Coordination versus Environmental Adaptation: How Much Does Standardized Time Change Behavior?

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Abstract

The practice of standardizing the designation of time is a central device for coordinating activities and economic behaviors across individuals. However, there is nearly always a tension between an individual coordinating activities and carrying out those activities at their own preferred time. When time is standardized across large geographic areas, that tension is enhanced, because norms about the "clock times" of activities conflict with local environmental conditions created by natural or "solar" time. We study this tension by examining how geographic and temporal variation in solar time within time zones affects the timing of a range of common behaviors in the United States. Specifically, we estimate the degree to which people shift their online behavior (through Twitter), their commute (using the Census), and there visits to businesses and other establishments (using foot traffic data). We find that, on average, a one hour shift in the differential between solar time and clock time—approximately the width of a time zone—leads to shifting behavior by between 10 and 20 minutes. This shows that while adapting to local environmental factors significantly offsets the differential between solar time and clock time, the behavioral nudge and coordination value of clock time has the larger influence on activity. We also study how the trade-off differs across activities and population demographics.

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1 Introduction

Coordinating the timing of activities with other people is both a fundamental characteristic of society and a hassle. Individuals face different constraints and have different preferences about when activities take place, so there is a constant tradeoff between coordinating with others and engaging in an activity when one personally prefers. The needs of modern society, particularly long-distance communication, mean that individuals must coordinate across locations with unsynchronized environmental changes, such as sunrise, sunset and weather, which exacerbates the tension between coordination and personal preferences or environmental constraints.

Technological advances in the U.S. during the 19th century, such as the adoption of the telegraph and telephone and the completion of the transcontinental railroad, increased pressure to coordinate the denomination of time, so-called "clock time," across locations. Prior to the 1880s, most towns in the US operated on their own local clock times, based on "solar time" at their location, with noon occurring when the sun was at its highest point. In 1886, the US became the first country to standardize clock time across large regions, known as time zones. The change was driven, and first implemented, by the railroads, who argued the previously existing system made scheduling trains across locations impossibly complex (Prerau 2009).

Expectations of activities occurring at certain clock times permeate society, whether "bankers hours" (9-to-3) or a standard workday (9-to-5) or lunch time (around noon). Recognizing the behavioral power of clock time, in the early 20th century many governments instituted "daylight saving time", an idea suggested more than a century earlier by Benjamin Franklin. Since time zones were created, they have become a device for coordinating activities across great distances. Beyond easing transportation scheduling, time zones made it possible to synchronize the timing of activities that occur across large geographies, such as telegraph and telephone communication, and radio and television broadcasting.

Clock time is a purely nominal metric, so in theory a re-denomination that preserves the correspondence to elapsed time need not have any impact on behavior, regardless of how it synchronizes with solar time. Yet, re-denomination does seem to affect behavior in practice, possibly because individuals anticipate that others will change their behavior and wish to coordinate on when activities occur. When such coordination occurs across distant locations, however, it is more likely to move the timing of activities away from the choices people would make based purely on solar time.

Fundamentally, standardizing the time of activities across longitudes means that they take place at different solar times of day. If there is an optimal solar time to awaken, eat meals, or begin the work day, one wouldn't expect it to be the same clock time in Boston as in Grand Rapids, Michigan. Both cities are in the Eastern time zone, but the sun rises one hour later in Grand Rapids. Thus, in order to understand how changing the denomination of time might alter behavior in the long run, a useful starting point would be to understand how behavior differs among people living under the same clock time, but different solar times. To what extent do their activities take place at the same clock time – due to widespread social norms, the desire to coordinate activities across locations, or other factors – and to what extent do they adapt to local solar time at the expense of coordination or norms?

We study this trade-off using three different datasets that focus on different behavior and have been collected in different ways. First, we examine data from Twitter, focusing on when individuals send out tweets. Second, we use data from the 2000 U.S. Census longform in response to a question asking when individuals leave for work. And third, we study aggregated foot traffic data from Safegraph on the timing of visits to retail establishments. In all three cases, we use the data to ask when certain behaviors take place as a function of local clock time and solar time. More simply, we ask whether, within a time zone, specific behaviors take place later (according to clock time) among people who are further west, which has a later solar time.

We control for many potential confounders in the analysis, including latitude, population density, employment types, age demographics and household compositions. One issue not captured by those covariates, however, is connectedness between locations. Nashville, TN, for instance, is in the Central time zone, but not far from Knoxville, TN, which is in the Eastern time zone. One would worry that a simple analysis of when activities occur might conflate the impact of solar time (relative to a location's clock time) with the impact of coordinating with other locations that are potentially in a different time zone. If two locations have the same solar time and clock time, but the individuals in one location have stronger ties to people in another time zone, then that connectedness might change their behavior.

We capture this effect with a connectedness index we have created from individual anonymized cell phone data that measures the tendency of a cell phone detected in one specific county to also be detected in another specific county. We have also carried out the analysis using two other measures of connectedness between locations: (1) the Social Connectedness Index created by Bailey et al. (2018), based on "friends" connections across counties on Facebook, and (2) a gravity model, hypothesizing that the influence of other counties will vary with their distance from the observed county and their population or economic size. We find that the new index based on cell phone locations has greater explanatory power, but the effect of solar time is not substantially changed by its inclusion.

The value of coordination across locations also likely differs depending on the activities that an individual is engaging in on a given day. So, for instance, leisure time might create different trade-offs between coordination and responding to local environmental factors than work time. Similarly, work or leisure activities taking place outdoors likely create different trade-offs than those occurring indoors. We incorporate these varying trade-offs by differentiating between weekend and weekday activities, as well as between workers in outdoor-oriented versus indoor-oriented occupations.[1]

A small body of literature examines the relationship between time and economic behavior. Empirical investigations into the relationship between time of day and human activity generally fall into two categories: those that examine the effects of Daylight Saving Time and those that examine how sleep, driven by sunrise time, impacts productivity.

In the area of environmental and energy economics, the impact of clock time has been examined by studying the effect of Daylight Saving Time (DST) on energy use, and more generally the possibility of reducing energy use by changing the denomination of time. Those studies have focused on the outcome variable – net change in energy use – but have not directly confronted the larger question of

1. It is also worth pointing out that technological progress in the last decade may be changing the value of coordination. The increasing availability of on-demand entertainment and technologies that accommodate more effective work from home may reduce the cost of unsynchronized leisure and work times.

the mechanism by which the denomination of time affects behavior. It is possible that re-denomination does change behavior, but the *net* impact on energy use is still near zero, as suggested by these studies, or that the re-denomination does not change behavior much at all.

In general, although DST was putatively designed to save energy, the evidence on that front is mixed at best. Kellogg and Wolff (2008) conclude that DST expansion in some Australian states to accommodate the 2000 Sydney Olympics did not lead to a net change in electricity consumption, only that it shifted the time of consumption. Kotchen and Grant (2011), examining household bills in Indiana, find instead that energy usage actually increases as a result of the DST changeover. By contrast, Rivers (2018) concludes that electricity demand decreases following the start of DST in Ontario. Shaffer (2019) provides some evidence to reconcile the disparate results in the literature: he investigates consumption across Canadian provinces and finds that places with later sunrises, i.e., those located farther west in a time zone, are more likely to experience energy use increases as a result of DST. Other work on DST examines its safety impacts: Barnes and Wagner (2009) look at sleep losses following the DST changeovers and find that mine accidents tend to increase following the "loss" of an hour due to the "spring forward" adjustment, while Smith (2016) suggests that an increase in fatal vehicle crashes following the spring DST change is due to the loss of sleep, not the shift in light. Doleac and Sanders (2015) find that the additional daylight in evening clock hours due to DST reduces crime.

The other category of studies instead uses geographically driven differences in sunset time to document the negative effects of sleep on productivity or performance in the classroom. Gibson and Shrader (2018) instrument sleep time with sunset time and find that both short-run variation in sunset/sleep time and long-run, cross-sectional variation in sunset/sleep time reduce earnings in the United States. In other words, living on the western edge of a time zone reduces wages, all else equal. Using data from several developing countries, Jagnani (2018) concludes that later sunset times reduce sleep, study effort, and eventually, education outcomes.[2]

In general, economic studies of time and behavior have uncovered several important relationships: DST switches do not generally lead to significant electricity savings, and the timing of sunlight time can alter safety, productivity, and even long-run earnings by disrupting sleep patterns. However, very few of these studies have been able to examine the precise nature of the shifts in activity that underlie these relationship. The sole exception of which we are aware is Hamermesh, Myers, and Pocock (2008). Using time use data from Australia, they examine how sleep, work, and television viewing are altered by sunlight time and the timing of network television.

Lawmakers in California, Florida, Illinois, Michigan, Mississippi, New Mexico, and Wyoming have recently considered changing time conventions by abandoning the semi-annual switch between standard and daylight saving time, while the state governments in Massachusetts and Alabama are studying the possibility of switching time zones.[3] The U.S. Congress is also considering national legislation (O'Kane (2021)). Almost all of the policy discussions we have found of these proposed changes, and most of the academic literature on these topics, assume that individuals will continue to engage in activities at the

2. See also Giuntella and Mazzonna (2019) and Ingraham (2019).

3. These are nearly identical policy debates, because choosing to live on standard time or DST is equivalent to choosing to adopt the clock time of one time zone or an adjacent time zone. Debates over DST amount to debates over how much of the year a location will choose to be in one time zone versus an adjacent time zone.

same clock time regardless of how it synchronizes with solar time.[4]

It is clear that the nudge of moving clock time away from solar time changes the timing of human behavior to a significant extent, but it is not clear how much local environmental conditions restrain that response. Assessing the potential impact of changing time conventions on energy use and human activity requires a deeper understanding of how and how much departures of clock time from solar time matter. This project is, to our knowledge, the first study of the topic.

2 A Model of Activity Timing

We illustrate the competing preferences of individuals through a simple model of two entities in locations with different solar time, but the same clock time. An entity could be a person, firm, or any other agent that interacts with others in the world, but for this illustration we will discuss entities as people. If the natural environment – *e.g.*, light, temperature, humidity – were constant, then coordinating the time of activities among people would not involve systematic mismatches of preferences between people in different locations. But because the natural environment changes at times that differ systematically across locations, preferences among people for when activities occur will also differ systematically across locations.

Assume that the utility that individual i gets from a specific activity is a declining function of the deviation of the time of the activity from the individual's own preferred time $\hat{t}$ and a declining function of deviation from the time at which another individual, j, engages in the activity,

$$U_i = U_{0i} - f_i(|t_i - \hat{t}_i|) - g_i(|t_i - t_j|).$$

And likewise for individual j,

$$U_j = U_{0j} - f_j(|t_j - \hat{t}_j|) - g_j(|t_i - t_j|).$$

We assume that $f(0) = 0$, $f'() > 0$ and $f''() > 0$, and $g(0) = 0$, $g'() > 0$ and $g''() > 0$. Arbitrarily, assume that $\hat{t}_i < \hat{t}_j$. Then, individual i's best response to t_j is determined by $f_i' + g_i' = 0$, where the first term is negative and the second term is positive. Conversely, j's best response to i's choice of t_i is $f_j' + g_j' = 0$ where the first term is positive in the second term is negative. Under the assumptions on $f(\cdot)$ and $g(\cdot)$, this yields a best response function for i that deviates further from $\hat{t}_i$ the further is t_j from $\hat{t}_i$, and likewise for j. Figure 1 illustrates the best responses of each individual and the unique equilibrium in which $\hat{t}_i < t_i^e < t_j^e < \hat{t}_j$. In the case illustrated here, j strongly prefers carrying out the activity near $\hat{t}_j$ relative to the value they get from carrying it out at a time near t_i, while i gets a relatively higher value from more coordinated timing.[5]

4. See, for instance, Farrell, Narasiman, and Ward Jr. (2016) and Bokat-Lindell (2021).

5. In an alternative model, one could think of a third party trying to schedule an activity with these (and many other) individuals who have different preferred times of the event (and no private value of coordination) – such as broadcasting a television show or setting standardized work hours for a multi-location firm – and the third party is trying to minimize the schedule hassle costs across all participants. In that case, the third party is trying to choose an activity time to minimize

$$Min_t \; f_i(|t - \hat{t}_i|) + f_j(|t - \hat{t}_j|).$$

Under the same regularity conditions, the optimal scheduling of the event occurs at $\hat{t}_i < t* < \hat{t}_j$.

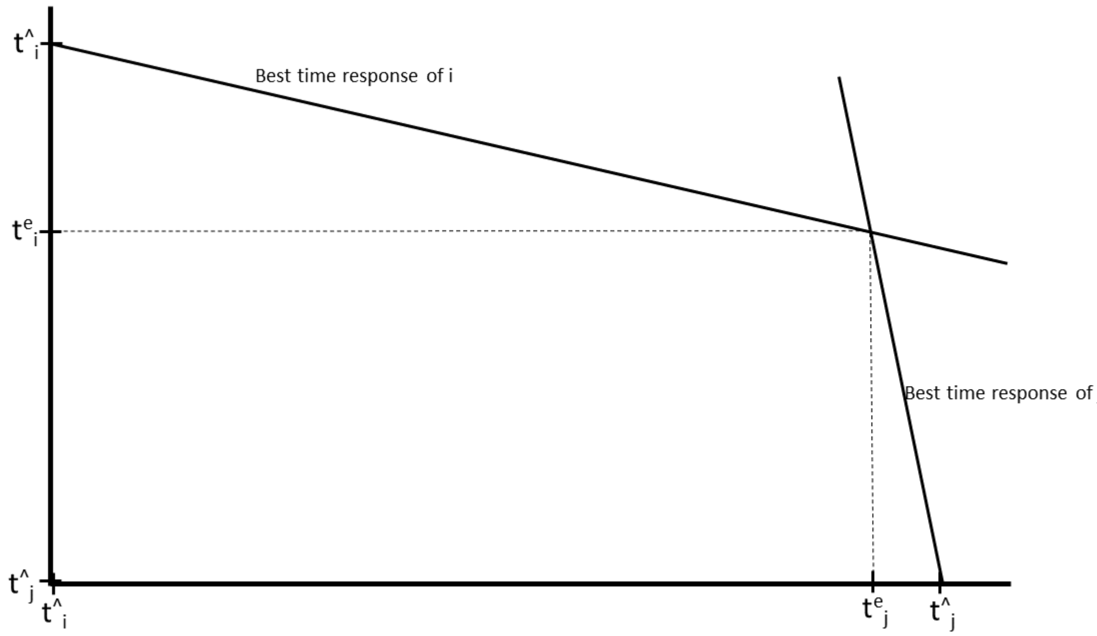


Figure 1: Best Response Time Choices and Equilibrium Timing of Activities

The model illustrates that, in equilibrium, activities will be influenced both by local factors that affect individuals' own preferred times for activities and by the value of coordinating activities across locations. This implies that individuals at the East end of a time zone are likely to engage in activities earlier than individuals at the West end of a time zone, measured in the same clock time. The relative weights on own preferred event time versus the value of coordination will determine how much activity times differ across a time zone. To determine that, we turn to empirical analysis.

3 Data

To give some context to the data we utilize for the analyses, we first introduce a conceptual estimating equation, variations of which we use in analyzing each of the three datasets.

None of the three datasets includes granular information on individuals engaging in the activity beyond the time and location, so in each case we aggregate the data by time and location. We then can observe the distribution of an activity over time of day for a given location.

Taking i as location and t as the observed day or week, the general empirical specification is as follows:

$$\text{Mean Activity Time}_{it} = \beta * \text{Sunrise Time}_{it} + \delta * \text{Connectedness}_i + \phi^{TZ} + X_{it} + \varepsilon_{it}.$$

ϕ^{TZ} is a set of time zone dummy variables that allow different baseline clock times for the activity in different time zones. Sunrise Time_{it} is the main variable of interest and represents the solar time for the location of the observation on the date of the observation. Connectedness_i controls for the degree to which a location is connected to other areas with different clock times, and X_{it} is a vector of controls that includes latitude bins and time of year fixed effects.[6]

A positive β would indicate that the timing of the observed activity is responsive to solar time, not just clock time. For instance, if eating lunch were the activity, $\beta = 1$ would indicate that people on the western edge of a time zone eat lunch one hour later than people on the eastern edge of the time zone, and would imply that only solar time matters for this activity. By contrast, $\beta = 0$ would indicate that the activity follows clock time alone. $\beta = 0.4$ would indicate a partial adherence to solar time, with people on the western edge of a time zone eating 0.4 hours (24 minutes) later than people on the eastern edge on average, even though solar time is one hour later.

We modify this general equation to accommodate the different temporal frequencies and locations available for each dataset, as well as to conduct a range of sensitivity tests.

The level of aggregation that represents an observation differs across the datasets. In the next three subsections, we outline in more detail how this estimation is implemented with each of the three datasets.

3.1 Twitter

We use data from the social media platform Twitter as one measure of activity timing across the United States. To do so, we downloaded approximately 2.5 billion geolocated tweets through a connection to Twitter's Streaming API.[7] For each date in our time period, which ranges from April 2014 to March 2019, we compute both the average time of the tweets on that date and the average time for tweets containing the following phrases: "breakfast", "lunch", "dinner", "good morning", and "good night".

The pattern of tweet timing for each of our phrases is broadly consistent with expected times. fig. 2 documents the occurrence of each phrase throughout the day: "good morning" occurs earliest in the day, followed by "breakfast", "lunch", "dinner" and "good night" (which actually has its peak late in the early morning hours).

Across all tweets, activity peaks around the middle of the day. Because all of the tweets we download and use are geolocated, we identify the county in which each tweet occurs. We then compute the average time of tweets overall – as well as tweets with each activity phrase – by county and date.

Across all three datasets, we measure the time of an activity in hours after 4 AM, because that is approximately the minimum activity time in these data. This minimizes concerns about whether a given activity is occurring late on one day or very early on the following day. Measuring activity time in hours

6. It is possible that connection to locations within the same time zone, but with different solar time, could also affect quantity of activity at a given location. None of our analysis, however, has found evidence of such an effect significantly changing behavior timing.

7. These are the approximately 2% of public tweets from users who have permitted geolocation, so they are not a random sample of tweets. Still, there's no obvious reason that this would bias our estimation of the impact of clock time versus solar time. A more comprehensive description of the methods by which we obtain, store, and process these data can be found in Baylis (2020), though that paper also computes sentiment for each tweet, which we do not use here.

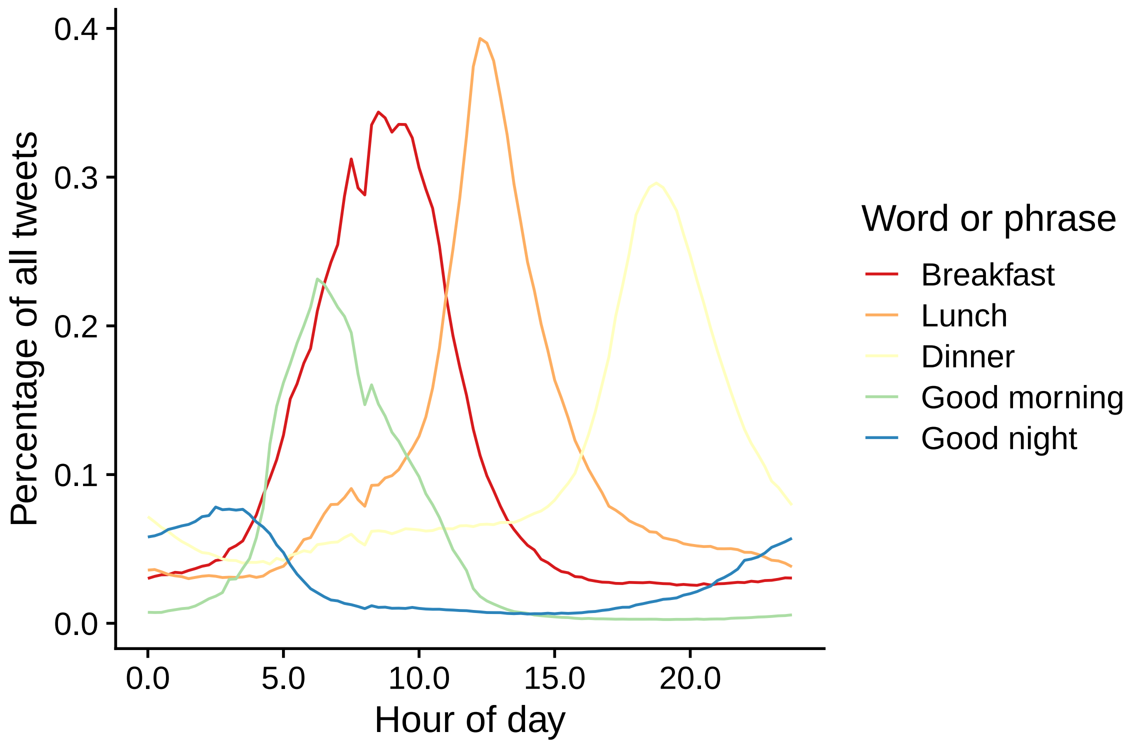


Figure 2: Twitter phrases by time of day

after midnight does not substantially change the results, but does indicate some activity very early in days that is almost certainly actually part of activity from the previous day.

3.2 Census

Census data contribute to our analysis based on questions about when the respondent leaves for and arrives at work. The 2000 census longform asked what time during the week prior to "Census Day" (which was April 1, 2000) the respondent typically left for work.[8] For each of slightly more than 200,000 census block groups, we use the average reported departure time as the primary variable of interest, but we also analyze the mean of arrival at work with nearly identical results.[9]

Unlike the other two datasets we study, the census data have no time-series variation. They are simply a cross-section snapshot. In addition, the measures of departure time and travel time are self-reported, with all of the potential recall error issues that creates. Still, there is no clear reason that would bias our estimation of the impact of solar time on this activity. These data also have the potential advantage of being a 17% sampling of the entire population with extremely high response rates.

8. This was question 24 of the long form: 24(a) What time did this person usually leave home to go to work last week? and 24(b) How many minutes did it usually take this person to get from home to work last week? In 2000, daylight saving time began on April 2 in the United States.

9. Arrival time is calculated as the average departure time plus average travel time to work.

3.3 Foot traffic

To analyze both the effects of time measurement on human mobility and the degree of *connectedness* between areas, we use cellphone-based foot-traffic data from SafeGraph (SafeGraph 2021b). These record data on visits to approximately 6.6 million points of interest (POIs) across the United States. SafeGraph defines a point of interest as any non-residential location a person can visit—ranging from restaurants and hardware stores to parks, post offices, and churches. These 6.6 million POIs cover 418 six-digit NAICS (North American Industry Classification System) codes during our sample period. We focus on visits during 2018 and 2019 due to that facts that (1) 2018 is the earliest year available and (2) data for 2020 and 2021 were distorted by COVID.

For the main analyses, we focus on POIs that satisfy three sample-inclusion criteria: POIs (1) have at least one visit each week during 2018-2019 (excludes POIs that open or close in the middle of the sample), (2) have a median of at least 14 weekly visits,[10] and (3) are not missing location-related data. The resulting dataset includes 22.4 billion visits (91.6% of all visits in the dataset) to 2.2 million POIs covering 378 six-digit NAICS codes.[11]

In raw form, this POI dataset[12] allows us to see the number of visits to a POI by hour of sample, for example, the number of visits to a specific Walmart between 8 AM and 9 AM on March 14, 2021. We also know each POI's Census block group (CBG). We then collapse the dataset to POI by week-of-sample. For each POI-week, we calculate the average visit time and the average time of sunrise (based upon the POI's CBG)—also summarizing each week's activity by weekdays and weekends.

3.4 Controlling for connectedness

A potential source of confounding in a regression of activity time on solar time (controlling for time zone) is that people in locations near the edge of a time zone border may be connected in some way to locations in other time zones and may shift their activities in order to coordinate with the neighboring time zone. For example, most of the Florida Panhandle west of Tallahassee is in the central time zone, but the closest large city (and the state capital) is Tallahassee. Someone working in Panama City, Florida (on the eastern edge of the Central time zone) may interact frequently with workers in Tallahassee. That person may adjust their schedule, for example, by working 8-4 instead of 9-5 in order to synchronize work time with Tallahassee. If locations near time zone borders are systematically more likely to link to locations on the other side of that border, a regression without a connectedness control could find a relationship between activity time and solar time even in the absence of a true causal effect.

To account for this possibility, we construct a set of variables that measure the proportion of observed visits from residents of one time zone that occur in other time zones. For this calculation, we use a second SafeGraph dataset that SafeGraph constructed to measure daily, Census block group (CBG)-level social distancing. These data are available starting in 2019 (SafeGraph 2021a). This dataset records $v[h_{CBG}, d_{CBG}, t]$, the number of visits v to destination CBG d_{CBG} from individuals who live in CBG h_{CBG} at

10. Because we weight regressions by the POI's number of visits, the POIs omitted by this second requirement do not contribute very much to point estimates—but still require substantial computation.

11. Our main analyses omit all of Arizona because most of Arizona does not participate in daylight savings time.. As Appendix Table 5 demonstrates, dropping Arizona does not affect our results.

12. We specifically use SafeGraph's "weekly" POI dataset.

time period t. We aggregate across time and within county. This aggregation produces a static, county-level matrix with cells $V[h,d]$: the number of visits V from residents of county h to county d. To normalize this measure (controlling for the population of h), we divide by the total visits generated by the residents of h, i.e., $V[h,\bullet]$. We define this ratio as county h's connectedness to county d: $C[h,d] = V[h,d]/V[h,\bullet]$, i.e., the share of visits from residents of h to county d.[13]

Counties with more eastern connections will presumably be pulled 'earlier' (by clock time) into their days. To measure this 'pull', we use the county-level connectedness $C[h,d]$ measure to calculate the average time zone offset for each county—weighting each county's connectedness to the time zones by its connections to the time zones' counties $C[h,d]$. For example, If 50% of a county's visits occur in its own time zone (where the time-zone difference is 0) and 50% of visits occur in the time zone to the east (where the time-zone difference is 1 hour), then we calculate the county's mean time-zone offset is 0.5 hours. This measure effectively gives the visits-weighted average clock-time difference. Appendix Table 4 summarizes this mean time-zone offset variable—in addition to summarizing counties' connectedness to each individual time zone and to their own time zones. Unsurprisingly, the average county is very strongly connected to its own time zone (with 97% of visits occur in its own time zone), yielding a mean time-zone offset near zero. Appendix Figures 5 and 6 illustrate the spatial distribution of these measures. As expected, connectedness to other time zones is strongest for counties near time-zone boundaries.

We also have estimated the models with a "gravity" measure of connectedness— where the strength of connection to another location is an inverse function of the distance to that location and a direct function of the population mass at that location—and with the Social Connectedness Index developed in "Social Connectedness: Measurement, Determinants, and Effects," by Bailey et al. (2018) based on "friends" connections across counties on Facebook. Neither of these variables appears to explain the measures of activity time we study as well as the measure that we develop with cell phone data. Nonetheless, the estimated effects of solar time on activity are reduced only slightly by inclusion of a connectedness variable.

4 The effect of solar time on activity

4.1 Twitter

For the Twitter dataset, we estimate the model

$$\text{Mean(Tweet time)}_{ct} = \beta * \text{Sunrise}_{ct} + \delta * \text{Connectedness offset}_c + \phi_c + \pi_t + \varepsilon_{ct}$$

for county c on date t. Sunrise time_{ct} is determined by county centroid and date, Connectedness offset_c is the average connectedness offset described in section 3.4, ϕ_c are time zone by one degree latitude bin fixed effects, $[\text{Time zone} \times \text{Lat. bin}]_c$, and π_t is a date-of-sample fixed effects. $\text{Mean(Tweet time)}_{ct}$ refers to the time-weighted average tweet time in that county-date for either all tweets in the dataset for that date-county, or, in the next section, tweets containing a specific key phrase. We compute the average

13. The vast majority of visits occur within individuals' counties of residence, so $C[h,h]$ is typically above 0.6.

tweet time for tweets from 4 a.m. that day to 4 a.m. the following day. We weight this regression by the average count of tweets for the county, and cluster standard errors by state.

Table 1: Effect of sunrise time on tweet time

	Avg. tweet time	
	(1)	(2)
Panel A: All days		
Sunrise time	0.3571***	0.3615***
	(0.0618)	(0.0982)
Avg. conn. offset		0.2514
		(3.051)
Panel B: Weekdays		
Sunrise time	0.3459***	0.3613***
	(0.0647)	(0.1067)
Avg. conn. offset		0.8766
		(3.393)
Panel C: Weekends		
Sunrise time	0.3856***	0.3621***
	(0.0569)	(0.0794)
Avg. conn. offset		-1.346
		(2.264)
TZ×Lat. bin fixed effects	✓	✓
Date fixed effects	✓	✓

Notes: Observations are county by date. Standard errors clustered by state.

The results in column (1) for all days indicate that tweets from people located at the west end of a time zone on average occur about 0.36 hours (22 minutes) later in clock time than from people located at the east end of a time zone, where the sun on average rises one hour earlier. In other words, for this activity at least, people have adjusted their behavior by slightly more than one third of the solar time differential between locations that have the same clock time. The effect is slightly larger on weekends than on weekdays—consistent with the hypothesis that on weekends individuals are more inclined to adapt to their local environment and less inclined to follow clock time—but the difference is not statistically significant.

The results in column (2) indicate that connectedness of a county to locations in other time zones does not significantly change when a person tweets. In fact, we would expect the sign of this coefficient to be negative in that greater connectedness with people in a "later" (further east) time zone would cause one to engage in activities earlier as measured in local clock time. That is consistent with the point estimate on weekends, but not the estimate on weekdays. Still, the coefficients are not estimated with sufficient precision to draw any concrete conclusions.

4.2 Census

For the census data analysis, we have a single observation for each CBG indicating the average time at which the respondent reported typically departing to go to work during the last week of March. As with the Twitter data, we control for time zones by latitude, but we do not need to control for date because this is a single cross-section.

$$\text{Mean(departure time)}_c = \beta * \text{Sunrise}_c + \delta * \text{Connectedness offset}_c + \phi_c + \varepsilon_c$$

for CBG c. Sunrise time$_c$ is determined for the CBG centroid on April 1, 2000. The other variables and coefficients are as defined in the Twitter analysis. This equation does not include time fixed effects, because the sample is a single cross-section. We weight this regression by the CBG population, and cluster standard errors by state.

Table 2: Effect of sunrise time on time left for work

	Time left for work	
	(1)	(2)
Sunrise time	0.3718***	0.4285***
	(0.0538)	(0.0570)
Avg. conn. offset		1.744**
		(0.8655)
N obs.	188,246	188,246
TZ × Lat. bin (1 deg.) fixed effects	✓	✓

Notes: Observations are CBGs. Excludes Indiana and Arizona. Standard errors clustered by state.

The results in column (1) are very consistent with the Twitter data results, indicating that people offset clock time by slightly more than one-third of the difference between clock time and solar time. Column (2) suggests that connectedness has a statistically significant, but surprising sign, impact on activity time. The positive sign indicates, for instance, that greater connectedness with locations to the east of one's own time zone causes one to leave for work later in the day, measured by local clock time. The effect, however, is estimated to be rather small and not very precisely estimated. A change in mean offset connectedness from the 25th to 75th percentile value adjusts the departure time for work by 2.8 minutes with a 95% confidence interval of $[0.15, 5.45]$ minutes.

4.3 Foot traffic

We estimate the model

$$\text{Mean(Visit time)}_{inw} = \beta * \text{Sunrise}_{cw} + \delta * \text{Connectedness offset}_c + \phi_c + \pi_w + \gamma_{nz} + \varepsilon_{inw}$$

for POI i in 6-digit NAICS category n during week w. CBGs, c, determine longitude and latitude bins, as well as the sunrise time during the observed week, w. Connectedness is determined by the county in which the POI's CBG is located, as with the analyses of Twitter and census data. This regression also includes fixed effects of NAICS code by time zone γ_{nz}. The Mean(Visit time) refers to the weighted average visit time to i during week w. We aggregate all days of the week and then break it out by weekday/weekend.

The results, presented in table 3, again show a statistically significant adaptation to solar time and away from purely following clock time, but the effect estimated in this case is slightly less than half as large as the results from the Twitter or census data. Including latitude bin by time zone fixed effects, the top panel of column (1) suggests that people on the west end of a time zone frequent similar points of interest about nine minutes later on average than people on the east end of the time zone. Somewhat surprisingly, the effect is nearly the same on weekdays as on weekends.

As before, adding the connectedness variable does not change the impact of solar time by much at all. For weekends, however, connectedness does have a very statistically significant effect of the expected negative sign, implying that stronger connectedness with people in a more easterly time zone causes one to operate on an earlier schedule in local clock time. The effect, however, is still quite small. The coefficient suggests that a change in mean offset connectedness from the 25th to 75th percentile value adjusts the time of visiting a POI by 2.2 minutes.

Table 3: Foot-traffic results: Effects of sunrise and connectedness on visit times

	Avg. visit time	
	(1)	(2)
Panel A: All days		
Time of sunrise	0.1544***	0.1645***
	(0.0261)	(0.0304)
Avg. conn. offset		0.4875
		(0.8864)
N obs. (millions)	159.43	159.43
Panel B: Weekdays		
Time of sunrise	0.1452***	0.1469***
	(0.0458)	(0.0462)
Avg. conn. offset		0.0813
		(1.042)
N obs. (millions)	159.4	159.4
Panel C: Weekends		
Time of sunrise	0.1428***	0.1200***
	(0.0316)	(0.0293)
Avg. conn. offset		-1.108**
		(0.4405)
N obs. (millions)	155.08	155.08
Week-of-sample fixed effects	✓	✓
TZ × NAICS (6 digit) fixed effects	✓	✓
TZ × Lat. bin (1 deg.) fixed effects	✓	✓

Notes: An observation in this table is a POI-week, for example, a single Walmart during the week of 2021-03-14. Even-numbered columns control for the average offset (in minutes) at the county level: More negative values of the connectedness variable imply a stronger connection to westward time zones. Clustered (state) standard-errors in parentheses. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

5 Heterogeneity in Adaptation to Solar Time

In the previous section, we presented average results for different types of activities controlling for only very basic heterogeneity: day, location, and connectedness to other locations. However, we have more detailed information about characteristics of the location and the observed activity. For each CBG, we know a number of demographic variables that could influence the degree of adaptation to solar time. In the Twitter dataset, we also have information from the content of the tweet. And in the foot traffic dataset, we know the line of business or activity associated with the POI.

In general, we would expect that greater association of the demographic characteristic or the activity with the outdoors would be lead to more adaptation to solar time. We now estimate the effect of solar time in separate regressions for the various demographic and activity categories, and report the estimated effect of sunrise on the timing of the activities.

Figure 3 presents separate estimates on the effect of sunrise time, with the dataset split along different dimensions. The top panel shows results for areas north and south of the median population-weighted latitude in the continental US. For all three datasets the point estimate of the effect of solar time on the clock time at which the activity occurs suggests that people in locations further north adapt to local solar time more than people who live in the southern part of the country. The pattern is consistent in all three datasets, statistically significant at 5% level in the foot-traffic data, and statistically significant at 10% level in the Twitter and census datasets. One possible explanation is that people living further north are used to adjusting to large variations in total sunlight time between the winter and summer, so they are more likely to also adjust to variations across longitude in the clock time of that sunlight.

The next panel differentiates between summer and winter, where we do not see a consistent pattern or statistically significant differences.

The following two panels attempt to get at outdoor activity. Rural areas are typically associated with living closer to nature, whether in line of work or choice of leisure activities. So we might expect that there is greater adaptation to solar time in rural than in urban locations. We see essentially no difference in analyzing the time of departure for work in the census data, but we do see a statistically significant difference in the foot-traffic dataset (and marginally significant differences in the Twitter data), suggesting that rural counties adapt more to solar time than do urban counties. That pattern, however, does not hold in the following panel where counties with larger shares of outdoor workers are, if anything, less likely to adapt to solar time.

In the fifth panel, we compare locations by their share of population in the workforce (splitting at the median workforce share). In all three datasets, counties with larger population shares in the workforce adapt more to solar time than counties with smaller shares; the differences are marginally significant in the foot-traffic and census datasets.

The bottom panel of Figure 3 takes advantage of the content of the tweets in the Twitter data, looking in particular at tweets that include the words "breakfast", "lunch", "dinner", "good morning", or "good night". The estimated solar time adaptation for "good night" is positive, but is very imprecise, likely due to the extremely wide range of times it shows up in the dataset, including hours that we count as early morning. The estimate for "good morning" is very much in line with overall adaptation at around 0.3.

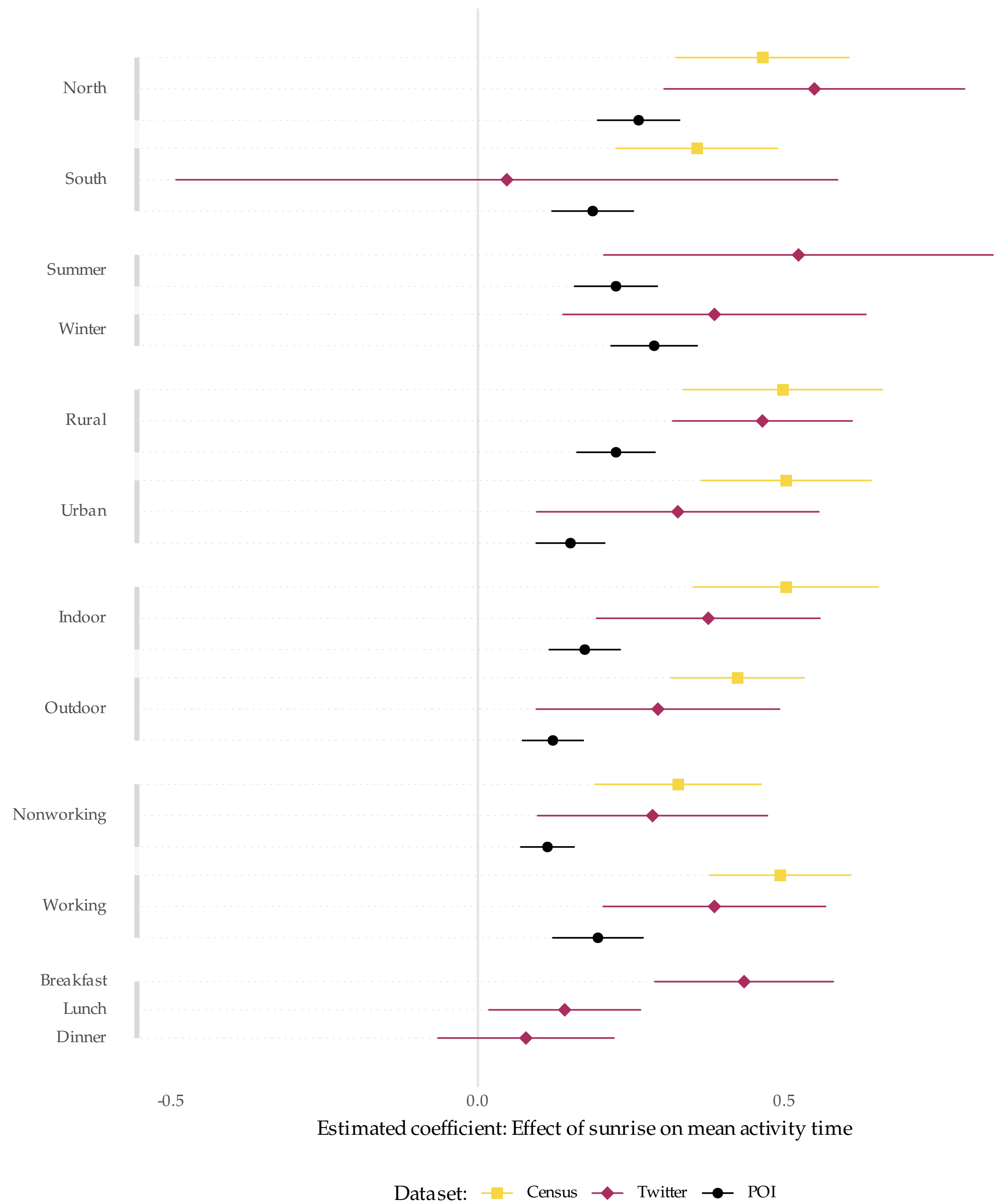
All three meal reference estimates suggest adaptation to solar time, but breakfast seems to have by far the largest adjustment, indicating that discussions of breakfast shift across the longitudes of a time zone by nearly half of the shift in solar time.

Figure 4 uses only the foot traffic data and focuses on POIs in the 25 most common establishment types, as indicated by six-digit NAICS code. The top nine types are all retail stores, and indicate a fairly consistent pattern of adjustment to solar time with most estimates between 0.25 and 0.35, except for auto parts and drugstores, which are around 0.1. Restaurants and hotels also are in the same general range of adaptation.

Operations support services at airports—which includes airport retail outlets as well as entities providing aircraft servicing and related operations—are not estimated to exhibit as much adaptation to solar time, though the estimate is not very precise.

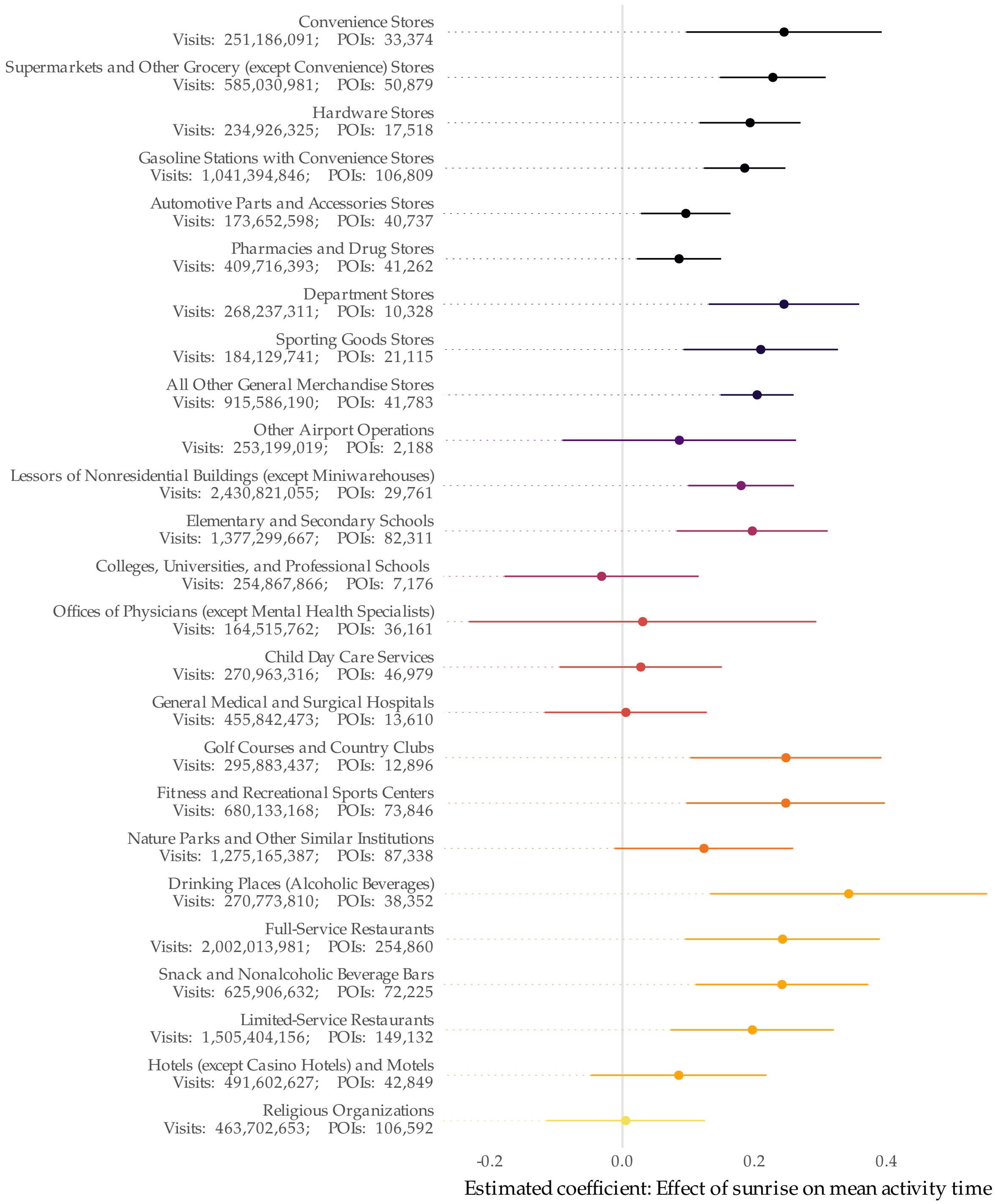
Among the other categories, the lack of adaptation at religious establishments (primarily churches, temples and mosques), colleges and universities, medical care, and child daycare are noteworthy. Also interesting, the fitness and outdoor categories are estimated to adapt to solar time, but no more so than the retail categories.

Figure 3: Coefficient heterogeneity by demographic, geographic, and temporal subsets



Notes: Each point-segment pair presents a coefficient and its 95% confidence interval from a separate regression. The regressions subset each dataset (differentiated by color and shape) by the dimension given on the left vertical axis. The x axis marks the size of the coefficient. The dimensions of heterogeneity: North/South (split at the 38.5$^{\text{th}}$ latitude); Summer/Winter (summer: April–September); Rural/Urban (split at 50% urban), Indoors/Outdoor (split at median share employed in farming/fishing/construction); Nonworking/Working (below/above median share of the population in workforce); meals (based upon Twitter text). All regressions include controls for connectedness and fixed effects corresponding to the appropriate dataset (see Section 4).

Figure 4: Foot-traffic results by establishment type, 25 most-visited NAICS codes



Notes: We estimate the coefficients in this figure with 25 separate regressions for each six-digit NAICS code (that otherwise match our main specifications). We order and color the coefficients and confidence intervals (clustering errors at the state) by the industries two-digit NAICS codes. The twenty-five codes represent the 25 most-visited six-digit NAICS codes in our dataset.

6 Conclusion

Regulators frequently fail to account for the incentives of regulated entities to reoptimize in the face of rule changes. Perhaps no regulation is as pervasive as the setting of time standards, yet policymakers continue to discuss alternatives with little or no recognition of how members of society will respond.

We have shown that individuals and firms systematically do change their behavior in response to changes in the standard for clock time in ways that partially offset those changes. People don't leave for work an hour earlier, in solar time, simply because clock time is advanced by an hour relative to solar time. We show that on average about one-third of that regulated change in clock time is offset by individuals adapting to their local environmental circumstances. We find similar results studying when individuals send out tweets. In looking at foot traffic around stores and other locations open to the public, we find a smaller, but still strongly statistically significant, offset of about one-sixth of the mismatch between solar time and clock time. Our results demonstrate that policy discussions of clock time—whether focused on the extent of observing Daylight Saving Time or the choice of which time zone a location will belong to—should recognize that individuals and firms will reoptimize in response to these policies, balancing the value of adapting to the local environment with the value of coordinating activities among different members of society.

At the same time, our results also demonstrate the very strong influence of coordinating behavior around clock time norms, which are perhaps the most ubiquitous behavioral nudges in society. Even after controlling for an area's connection with areas living on different clock time, we still find that local clock time plays a dominant role in the timing of activities. Given that all residents of a large metropolitan area face essentially the same environmental factors associated with shifting activities to different solar times, this suggests a very high social value of coordinating activity time. It also suggests a relatively high cost of shifting those times in ways that are not coordinated across society. Shifting clock time appears to be a uniquely powerful device for making coordinated changes in the timing of activities so that, for instance, a change in school opening times is coordinated with a change in daycare times and a change in work hour times, thus allowing a parent of children of different ages to maintain a schedule that was probably quite complicated to establish in the first place.

Our results also show that the trade-off between coordinating activities and adapting to local environmental factors varies across activities and environmental factors. The evidence, however, that outdoor activities exhibit greater adaptation to solar time is mixed, with rural areas showing more adaptation than urban, but areas with a larger share of the workforce working outdoors not associated with greater adaptation.

Discussions of breakfast, at least on Twitter, are much more adaptive to solar time than discussions of lunch or dinner. This may be because breakfast is the meal typically eaten closest to sleeping time, and sleep adaptation to solar time may be most significant, but our current datasets don't allow us to explore that.

Our results from analysis of foot traffic indicate that retail establishments—both good sellers and restaurants—adapt to solar time more than religious organizations, higher education and health services offices. Surprisingly, however, foot traffic at parks and golf courses does not show substantially more adaptation to solar time than retail establishments.

Our results show clearly that people do not operate purely on clock time, regardless of environmental factors, but also that clock time plays a dominant role in human activity even for activities that are very much influenced by sunlight and weather. The pattern of adaptation to solar time across demographics and activities, or paucity of clear patterns, suggests that the relationship is more nuanced than it might at first appear.

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Appendix A Connectedness

Table 4 summarizes the measures of connectedness we use.

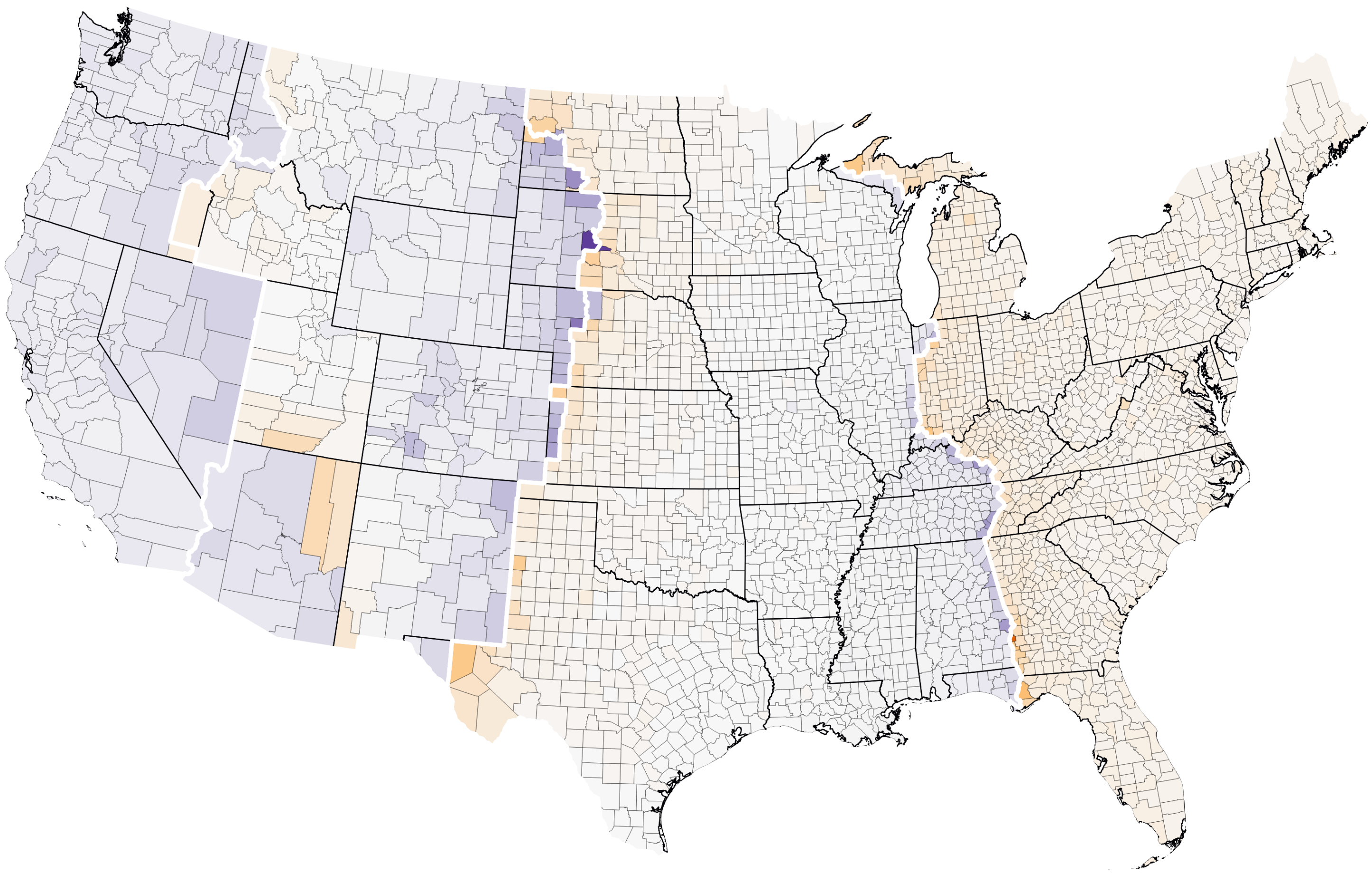
Table 4: Summary of county-level connectedness

Variable	Min.	5^{th} Pctl.	25^{th} Pctl.	Median	Mean	75^{th} Pctl.	95^{th} Pctl.	Max.
Mean offset (hrs.)	-0.463	-0.040	-0.020	-0.007	-0.002	0.007	0.057	0.487
% ET	0.001	0.005	0.008	0.016	0.372	0.982	0.991	0.995
% CT	0.002	0.006	0.010	0.082	0.478	0.979	0.987	0.993
% MT	0.000	0.001	0.001	0.002	0.091	0.006	0.942	0.972
% AZ	0.000	0.000	0.000	0.001	0.005	0.001	0.004	0.957
% PT	0.000	0.001	0.002	0.002	0.053	0.004	0.925	0.988
% own time zone	0.513	0.918	0.971	0.981	0.971	0.986	0.991	0.995

Notes: The variable *Mean offset* is a 'ping'-weighted mean of time zone offsets relative to the given county. A county whose residents only ping in their home county will have a mean offset of zero. If all residents of a county only show up in the time zone to the west of their home county, then their home county would have a mean offset of -1. Rows 2–5 summarize counties' (ping-based) connectedness to US time zones. The variable *% own time zone* summarizes counties' shares of pings in their own time zone. Note that 11 counties include multiple time zones: FIPS 12045, 16049, 31031, 38025, 38053, 38085, 41045, 46117 are bisected by time zone borders, and Arizona counties 04001, 04005, 04017 include tribal land that follow daylight savings time (while the rest of Arizona does not). The unit of observation in this table is a county in the contiguous US. The summary columns are not weighted by population.

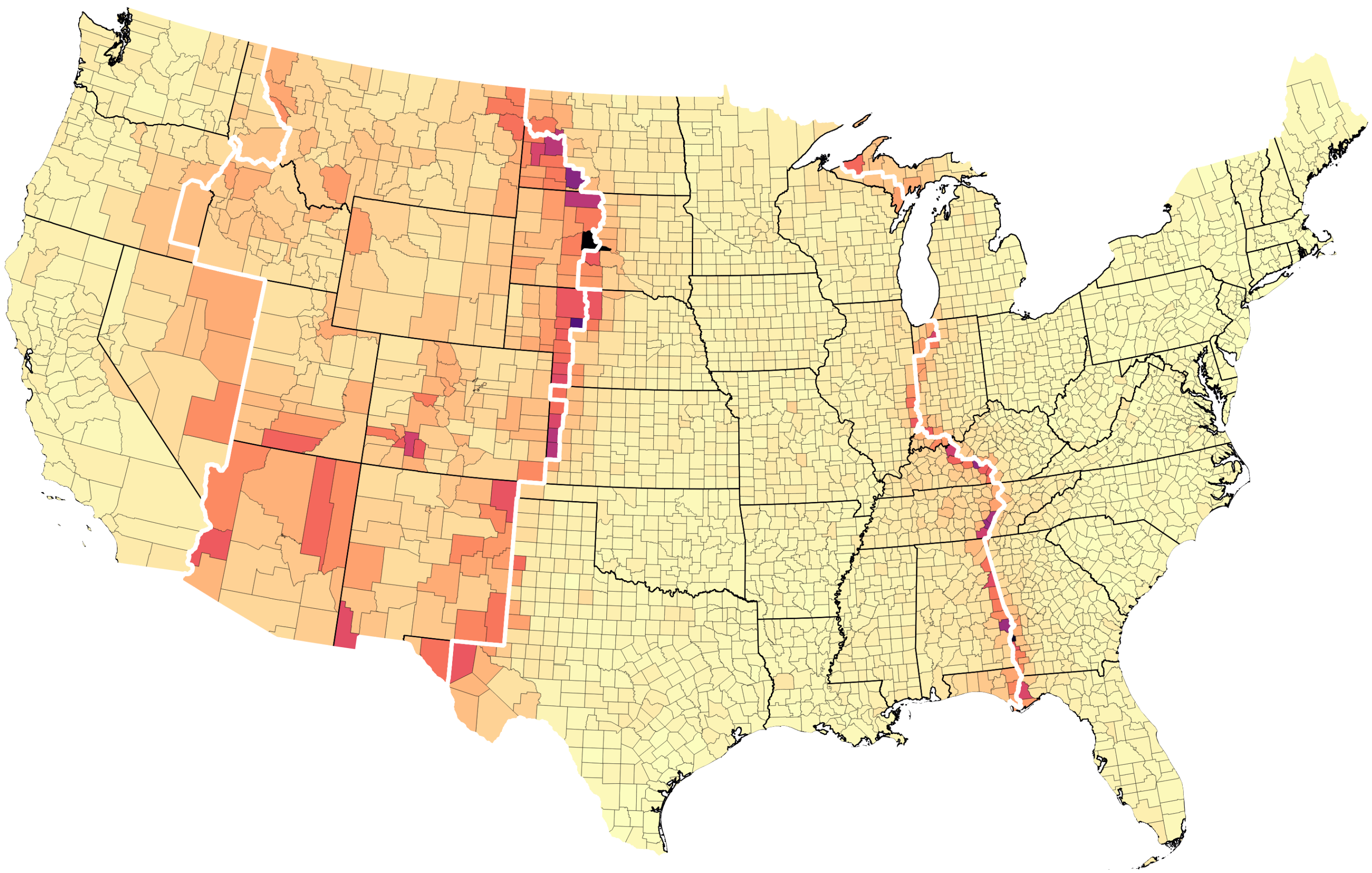
The following figures—i.e., Figures 5 and 6—illustrate counties' (1) mean offsets and (2) connectedness to their own time zones (along with state and time-zone borders).

Figure 5: County connectedness: Counties' mean offset



Dark purple denotes an average (visit-based) offset adjustment that pulls the county approximately 30 minutes to the east; dark orange gives approximately 30 minutes to the west. White/grey signifies 'no average offset,' which could come from not being connected to other time zones or being equally connected to time zones to the east and to the west.

Figure 6: County connectedness: Share of counties' visits to their own time zone



Appendix B   Robustness

Table 5: Foot-traffic results: Robustness to timezone 'issues'

	Avg. visit time		
	All days (1)	*Weekdays* (2)	*Weekends* (3)
Panel A: Standard dataset			
Time of sunrise	0.1650***	0.1411***	0.1281***
	(0.0287)	(0.0445)	(0.0300)
Avg. conn. offset	0.4977	0.2121	-1.353***
	(0.8573)	(0.9816)	(0.4215)
N obs. (millions)	162.54	162.52	158.1
Panel B: Drop all of Arizona			
Time of sunrise	0.1645***	0.1469***	0.1200***
	(0.0304)	(0.0462)	(0.0293)
Avg. conn. offset	0.4875	0.0813	-1.108**
	(0.8864)	(1.042)	(0.4405)
N obs. (millions)	159.43	159.4	155.08
Panel C: Drop Arizona; drop counties in multiple time zones			
Time of sunrise	0.1648***	0.1452***	0.1100***
	(0.0306)	(0.0465)	(0.0297)
Avg. conn. offset	0.5057	0.1209	-1.826***
	(0.9046)	(1.066)	(0.4812)
N obs. (millions)	159.39	159.36	155.04
Panel D: Drop Arizona; drop counties that border time zones			
Time of sunrise	0.1721***	0.1449***	0.1011***
	(0.0366)	(0.0507)	(0.0317)
Avg. conn. offset	1.438	0.9824	-2.248**
	(1.330)	(1.946)	(1.064)
N obs. (millions)	146.27	146.25	142.27
Week-of-sample fixed effects	✓	✓	✓
NAICS (6 digit) × TZ fixed effects	✓	✓	✓
Lat. bin (1 deg.) × TZ fixed effects	✓	✓	✓

Notes: An observation in this table is a POI-week. Clustered (state) standard-errors in parentheses. Significance codes: ***: 0.01, **: 0.05, *: 0.1.