Does time shift behavior? The clock- vs. solar-time tradeoff

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Abstract

Standardized clock time helps individuals and society coordinate activities and economic behaviors. However, standardizing time across large areas creates tension when the clock time conflicts with the local "solar time." Contemporary debates about daylight saving time and areas switching time zones center on this tension. We estimate the clock- vs. solar-time tradeoff by examining the degree to which people shift their online behavior (Twitter data), commute times (Census), and daily movement (SafeGraph). On average, a one-hour change in the wedge between solar time and clock time shifts behavior 10–35 minutes, with larger effects in northern latitudes and for activities that occur closer to the beginning of the day. These results suggest debates about daylight saving time and switching time zones should account for behavioral responses to changing standardized time.

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1 Introduction

Coordinating the timing of activities with other people is a fundamental characteristic of society. But it's also 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. In a modern society with instantaneous long-distance communication and high-speed travel, differences in environmental drivers of activity times – such as sunrise, sunset and temperature – exacerbate the tension between coordination and personal preferences or environmental constraints.

Technological advances in the U.S. during the 19^{th} century – especially 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 previous system made scheduling trains across locations impossibly complex (Prerau 2009). Figure 5 in the appendix, a table from Dinsmore's 1857 *American Railroad and Steam Navigation Guide and Route-Book*, illustrates the complexity coordinating a railroad schedule when every station operates on a different local time.

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 change in the metric that preserves the correspondence to elapsed time need not have any impact on behavior, regardless of how it synchronizes with solar time. Yet, such changes – in the form of time zones and daylight saving time – do seem to affect behavior in practice, possibly because individuals anticipate that others will change their behavior and wish to coordinate on when activities occur (Barnes and Wagner 2009; Gibson and Shrader 2018; Giuntella and Mazzonna 2019; Hamermesh, Myers, and Pocock 2008). 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 clock time of activities across longitudes within a time zone means that they take place earlier in solar time in locations that are further west. If there is an optimal solar time to wake up, eat meals, or begin the work day, one wouldn't expect it to be the same clock time in Portsmouth, New Hampshire as in Grand Rapids, Michigan. Both cities are in the Eastern time zone and at about the same latitude, but the sun rises about 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, cellphone-based 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, and workforce participation. 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 a location's solar time relative to its clock time with the impact of coordinating with other locations that are 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 anonymized cellphone data that measures the tendency of a phone that homes in one county to also be detected in other counties. 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 none of the measures has a strong or consistent impact, and the effect of solar time is not substantially changed by including any of them.

The solar time versus clock time trade-off 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 study heterogeneity in these trade-offs by differentiating between weekend and weekday activities, outdoor-oriented versus indoor-oriented activities, rural versus urban communities, and other factors.[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 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 may be 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 extension 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 DST. 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

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 additional daylight in evening clock hours due to DST reduces crime.

The other category of studies uses geographically driven differences in sunset time to document the negative effects of sleep on productivity or performance in the classroom. Heissel and Norris (2018) instrument hours of sleep with sunrise time to show that more sleep leads to improvements in test scores for adolescents. Gibson and Shrader (2018) similarly instrument sleep time with sunset time and find in the US that both short-run variation in sunset/sleep time and long-run, cross-sectional variation in sunset/sleep time change earnings: living on the western edge of a time zone reduces sleep and wages, all else equal. Using data from several developing countries, Jagnani (2018) concludes that later sunset times reduce sleep, study effort, and eventually, educational 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.

Between 2020 and 2022, at least 33 states have considered legislation to change their use of daylight saving time or to change their time zone, either of which also requires federal action.[3] Nearly all proposals would abandon the semi-annual switch between standard and daylight saving time. In 2022, federal legislation to put all of the US on permanent daylight saving time passed the Senate, but died in the House.[4] Policy debates over DST and changing time zones are very similar, 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. Nearly all policy discussions of these proposed changes, and most of the previous academic literature on these topics, have assumed that individuals will continue to engage in activities at the same clock time regardless of how it synchronizes with solar time.[5]

It seems 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

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

3. https://www.ncsl.org/transportation/daylight-saving-time-state-legislation

4. https://www.businessinsider.com/house-failed-vote-daylight-savings-time-permanent-sunshine-protection-act-2022-12

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

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. We provide both a simple theoretical model of these tradeoffs and a detailed investigation of the degree to which they do in three different large-scale datasets on human activity timing. This project is, to our knowledge, the first study of the topic.

2 A Model of Coordination and 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. Because the natural environment – *e.g.*, light, temperature, humidity – 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 t_i^* and a declining function of deviation from the time at which another individual, j, engages in the activity,

$$U_i = U_{0i} - f_i(|t_i - t_i^*|) - g_i(|t_i - t_j|).$$

And likewise for individual j,

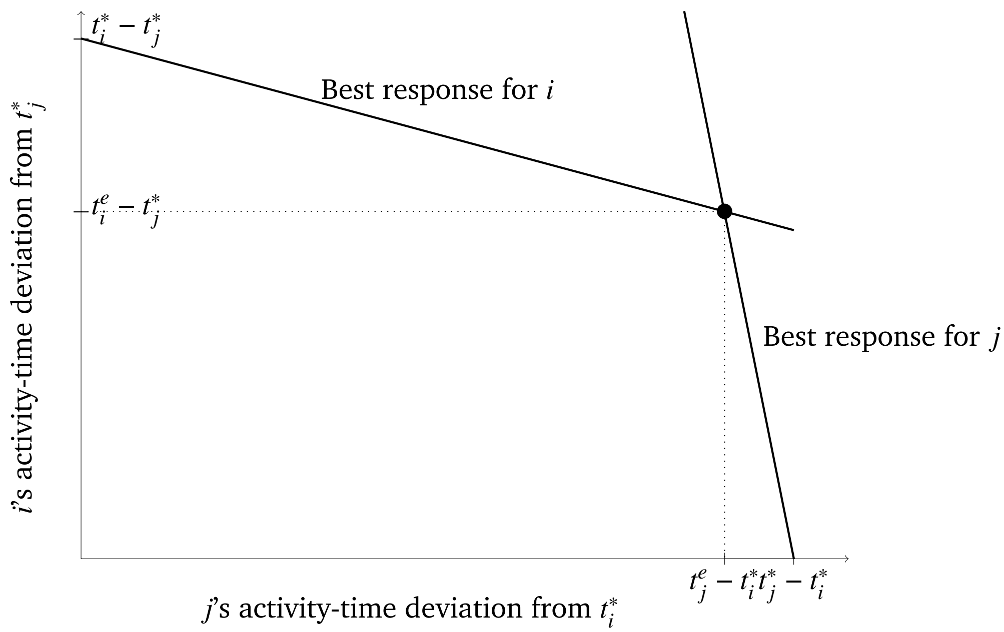
$$U_j = U_{0j} - f_j(|t_j - t_j^*|) - g_j(|t_i - t_j|).$$

We assume that $f(0) = 0$, $f'() > 0$ and $f''() > 0$, and $g(0) = 0$, $g'() > 0$ and $g''() > 0$ for both i and j.[6] Arbitrarily, assume that $t_i^* < t_j^*$, so each individual will be engaging in the activity between $t = t_i^*$ and $t = t_j^*$. Then, individual i's best response to t_j is determined by $-f_i' + g_i' = 0$. Conversely, j's best response to i's choice of t_i is $f_j' - g_j' = 0$. Under the assumptions on $f(\cdot)$ and $g(\cdot)$, this yields a best response function for i that deviates further from t_i^* (i's preferred time) the further is t_j from t_i^*. Thus, if j engaged in the activity at t_i^*, then i would also do so at t_i^*. And as j acts at a time further from t_i^* towards t_j^*, i would shift their activity time towards t_j^*. Likewise, if i engaged in the activity at t_j^*, then j would also do so at t_j^*, and as i acts at a time further from t_j^* towards t_i^*, j would shift their activity time towards t_i^*.

Figure 1 illustrates the best responses of each individual and the unique equilibrium in which $t_i^* < t_i^e < t_j^e < t_j^*$. In the case illustrated here, j strongly prefers carrying out the activity near t_j^*

6. To assure an interior equilibrium, we also assume that $f_i' > g_i'$ and $f_j' > g_j'$ for all t.

Figure 1: Best-response time choices and equilibrium timing of activities



Notes: Figure shows best-response choices for activity with two individuals. The horizontal axis is the deviation in j's activity time from the optimal activity time for i. The vertical axis is the deviation in i's activity time from the optimal activity time for j. The best responses lines indicate each individual's best response to the other's choice of activity time, and the intersection point is the equilibrium where neither individual would choose a different time for their activity.

compared 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.

An alternative model might constrain different individuals to act at the same time. For instance, a third party might try to schedule a single time for an activity with these (and potentially many other) individuals who have different preferred times of the event (and little or no private value of coordination) – such as broadcasting a television show or setting standardized work hours for a multi-location firm. The third party – such as the broadcaster or employer – 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

$$\min_t \; f_i(|t - t_i^*|) + f_j(|t - t_j^*|).$$

Under the same regularity conditions, the optimal scheduling of the event occurs at $t_i^* < t^{opt} < t_j^*$.

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, our general empirical specification is:

$$\text{Mean Activity Time}_{it} = \beta * \text{Sunrise Time}_{it} + \delta * \text{Connectedness}_i + \phi^{TZ} + X_{it} + \varepsilon_{it} \tag{1}$$

Mean Activity Time$_{it}$ is the average local clock time of the activity for the aggregation of observations in location i during time interval t. For the Twitter and census data analyses, time is measured in hours after 4 AM, because that is approximately the minimum activity time in these data. Measuring activity time in hours 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. For the foot traffic analyses, time is measured in hours after midnight. We do this because the set of cell phones monitored changes each week at midnight on Sunday. So, measuring days as starting at 4 AM would require throwing out information on Sundays and make it difficult to compare weekdays and weekends. Furthermore, in aggregate the foot traffic observed is very low and fairly constant across the hours between midnight and 4 AM.

Sunrise Time$_{it}$ is the main variable of interest. For a given latitude on a given day, within a time zone, it indicates the extent to which the solar time at location i on date t differs from clock time. Connectedness$_i$ controls for the degree to which a location is connected to other areas with different clock times (explained in greater detail below).[7] ϕ^{TZ} is a set of time zone dummy variables that allow different baseline clock times for the activity in different time zones, so

7. 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.

they capture whether the activity on average occurs at different clock times in different time zones. X_{it} is a vector of controls that always include latitude bins, and time of year fixed effects for Twitter and foot traffic, but in our preferred specification also include demographics of the location, as discussed later.

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, so solar time is the dominant driver for this activity. By contrast, $\beta = 0$ would indicate that the activity follows clock time alone, ignoring solar time differences. $\beta = 0.4$ 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. Our results omit Hawaii, Alaska, and Arizona. Hawaii and Alaska are not part of the Twitter data, and Hawaii also does not observe daylight saving time and is in its own time zone. Most of the population of Arizona does not observe daylight saving time, but the Navajo Nation that covers much of the northeast corner of the state does. Our results are very similar when we include Arizona.

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

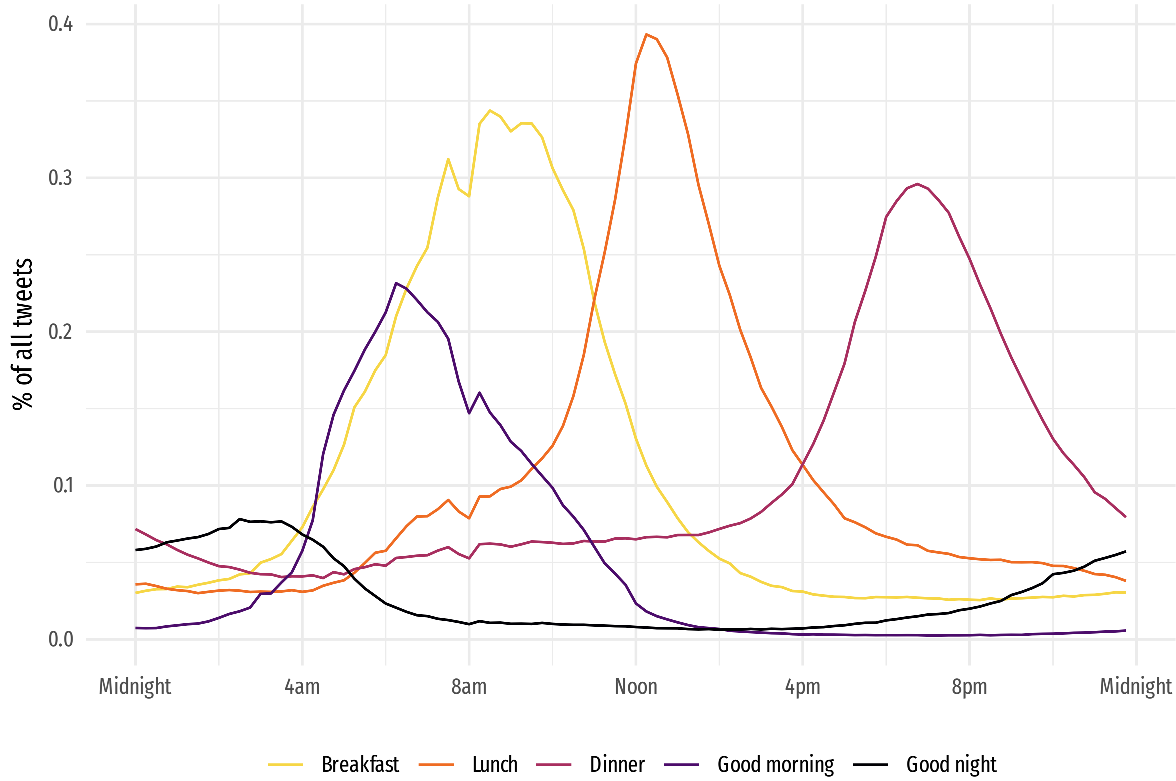
We use data from the social media platform Twitter (since renamed “X”) as one measure of activity timing across the United States. To do so, we downloaded approximately 2.5 billion geolocated tweets through a connection to Twitter’s Streaming API.[8] For each date in our time period, which ranges from April 2014 through March 2019, we compute both the average time (since 4 AM) 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. Figure 2 documents the occurrence of each phrase throughout the day: “good morning” occurs

8. 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 these data were obtained, stored, and processed can be found in Baylis (2020). That paper also computes sentiment for each tweet, which we do not use here.

earliest in the day, followed by "breakfast", "lunch", "dinner" and "good night" (which actually has its peak in the early morning hours).

Figure 2: Twitter Phrase Frequency by Time of Day



Notes: Figure shows the percentage of tweets using the given phrases by time of day. The horizontal axis is all hours in the day from midnight to midnight, plotted at each 15-minute interval. The height of each line is the percentage of all tweets in that 15-minute interval that included the given phrase. Lines are colored by phrase.

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.

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 Saturday, April 1, 2000) the respondent typically left for work.[9] For

9. 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,

each of slightly more than 200,000 census block groups, we use the time elapsed between 4 AM and the average reported departure time as the primary variable of interest, but we also analyze the mean time of arrival at work with nearly identical results.[10]

Unlike the other two datasets we study, the census data have no time-series variation. They are simply a cross-sectional 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.

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,[11] 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. The overall distribution of visits across the day on weekends and weekdays is presented in Appendix figure 8.

In raw form, this POI dataset[12] allows us to see the number of visits to a POI by hour of sample, such as 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 (since midnight) and the average time of sunrise (based upon the POI's CBG)—also summarizing each week's activity by weekdays and weekends.

daylight saving time began on April 2 in the United States.

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

11. 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.

12. Specifically, we use SafeGraph's "weekly" POI dataset.

3.4 Controlling for connectedness

A potential source of confounding in a regression of activity time on sunrise time (controlling for time zone) is that people in locations in one time zone may be connected in some way to locations in other time zones and may shift their activities in order to coordinate with the other time zone. This is likely more common in areas near time zone borders. 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 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 whose home is in CBG h_{CBG} during 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 county h that are to county d.[13]

Counties with connections in time zones more to the east of their own will presumably be pulled 'earlier' (measured in 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 60% of a county's visits occur in its own time zone (where the time-zone difference is 0) and 40% of visits occur in the adjoining time zone to the east (where the time-zone difference is 1 hour), then we calculate the county's mean time-zone offset is 0.4 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.

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

Unsurprisingly, the average county is very strongly connected to its own time zone (with 97% of visits occuring in its own time zone), yielding a mean time-zone offset near zero. Appendix Figures 6 and 7 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. None of these measures yields consistent effects of connectedness, though the cell phone-based variable that we develop appears to have somewhat more explanatory power. Nonetheless, the estimated effects of solar time on activity are changed only slightly by inclusion of any connectedness variable.

4 The effect of solar time on activity

4.1 Twitter

For the Twitter dataset, we estimate the model

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

for county c on date t. Sunrise time$_{ct}$ is determined by county centroid and date, Connectedness offset$_c$ is the average connectedness offset for the county described in Section 3.4, ϕ_c are time zone by one-degree latitude bin fixed effects, [Time zone $\times$ Lat. bin]$_c$, and π_t is a date-of-sample fixed effects. Mean(Tweet time)$_{ct}$ refers to the average tweet time (measured in hours after 4 AM) for either all tweets in the dataset for that date-county, or, in the next section, tweets containing a specific key phrase. Observations from different counties are weighted by the average number of daily tweets for the county, and standard errors are clustered by state. Summary statistics for all variables are shown in Appendix table 5.

The results in column (1) indicate that tweets from people located at the west end of a time zone on average occur 0.357 hours (about 22 minutes) later in clock time than tweets 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 about one-third of the solar time differential between locations that have the same clock time. The results in column (2) indicate that connectedness of a county to locations in other time zones does not significantly affect when a person tweets. In fact, we would expect the sign of this coefficient to be negative to the extent that greater connectedness with people in a "later" (further east)

Table 1: Effect of sunrise time on tweet time

	Time of tweet		
	(1)	(2)	(3)
Sunrise time	0.357***	0.361***	0.343***
	(0.062)	(0.098)	(0.072)
Avg. conn. offset		0.251	−0.286
		(3.051)	(1.705)
Urban (proportion)			0.505***
			(0.155)
Outdoor (proportion)			4.943***
			(1.436)
Working (proportion)			−1.565***
			(0.485)
Log population			−0.035
			(0.021)
TZ × Lat. bin fixed effects	✓	✓	✓
Date-of-sample fixed effects	✓	✓	✓
Observations	3,879,339	3,879,339	3,876,347

Notes: Table shows the effect of regressors on a county's average time of tweeting. Each observation is a county-date. Time of tweet is the average tweet time within a day, where day is defined as starting and ending at 4am. Avg. conn. offset is the weighted average time for locations with connections to the county. Urban, Outdoor, and Working are the percent of respondents in urban areas, working in outdoor occupations, and working overall in the county. Sunrise time is the time of sunrise in that county on that date. Regressions weight observations (counties) by their average number of tweets. Standard errors clustered by state. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

time zone would cause one to engage in activities earlier as measured in local clock time.

The coefficient on connectedness is negative in column (3), though still far from statistically significant. In column (3), we also include measures that might affect how individuals relate to their environmental surroundings. Individuals tweet later in urban areas compared to rural. The estimated coefficient implies that a one standard deviation increase in the share of the population in a county that lives in urban areas causes tweets to occur about 8 minutes later on average. Perhaps surprisingly, people tweet later in counties with a higher share of the population working outside, about 20 minutes later for a one standard deviation increase in the share of the working population that works outside in the observed county. Less surprisingly, a county with a higher share of the population in the workforce tends to tweet earlier, about 11 minutes earlier for a one standard deviation increase. The result for population suggests that high-population counties tweet earlier, though it is only borderline statistically significant, and a one standard deviation increase in log (population) only causes a two minute shift in average tweet time. Overall, however, controlling for these demographic factors does not substantially change the impact of sunrise time on activity.[14]

4.2 Census

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

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

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, except defined at the CBG, rather than county, level. We weight this regression by the CBG population, and cluster standard errors by state. Summary statistics for all variables are shown in Appendix table 5.

The results in column (1) are 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 impact on activity time, but not with the expected sign. 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 one standard deviation change in mean connectedness offset adjusts the departure time for work by 3 minutes with a 95% confidence interval of $[0, 6]$ minutes.

The coefficient on connectedness, however, is larger in column (3), indicating that a one standard deviation increase in connectedness causes one to leave for work about 5 minutes later. As with the Twitter analysis, workers in locations that are more urban tend to leave for work later. But more outdoor workers is now associated with leaving for work earlier on average, with a one standard deviation increase in the proportion of outdoor workers causing the average departure time for work to be 8 minutes earlier. And as was found in the Twitter data, a higher proportion of the population in the workforce is associated with leaving for work

14. When interpreting the coefficients on Urban, Outdoor, and Working, it's worth noting that these variables are relatively highly correlated (e.g., Urban and Outdoor have a -0.38 correlation)—which could explain some fairly large estimated effects—and that Urban is very bimodal with the proportion in some counties near 0 and in others near 1.

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

	Time left for work		
	(1)	(2)	(3)
Sunrise time	0.372***	0.428***	0.535***
	(0.054)	(0.057)	(0.064)
Avg. conn. offset		1.744**	3.227***
		(0.866)	(0.830)
Urban (proportion)			0.435***
			(0.017)
Outdoor (proportion)			−1.879***
			(0.145)
Working (proportion)			−0.927***
			(0.114)
Log population			−0.072***
			(0.014)
TZ × Lat. bin fixed effects	✓	✓	✓
Observations	188,246	188,246	188,237

Notes: Table shows the effect of regressors on the time that respondents to the 2000 Decennial Census report leaving for work. Each observation represents the average within one Census Block Group (CBG). Time left for work is the average reported time left for work for respondents in the CBG. Sunrise time is the time of sunrise for that CBG on April 1, 2000, when the Census was conducted. Avg. conn. offset is the weighted average time for locations with connections to the CBG. Urban, Outdoor, and Working are the percent of respondents in urban areas, working in outdoor occupations, and working overall in the CBG. Regressions weight observations (CBGs) by their population. Standard errors clustered by state. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

earlier. County population is also statistically significant in this dataset, with a one standard deviation increase in log population causing people to leave 3 minutes earlier for work. It's possible that the more populated counties have more workers living far from their jobs, but that doesn't seem to explain the result, because it also holds for time arriving at work.

Adding the demographic and connectedness controls has a substantial effect on the impact of solar time, however. With these controls, the estimates suggest that people on the western end of a time zone leave for work about 32 minutes later than people on the eastern end of the time zone, offsetting more than half of the change in the solar time/clock time mismatch.

4.3 Foot traffic

Using the foot traffic data, we estimate the model

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

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 average visit time to i during week w, in this analysis measured as hours after midnight. Summary statistics for all variables are shown in Appendix table 5.

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 less than half as large as the results from the Twitter or census data. Column (1), which includes latitude bin by time zone fixed effects, suggests that people on the west end of a time zone frequent similar points of interest about 9 minutes later on average than people on the east end of the time zone.

As before, adding the connectedness variable, column (2), does not change the impact of solar time by much at all. Column (3) adds Census Block Group (CBG) demographics.[15] Once again, a higher share of the population in urban areas is associated with activities taking place later in the day, though a one standard deviation increase in urban population share only moves the average foot traffic time by one minute. The effect of outdoor working share is not statistically significant, while the effect of the share population in the workforce is. Still, a one standard deviation increase in the share of the population in the workforce only moves foot traffic time later by about 1 minute.

15. For the foot-traffic data, we use the 2019 ACS five-year aggregate (rather than the 2000 full-count Census that we use for Twitter and commute time). The later ACS provides a better temporal match for the SafeGraph data.

Table 3: Effect of sunrise time on visit times

	Avg. visit time		
	(1)	(2)	(3)
Sunrise time	0.154***	0.165***	0.166***
	(0.026)	(0.030)	(0.030)
Avg. conn. offset		0.488	0.640
		(0.886)	(0.872)
Urban (proportion)			–0.003
			(0.029)
Outdoor (proportion)			0.303**
			(0.154)
Working (proportion)			0.043
			(0.073)
Log population			0.055***
			(0.006)
Lat. bin (1 deg.) $\times$ TZ fixed effects	✓	✓	✓
Week-of-sample fixed effects	✓	✓	✓
NAICS (6 digit) $\times$ TZ fixed effects	✓	✓	✓
N obs. (millions)	159.43	159.43	159.08

Notes: An observation in this table is a POI-week, for example, a single Walmart during the week of 2021-03-14. Column (2) controls for the county's average connectedness offset (in minutes): More negative values of 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

The analysis in the previous section constrained the response of activities to sunrise time to be the same for different demographics and types of activities. It is quite possible, however, that the trade-off between operating on standardized clock time and local solar time varies depending on people, places, and activities. These might be indicated by the demographics of the locations, but also by the content of the tweets in the Twitter data and by the types of businesses or activities associated with the points of interest in the foot traffic data. For instance, one might expect that activities (or CBGs) more strongly linked to the outdoors would produce a stronger response to solar time. In this section, we 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 point estimates and 95% confidence intervals of the effect of sunrise time, with the datasets split along demographic and geographic dimensions. The top panel compares results for areas north or south of the population-weighted median latitude in the continental US. The point estimates 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 1% level in the census data, and statistically significant at 5% level in the Twitter data.[16] One possible explanation is that people living further north are used to adjusting to large variations in sunrise, sunset and total sunlight time between the winter and summer, which makes time norms less rigid. As a result, they are more likely to also adjust to variations across longitude in the clock time of that sunlight.

The next panel separates summer and winter. The foot-traffic data suggest visits to points of interest adapt significantly more to sunlight in winter months, when sunlight hours are shortest (p-value 0.01) with the difference implying about six minutes more time shifting of activities in the winter between the East and West end of a time zone. The Twitter results, however, suggest a statistically significant difference in the opposite direction (p-value 0.01). The difference implies that across a time zone tweeting activities time shift by about seven minutes more in the summer than in the winter.

The following two panels attempt to document the impact of outdoor activity. Rural areas are typically associated with living closer to nature, whether in line of work or choice of leisure activities.[17] Consequently, we might expect greater adaptation to solar time in more rural locations. However, we see no significant difference. The same is true in the next panel, where

16. The p-value for the north-south difference in the foot-traffic data is 0.12.
17. As mentioned earlier, the Urban variable is very bimodal, with most observations near 0 or 1, so we have split the sample at 50%, rather than at the sample median, which is close to 1.

counties with larger shares of outdoor workers do not differ statistically from those with smaller shares for any of the activity measures.[18]

In the fifth panel, we compare locations by their share of population in the workforce (split at median workforce share). In all three datasets, counties with larger population shares in the workforce are estimated to adapt more to solar time than counties with smaller shares. This difference, however, is only statistically significant in the foot-traffic dataset (p-value 0.02).

One might hypothesize that weekend activities are more influenced by solar time than weekdays. The next panel does not support this hypothesis. The Twitter-based point estimates for weekdays and weekends are nearly identical (and not statistically different). In the foot-traffic data, *weekday* visits are in fact slightly more affected by the time of sunrise (p-value 0.07). Thus, we observe no evidence that days more commonly associated with leisure are more influenced by solar time than days typically associated with work.

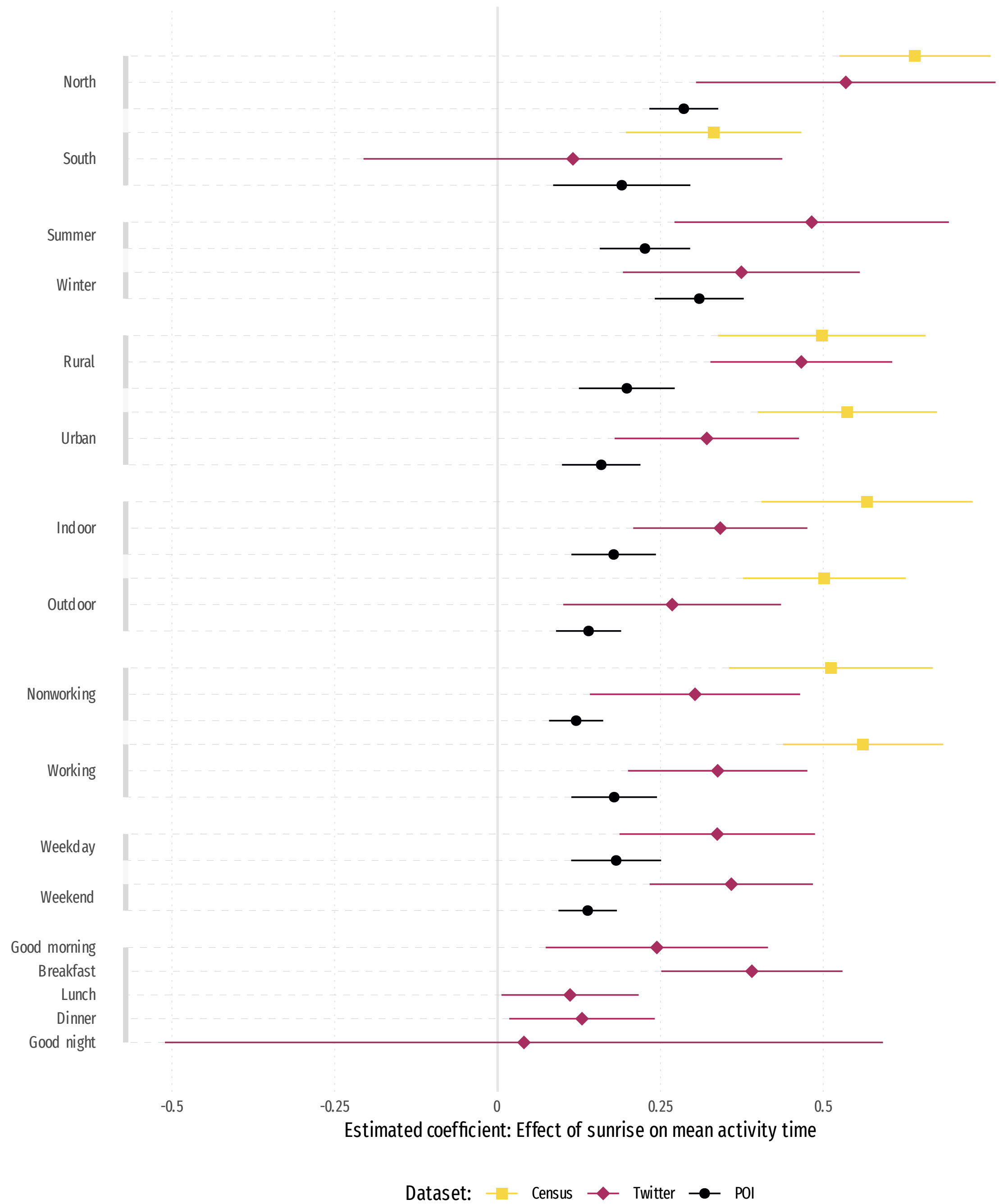
The bottom panel of Figure 3 takes advantage of the content of the tweets in the Twitter data, looking in particular at tweets that include the words "breakfast", "lunch", "dinner", "good morning", or "good night". The estimated solar time adaptation for "good night" is positive, but is very imprecise, likely due to the extremely wide range of times it shows up in the dataset, including hours after 4 AM, which we count as early morning. The estimate for "good morning" is in line with overall adaptation at around 0.25. 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 about 40% of the shift in solar time.

Figure 4 uses only the foot traffic data and focuses on POIs in the 25 most-visited establishment types, based upon establishments' six-digit NAICS codes. The first ten establishment types in Figure 4 are varieties of retail stores—*e.g.*, department, convenience, sporting goods—and indicate a fairly consistent pattern of adjustment to solar time with most estimates between 0.15 and 0.3—with the exception of pet stores and drugstores, which are somewhat lower. Restaurants and snack bars (bright orange, near the bottom) also exhibit a similar degree of adaptation. Bars (*Drinking Places*) exhibit the largest adaptation to solar time (*i.e.*, largest point estimate).

Our estimates for operations support services at airports—which includes airport retail outlets as well as entities providing aircraft service and related operations—do not exhibit significant adaptation to solar time, but 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—suggesting more

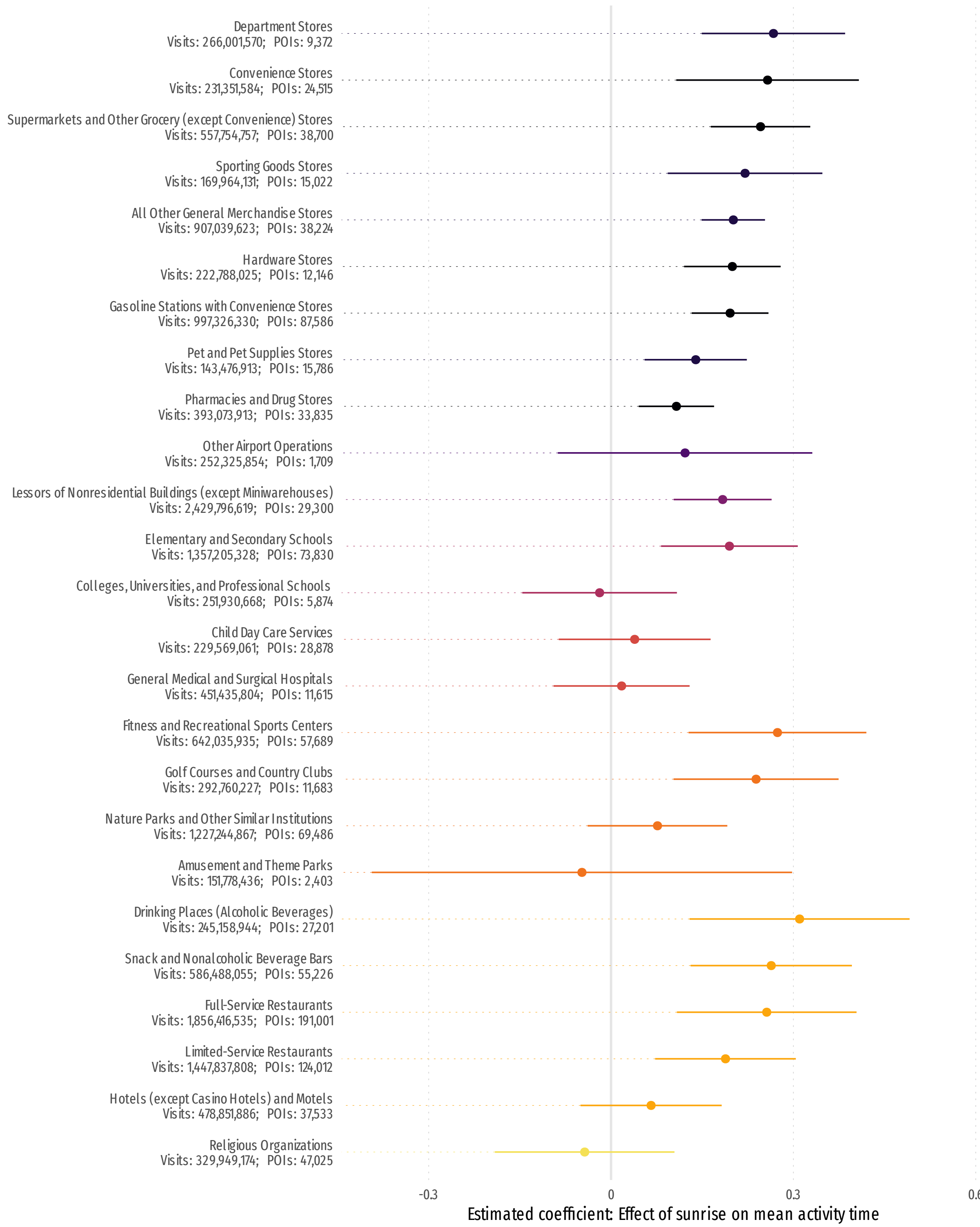
18. The indoor-outdoor difference for the foot-traffic data has a p-value of 0.09.

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, demographics, and fixed effects corresponding to the appropriate dataset (see Section 4).

Figure 4: Foot-traffic results by establishment type, 25 most-visited 6-digit 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—*i.e.*, column (3) of Table 3). We group 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.

rigid scheduling independent of sunlight. Also interesting, fitness and golf establishments appear to adapt to solar time, but no more so than restaurants and bars.

Overall, while we see consistent support for the idea that social behavior deviates significantly from clock time in order to adapt to solar time, we do not see a consistent pattern across the types or locations of behavior.

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 time standardization, 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 half of a regulated change in clock time is offset by individuals adapting to solar time in choosing when to leave for work. We find somewhat smaller effects on when individuals send out tweets; shifting solar time one hour later causes tweeting to occur about 20 minutes later. In looking at foot traffic around stores and other locations open to the public, we find a smaller, but still strongly statistically significant, offsetting 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, as Daylight Saving Time does, appears to be a uniquely powerful device for making coordinated changes in the timing of activities. Doing so allows a change in school opening times to be more easily 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.

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. Our current datasets, however, don't allow us to tests that hypothesis.

Our results from analysis of foot traffic indicate that retail establishments—both goods 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 findings also help illuminate the mechanisms underlying previous empirical work. First, the mixed evidence of the effect of daylight saving time (DST) on energy usage (Kellogg and Wolff 2008; Kotchen and Grant 2011) can be understood partly as resulting from the influence of natural sunrise time on morning activity pattern. Individuals located farther west in the time zone wake up earlier in local solar time and are therefore more likely to increase early morning usage in response to DST, washing out or even reversing the savings from reduced evening light usage (this explanation supports the findings in Shaffer (2019)).

Second, the electricity-usage effects cited above, and the findings of increased vehicle crashes and decreased crime, Smith (2016) and Doleac and Sanders (2015), should be viewed as net of the shifting effect we observe, since the response of individuals to DST shift are likely, to some degree, to be mediated by their natural response to sunlight. Whether the degree of this mediation is large or small in the day or two following the changeover is an empirical question we leave for future work.

Third, our work provides supporting evidence for how differences in sunset time affect outcomes such as productivity, earnings, and sleep (Gibson and Shrader 2018; Jagnani 2018). Our findings suggest that waking, sleeping, commuting to work, and mealtimes are all shifted by solar time, indicating that while sleep is likely an important driver of these impacts, they could also be driven by all of the other shifts in activity that relate to the presence of sunlight.

Broadly, our results show that people do not operate purely on clock time, ignoring 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.	5th Pctl.	25th Pctl.	Median	Mean	75th Pctl.	95th 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.

Figure 5: Comparative Time-Table for Railroad Coordination (1857)

COMPARATIVE TIME-TABLE,

SHOWING THE TIME AT THE PRINCIPAL CITIES OF THE UNITED STATES,

COMPARED WITH NOON AT WASHINGTON, D. C.

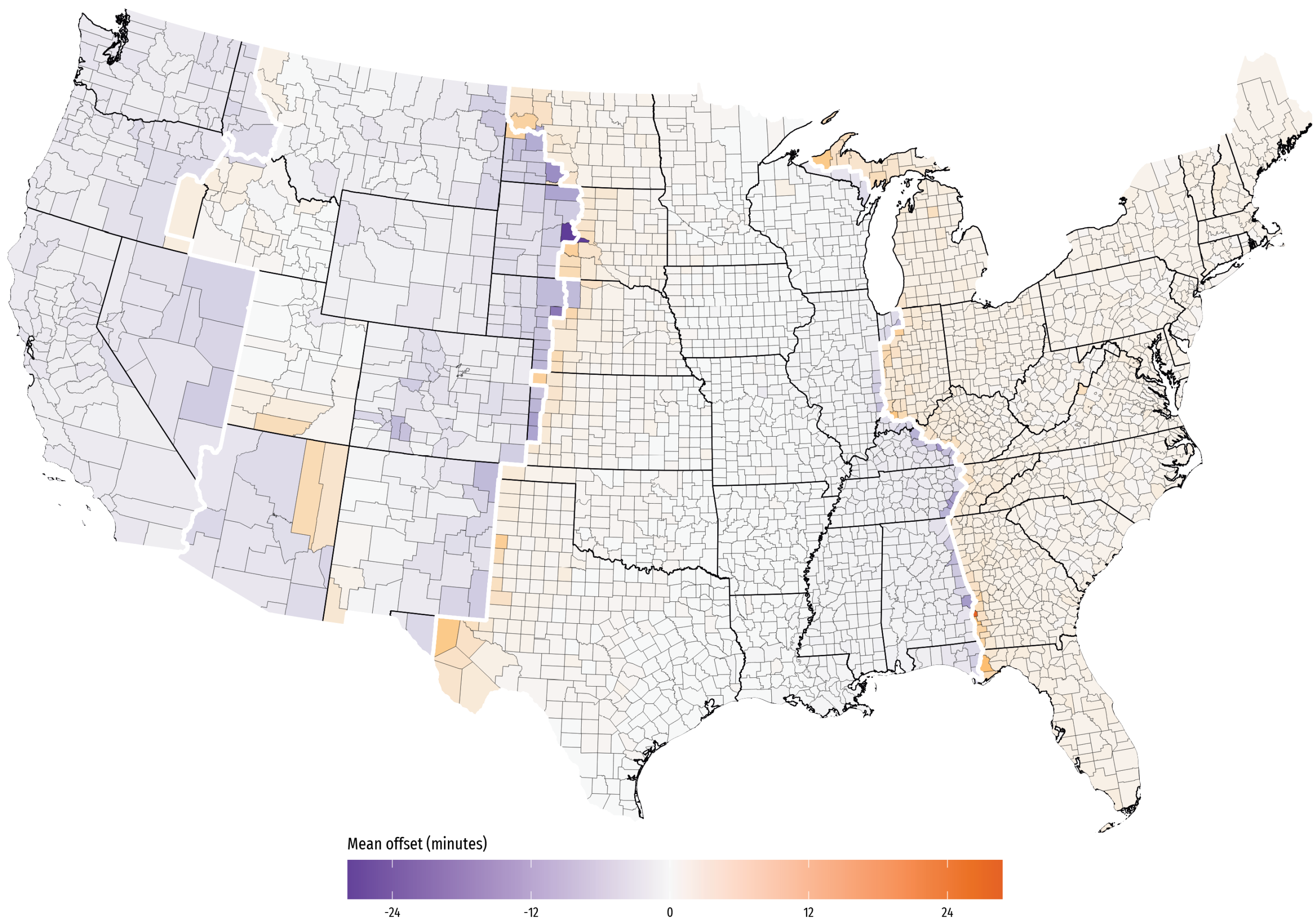
There is no "Standard Railroad Time" in the United States or Canada; but each railroad company adopts independently the time of its own locality, or of that place at which its principal office is situated. The inconvenience of such a system, if system it can be called, must be apparent to all, but is most annoying to persons strangers to the fact. From this cause many miscalculations and misconnections have arisen, which not unfrequently have been of serious consequence to individuals, and have, as a matter of course, brought into disrepute all Railroad-Guides, which of necessity give the local times. In order to relieve, in some degree, this anomaly in American railroading, we present the following table of local time, compared with that of Washington, D. C.

NOON AT WASHINGTON, D. C.		NOON AT WASHINGTON, D. C.		NOON AT WASHINGTON, D. C.	
Albany, N. Y.	12 14 P.M.	Indianapolis, Ind.	11 26 A.M.	Philadelphia, Pa.	12 08 P.M.
Augusta Ga.	11 41 A.M.	Jackson, Miss.	11 08 "	Pittsburg, Pa.	11 48 A.M.
Augusta, Me.	11 31 "	Jefferson, Mo.	11 00 "	Plattsburg, N. Y.	12 15 P.M.
Baltimore, Md.	12 02 P.M.	Kingston, Can.	12 02 P.M.	Portland, Me.	12 28 "
Beaufort, S. C.	11 47 A.M.	Knoxville, Tenn.	11 33 A.M.	Portsmouth, N. H.	12 25 "
Boston, Mass.	12 24 P.M.	Lancaster, Pa.	12 03 P.M.	Pra. du Chien, Wis.	11 04 A.M.
Bridgeport, Ct.	12 16 "	Lexington, Ky.	11 31 A.M.	Providence, R. I.	12 23 P.M.
Buffalo, N. Y.	11 53 A.M.	Little Rock, Ark.	11 00 "	Quebec, Can.	12 23 "
Burlington, N. J.	12 09 P.M.	Louisville, Ky.	11 26 "	Racine, Wis.	11 18 A.M.
Burlington, Vt.	12 16 "	Lowell, Mass.	12 23 P.M.	Raleigh, N. C.	11 53 "
Canandaigua, N. Y.	11 59 A.M.	Lynchburg, Va.	11 51 A.M.	Richmond, Va.	11 58 "
Charleston, S. C.	11 49 "	Middletown, Ct.	12 18 P.M.	Rochester, N. Y.	11 57 "
Chicago, Ill.	11 18 "	Milledgeville, Ga.	11 35 A.M.	Sacketts H'bor, NY.	12 05 P.M.
Cincinnati, O.	11 31 "	Milwaukee, Wis.	11 17 A.M.	St. Anthony Falls,	10 56 A.M.
Columbia, S. C.	11 44 "	Mobile, Ala.	11 16 "	St. Augustine, Fla.	11 42 "
Columbus, O.	11 36 "	Montpelier, Vt.	12 18 P.M.	St. Louis, Mo.	11 07 "
Concord, N. H.	12 23 P.M.	Montreal, Can.	12 14 "	St. Paul, Min.	10 56 "
Dayton, O.	11 32 A.M.	Nashville, Tenn.	11 21 A.M.	Sacramento, Cal.	9 02 "
Detroit, Mich.	11 36 "	Natchez, Miss.	11 03 "	Salem, Mass.	12 26 P.M.
Dover, Del.	12 06 P.M.	Newark, N. J.	12 11 P.M.	Savannah, Ga.	11 44 A.M.
Dover, N. H.	12 37 "	New Bedford, Mass.	12 25 "	Springfield, Mass.	12 18 P.M.
Eastport, Me.	12 41 "	Newburg, N. Y.	12 12 "	Tallahassee, Fla.	11 30 A.M.
Frankfort, Ky.	11 30 A.M.	Newburyport, Ms.	12 25 "	Toronto, Can.	11 51 "
Frederick, Md.	11 59 "	Newcastle, Del.	12 06 "	Trenton, N. J.	12 10 P.M.
Fredericksburg, Va.	11 58 "	New Haven, Conn.	12 17 "	Troy, N. Y.	12 14 "
Frederickton, N. Y.	12 42 P.M.	New London, "	12 20 "	Tuscaloosa, Ala.	11 18 A.M.
Galveston, Texas	10 49 A.M.	New Orleans, La.	11 08 A.M.	Utica, N. Y.	12 08 P.M.
Gloucester, Mass.	12 26 P.M.	Newport, R. I.	12 23 P.M.	Vandalia, Ill.	11 18 A.M.
Greenfield, "	12 18 "	New York, N. Y.	12 12 "	Vincennes, Ind.	11 19 "
Hagerstown, Md.	11 58 A.M.	Norfolk, Va.	12 03 "	Wheeling, Va.	11 45 "
Halifax, N. S.	12 54 P.M.	Northampton, Ms.	12 18 "	Wilmington, Del.	12 06 P.M.
Harrisburg, Pa.	12 01 "	Norwich, Ct.	12 20 "	Wilmington, N. C.	11 56 A.M.
Hartford, Ct.	12 18 "	Pensacola, Fla.	11 20 A.M.	Worcester, Mass.	12 21 P.M.
Huntsville, Ala.	11 21 A.M.	Petersburg, Va.	11 59 "	York, Pa.	12 02 "

By an easy calculation, the difference in time between the several places above named may be ascertained. Thus, for instance, the difference of time between New York and Cincinnati may be ascertained by simple comparison, that of the first having the Washington noon at 12 12 P. M., and of the latter at 11 31 A. M.; and hence the difference is 43 minutes, or, in other words, the noon at New York will be 11.17 A. M. at Cincinnati, and the noon at Cincinnati will be 12 43 P. M. at New York. Remember that places *West* are "slower" in time than those *East*, and *vice versa*.

Notes: Figure reproduces the time-table from Dinsmore's *American Railroad and Steam Navigation Guide and Route-Book* (1857).

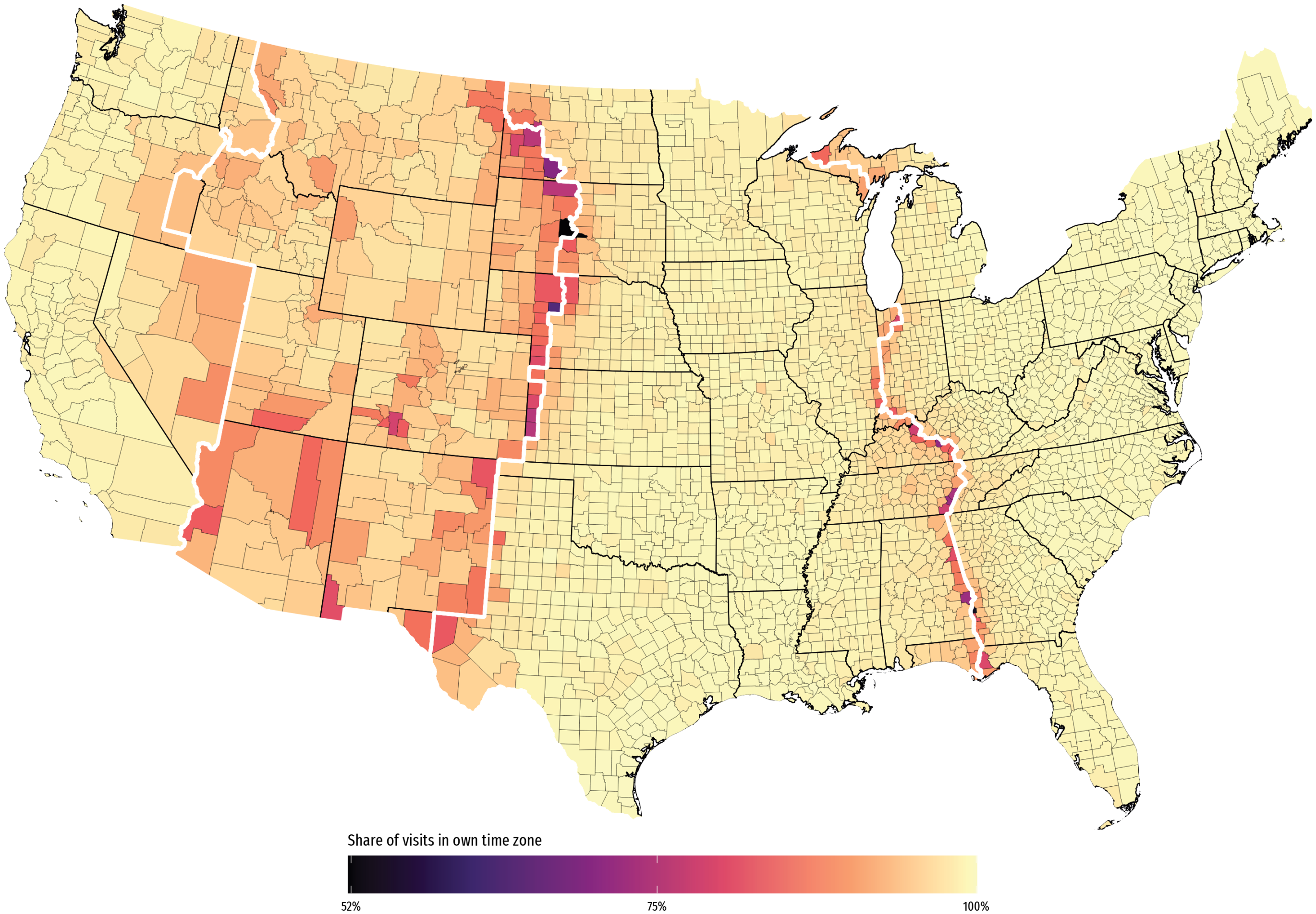
Figure 6: County connectedness: Counties' mean offset



Notes: This figure illustrates counties' mean 'offset' based upon visits to other time zones. For example, dark purple denotes an average (visit-based) offset that pulls the county approximately 30 minutes to the east. White/grey signifies *no average offset* which could result from not being connected to other time zones or being equally connected to time zones to the east and to the west.

Figures 6 and 7 illustrate counties' (1) mean offsets and (2) connectedness to their own time zones (along with state and time-zone borders).

Figure 7: County connectedness: Share of counties' visits to their own time zone



Notes: This figure illustrates each county's share of visits that occur within the county's time zone. Counties near time-zone borders tend to spend more time in other time zones.

Appendix B Descriptive statistics

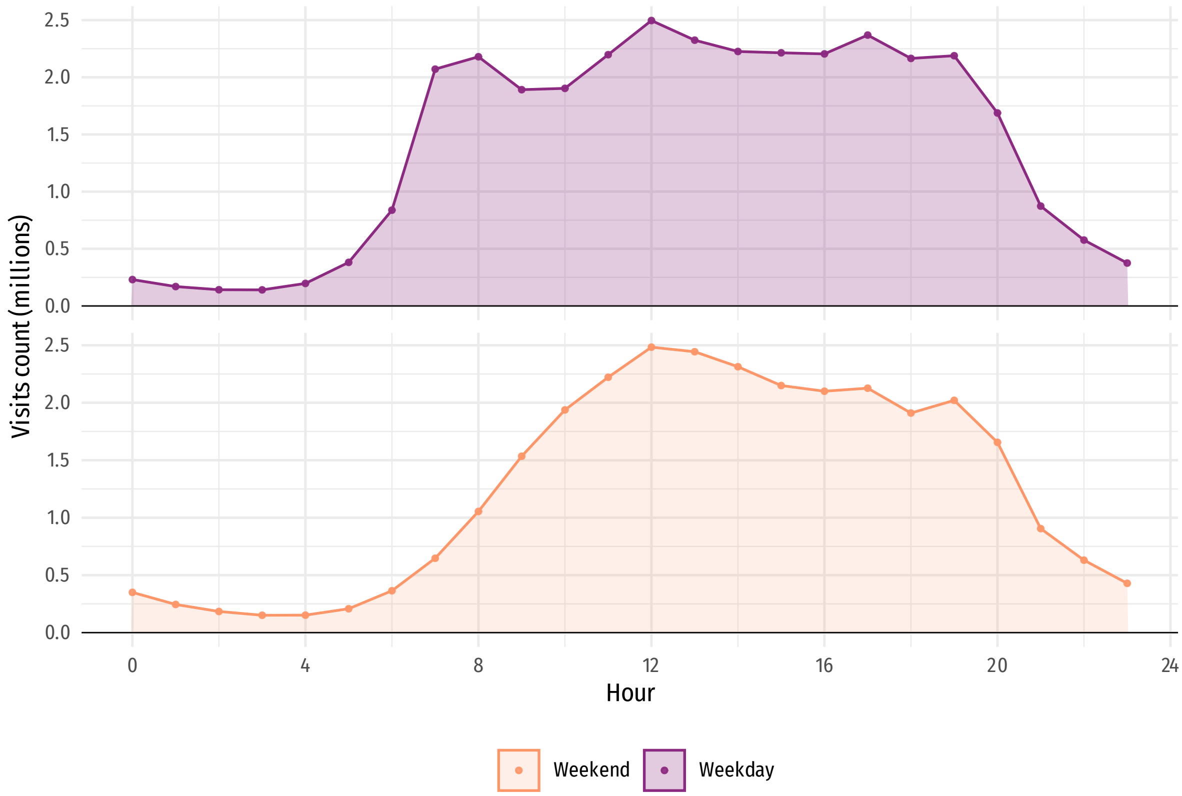
Table 5: Summary statistics of demographics

Variable	Mean	Stnd. dev.	
Panel A: Twitter			
Tweet time	16.4	2.76	
Sunrise time (hr)	6.81	0.663	
Urban (prop.)	0.441	0.297	
Outdoor (prop.)	0.138	0.035	
Working (prop.)	0.421	0.051	
Log(Population), county	10.4	1.31	
Mean conn. offset (hr)	–0.001	0.035	
Panel B: Census			
Time left for work	8.78	0.830	
Sunrise time (hr)	5.90	0.284	
Urban (prop.)	0.773	0.393	z
Outdoor (prop.)	0.107	0.069	
Working (prop.)	0.436	0.101	
Log(Population), CBG	7.05	0.577	
Mean conn. offset (hr)	–0.001	0.027	
Panel C: SafeGraph foot-traffic			
Visit time (hr)	13.5	1.57	
Sunrise time (hr)	6.77	0.618	
Urban (prop.)	0.860	0.196	
Outdoor (prop.)	0.029	0.035	
Working (prop.)	0.493	0.122	
Log(Population), CBG	7.41	0.738	
Mean conn. offset (hr)	–0.003	0.028	

Notes: Demographics match to observations at the county for Twitter data and Census Block Group (CBG) for the Census and SafeGraph data. Obsevation counts: 3.9 million observations for Twitter data (2,875 counties; 1,512 days); 189,335 observations for Census data (2,877 counties); 159.4 million obserations for foot-traffic data (20.5 billion *visits*; 178,811 CBGs; 3,068 counties; 105 weeks).

Appendix C SafeGraph visits

Figure 8: Distribution of visit times: Average daily visits for each hour, split by weekday/weekend



Notes: This figure displays the average number of daily visits for each hour of the day throughout the sample period—split by weekdays and weekends. For instance, on average, we observed 2.5 million visits each weekday at 12 PM (noon)—approximately the same number of visits on weekend days at 12 PM. Visits are quite low between midnight and 4 AM. While the time of the minima and maxima match across weekdays and weekends, weekdays have many more total visits, start earlier, and sustain a high level of visits later into the evening.