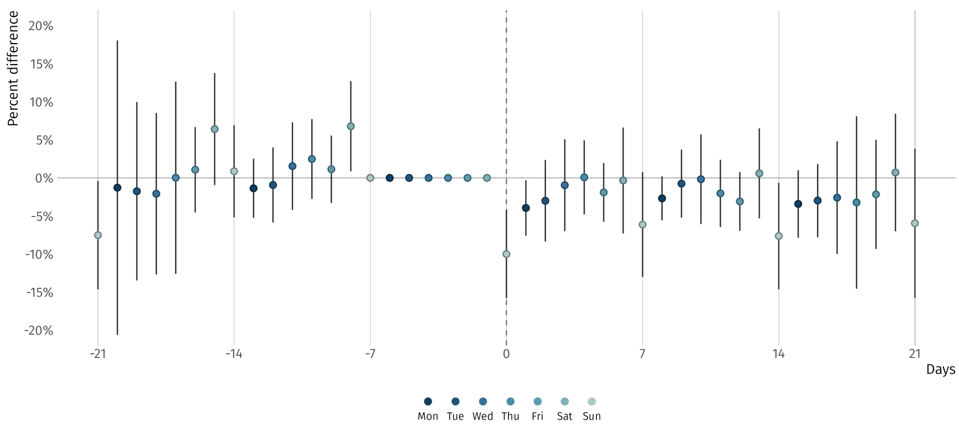
(ii) European Union



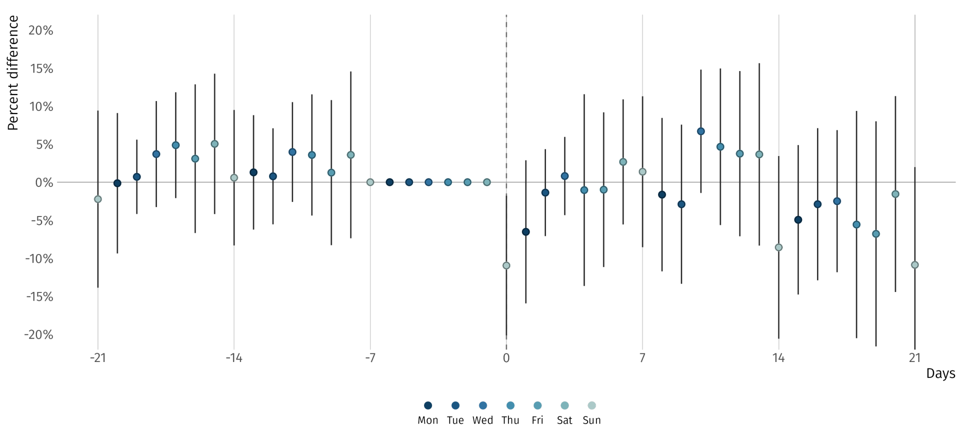
Notes: In Panel A we plot the mean number of hourly events in the one week before and one week after DST, separately for North America and Europe. In Panel B we plot the difference in means, subtracting hourly averages by treatment status separately for pre- and post-treatment period. In Panel C we plot the "second difference" in means, subtracting the post-treatment differences by pre-treatment differences.

Figure A2: Do we see different responses across North America and Europe?

A: Total events, North America and never treated



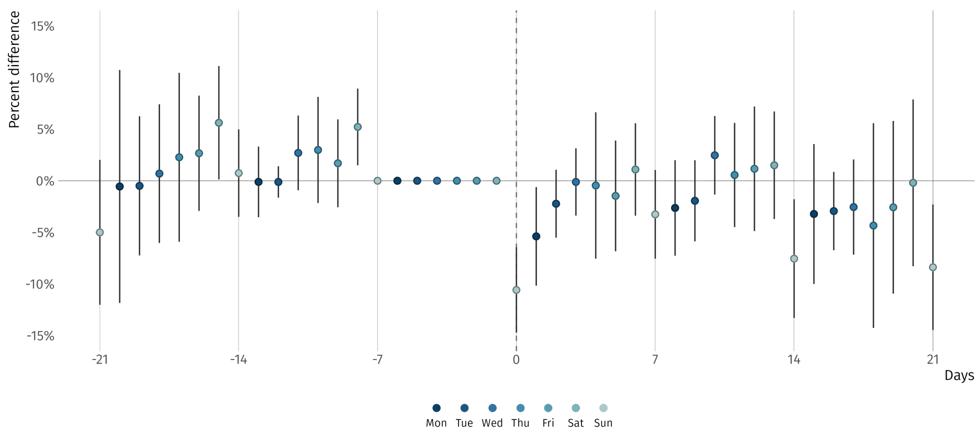
A: Total events, European Union and never treated



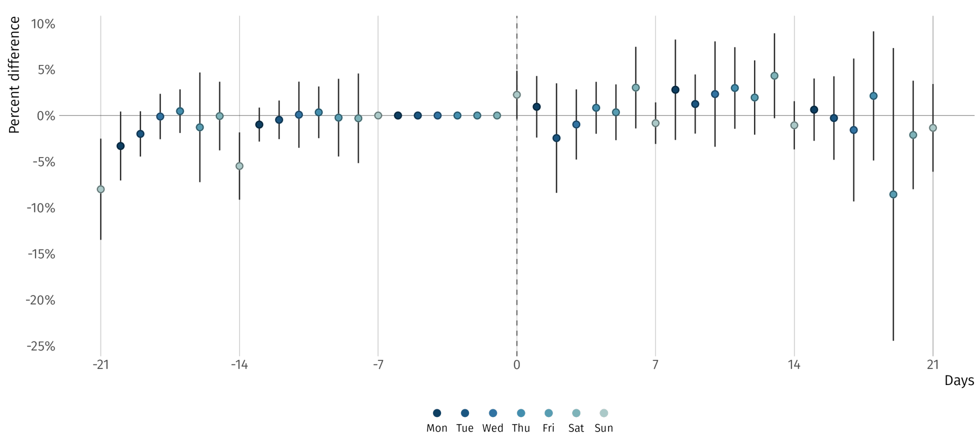
Notes: The sample includes the observations of the total (logged) number of GitHub events three weeks before and after DST, for the 50 most-active cities. In both panels we estimate seven separate models (i.e., one model for each day of the week). In Panel A we model the (logged) total number of GitHub events that originate in North America and never-treated cities (representing 10,374 city-day observations). In Panel B we model the (logged) total number of GitHub events that originate in Europe and never-treated cities (representing 9,772 city-day observations).

Figure A3: Daily estimates of the effect of DST and the return to standard time on the total number of daily GitHub events?

A: Spring transition to DST, as in Figure 2B.
Separate models (by day of week), with events normalized to the week prior to treatment



B: Fall return to standard time.
Separate models (by day of week), with events normalized to the week prior to treatment

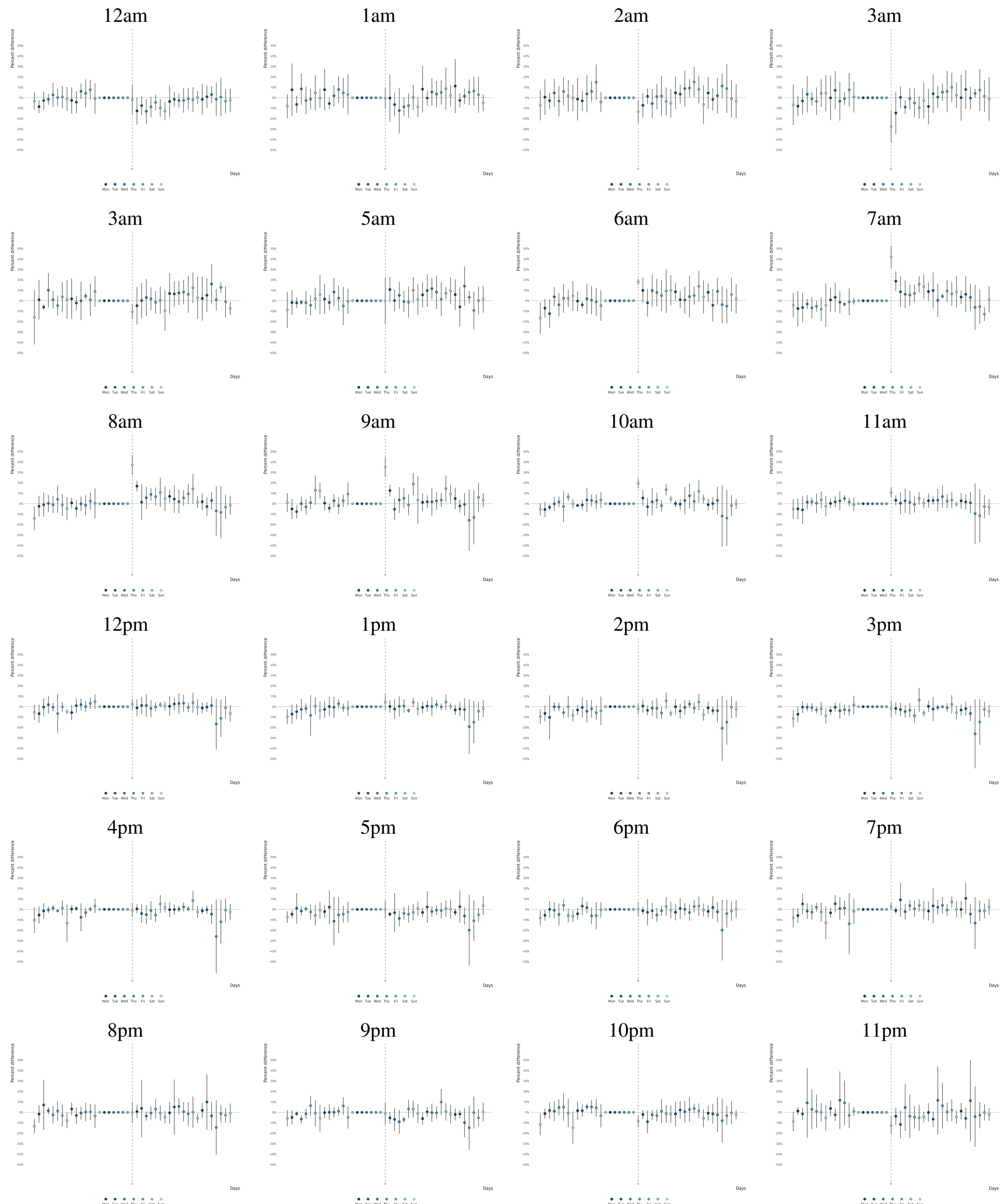


Notes: The sample includes the observations of the total (logged) number of GitHub events three weeks before and after DST, for the 50 most-active cities. Panel A is the same as was reported in Figure 2B. In Panel B we estimate similar models for the fall return to standard time—seven separate models (i.e., one model for each day of the week) where the city fixed effect then implicitly absorbs any day-of-week differences. In Panel A, observations represent 16,394 city-day observations of 174,505 unique users. In Panel B, observations represent 15,778 city-day observations of 174,505 unique users.

Figure A4: Hour-specific estimates of the effect of DST on GitHub events

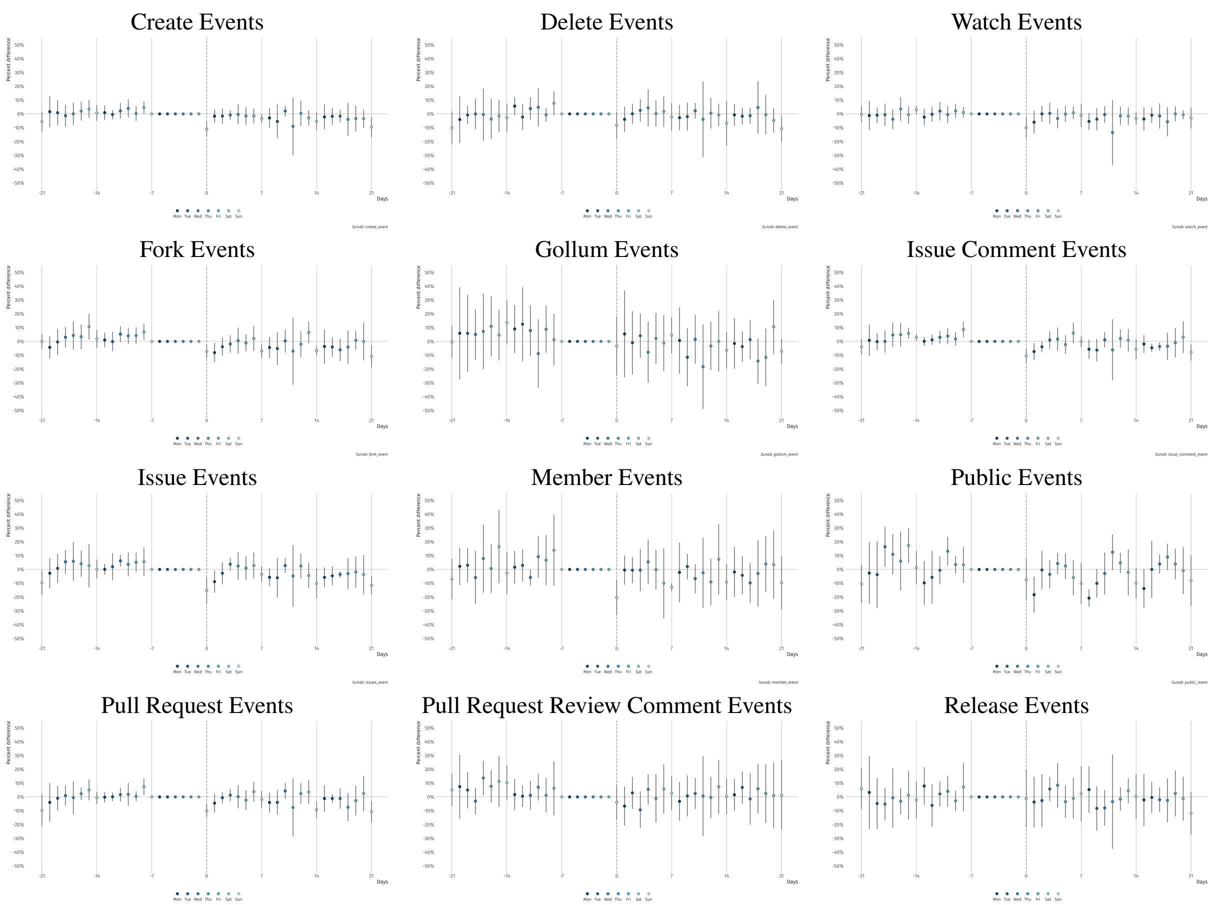
Notes: Estimates are extracted from models of the (logged) total number of GitHub events. The sample includes observations three weeks before and after DST (represent 393,162 city-hour observations of 174,505 unique users).

Figure A5: Hour-specific estimates of the fall return to standard time



Notes: Estimates are extracted from models of the (logged) total number of GitHub events. The sample includes observations three weeks before and after the return to standard time (representing 378,672 city-hour observations of 174,505 unique users).

Figure A6: Additional GitHub events, and the declines in activity induced by DST



Notes: Estimates are extracted from models of the (logged) number of events, separately by event category. (Recall, from Table A1, that "Pushes" account for 46.6 percent of all GitHub events—this figure collectively accounts for all other activities.) The sample includes observations three weeks before and after DST (representing 16,394 city-day observations of 174,505 unique users).