Does Time Shift Behavior?
The Clock- vs. Solar-Time Tradeoff

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Abstract

Standardized clock-time is perhaps the most ubiquitous behavioral nudge on the planet. It helps schedule and coordinate economic behavior but also creates tension when it shifts activities away from their locally optimal solar-time. Debates about daylight saving time and areas switching time zones center on this tension. We directly measure the clock- vs. solar-time tradeoff using geolocated data on online behavior (Twitter), commute departures (Census), and foot traffic (SafeGraph). A one-hour change in the wedge between solar-time and clock-time shifts behavior 15–27 minutes, with larger effects in northern latitudes and for activities occurring closer to sunrise.

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1 Introduction

Coordinating the timing of activities with other people is a fundamental requirement of society. But it is also a hassle. Individuals face different constraints and have different preferences about when activities should take place. 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 differences in circadian rhythms, personal preferences, or environmental constraints.

Technological advances in the US during the 19th century—particularly 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.[1] Expectations of activities occurring at certain clock-times now permeate society, e.g., "bankers' hours" (9-to-3), the standard workday (9-to-5), or lunch time (noon). Since time zones were created, they have been a device for coordinating activities locally and across great distances. Beyond easing transportation scheduling, time zones made it possible to synchronize the timing of activities that occur across large geographies—e.g., telegraph and telephone communication—and radio and television broadcasting, while still allowing standardized time to partly follow the sun. Then in the early 20th century, much of the US adopted daylight saving time (DST), another adjustment to clock-time intended to alter behavior, with hopes of energy savings.

Debates regarding the appropriate balance between synchronization of time across locations and alignment of activities with sunlight began with the introduction of time zones and DST—continuing to this day (Latson 2015). Between 2020 and 2022, at least 33 states considered legislation to change their use of DST or their time zone, either of which also requires federal action.[2] Nearly all proposals abandon the semi-annual switch between standard and daylight saving time. In 2022, federal legislation to put all of the US on permanent DST passed the Senate but died in the House (Metzger 2022). Policy debates over DST and time zones are very similar: 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. Nearly all policy discussions of these proposed changes—and most of the previous academic literature on these topics—have assume individuals will continue to engage in activities at the same clock-time regardless of how it

1. The advent of time zones was driven, and first implemented, by the railroads, who argued the previous system made scheduling trains across locations impossibly complex (Prerau 2009)—illustrated by Figure 4 in the appendix, a table from Dinsmore's 1857 *American Railroad and Steam Navigation Guide and Route-Book*.

2. The National Conference of State Legislatures provides an up-to-date list of DST legislation at https://www.ncsl.org/transportation/daylight-saving-time-state-legislation.

synchronizes with solar-time.[3]

clock-time is a purely nominal metric. In theory, any change in the metric that preserves the correspondence to elapsed time need not affect behavior, regardless of its link to solar-time. Yet, in practice such changes—like delineating time zones and establishing DST—do seem to affect behavior, possibly because individuals anticipate that others will change their behavior and wish to coordinate activities' timing. When such coordination occurs across distant locations, it likely moves the timing of activities away from purely solar-time-based choices.

In order to understand how changing the denomination of time might alter behavior in the long run, a useful starting point is 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 and to what extent do they adapt to local solar-time at the expense of coordination or norms? Appendix Section B provides a simple theoretical model to help ground the empirical approach. The model captures the clock- vs. solar-time tradeoff as two individuals who trade off the benefits of synchronizing an activity together with the costs of undertaking that activity at a less-preferred time. We show that the best response for both parties is to compromise between clock and solar-time. The degree of this compromise is the clock- vs. solar-time tradeoff.

We analyze the tradeoff using three different datasets that measure different behaviors and have been collected in different ways. First, we examine social media usage data from Twitter, focusing on when individuals tweet. Second, we use data from the 2000 US Census Long Form regarding when individuals depart for work. Third, we study aggregated, cellphone-based foot-traffic data from Safegraph on the time individuals visit commercial establishments. In all three cases, we use the data to document 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.

The findings are fairly consistent across the datasets. Within the same time zone, locations where sunrise occurs an hour later have an average tweet time that is about 27 minutes later, a finding that is not substantially changed by the inclusion of various demographic controls and after accounting for potential social or economic connections to places in other time zones. The estimates using commute departure time in the Census are in the same range: a 26-minute later departure time in response to a one-hour later sunrise time. The timing of foot traffic at retail and other public establishments is the least sensitive to sunlight time but still strongly statistically significant: visit time shifts approximately 15 minutes in response to an hour difference in sunrise time.

The clock-time versus clock-time tradeoff could also differ depending on the activities that

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

an individual is engaging in on a given day. We document how this tradeoff differs between weekend and weekday activities, outdoor-oriented versus indoor-oriented activities, rural versus urban communities, and other factors. The foot-traffic data also include variation in visits to establishments by sector. The pattern of heterogeneous responses suggests that the annual variation in length of daylight and the proximity of the activity to sunrise both matter: northern US locations respond more than southern locations; tweets about breakfast are more responsive than tweets about lunch or dinner. Foot traffic at certain types of establishments is also more responsive than at others; for example, visits to department and convenience store are more sensitive to sunlight than visits to hospitals or religious organizations.

Assessing the potential impact of changing time conventions on human activities requires a deeper understanding of whether and how much clock-time departures from solar-time matter. This paper provides direct measurements of this clock- vs. solar-time tradeoff using plausibly exogenous variation in solar-time and three different large-scale datasets on activity timing.

2 Existing Literature

Empirical investigations into the relationship between the clock-time/solar-time relationship and human activity generally fall into three partially-overlapping categories: those that examine the effects of Daylight Saving Time on aggregate measures of activity, those that measure the impact of sleep on various measures of productivity, and those that examine how the mismatch of clock-time and solar-time affects the timing of activities.

The first literature has uncovered several important relationships. Adoption of DST does not substantially change aggregate electricity usage (Kellogg and Wolff 2008; Kotchen and Grant 2011; Rivers 2018; Shaffer 2019). The semi-annual time shifts associated with DST increase automotive and work-place accidents (Barnes and Wagner 2009; Smith 2016). DST's later sunsets, however, reduce crime (Doleac and Sanders 2015). None of these papers' results shed light on the extent to which a later clock-time relative to solar-time changes the timing of behavior.

The second literature focuses on the effect of additional sleep on various productivity outcomes. Along the way some of these papers estimate the shift in timing of behaviors. Papers in this literature use self-reported time-use surveys with 10,000–100,000 observations and primarily study shifts in the time at which respondents go to sleep and/or wake up. Heissel and Norris (2018) and Jagnani (2024) examine the impacts of sleep time on academic performance, and Gibson and Shrader (2018) study disrupted sleep patterns and long-run earnings. Giuntella, Han, and Mazzonna (2017) and Giuntella and Mazzonna (2019) examine the solar-/clock-time mismatch impact on sleep time and cognitive skills using data from China and the US, respectively. The results in Gibson and Shrader (2018) imply a 60 minute later sunset (the width of one time zone) on average delays bedtime by 28 minutes and wake-time by 19 minutes. Estimates in Heissel and Norris (2018) imply that a 60 minute later sunset is associated school start times that are 25 minutes later for younger children and 41 minutes for older children.

Roenneberg, Kumar, and Merrow (2007) and Roenneberg, Winnebeck, and Klerman (2019) report results that are directly on point for our study using a German time-use survey. Using self-reported sleep times, results in the former paper imply a 60-minute later sunset shifts sleep times 57 minutes later in cities with populations under 300,000, 40 minutes later in cities with populations 300,000–500,000, and 23 minutes later for cities above 500,000. The latter paper reports an average shift of 35 minutes in work start times.

Finally, Hamermesh, Myers, and Pocock (2008) use time-use survey data from the United States and Australia to examine how the probability of sleep, work, and television viewing in 15-minute intervals are shifted by sunlight time and the timing of network television. While their approach does not directly quantify the clock- vs. solar-time tradeoff, it is consistent with our findings in that it documents the competing importance of sunlight and time zones in determining the timing of activities throughout the day.

We provide the most comprehensive measurement of the clock- vs. solar-time tradeoff to date. Our datasets measure the tradeoff across nearly the entire contiguous United States and for a wide range of activities throughout the week and during the day. The size and focus of the datasets and the accompanying locational information allow us to examine a wider variety of activities and to analyze heterogeneity in the relationship to a greater extent than previous studies. Accordingly, we can document the geographic locations and activities that will be most (and least) affected by nominal clock shifts like time zone switches and DST legislation.

3 Estimating the Clock- vs. Solar-Time Tradeoff

This section describes the paper's empirical approach. Section 3.1 provides the overall empirical approach, and Sections 3.2 to 3.4 describe the data and estimation of the clock- vs. solar-time tradeoff for each of the datasets.

3.1 Empirical Approach

We first introduce a generalized estimating equation that represents our empirical approach for each of the three datasets. The datasets do not include granular information on the individuals engaging in the activity beyond the time and location, so in all cases we aggregate the data by time and location. The resulting dataset represents the distribution of activity over time of day for a given location.

Letting c denote location and t the observed day or week, our general specification is

$$\text{Mean(Activity Time)}_{ct} = \beta \text{ Sunrise}_{ct} + \sum \delta_{1zbt}\, \phi_{zbt} + \sum \delta_{2c}\, X_c + \varepsilon_{ct} \tag{1}$$

The outcome Mean(Activity Time)$_{ct}$ is the average local clock-time of the activity aggregated across observations in location c during time interval t. For the tweet and commute departure analyses, we measure time in hours after 4 AM, as 4 AM is approximately the minimum activity time in these datasets. Measuring activity time in hours after midnight does not substantially change the results, but it 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 because the set of cell phones monitored changes at midnight on Sunday. Consequently, measuring days as starting at 4 AM would require throwing out information—particularly complicating comparisons between weekdays and weekends. Further, in aggregate, observed foot traffic between midnight and 4 AM is very low and fairly constant (See Appendix Fig. 7).

Sunrise$_{ct}$ is the main variable of interest: the time of sunrise at location c on time t. Given a latitude, a day, and a time zone, Sunrise$_{ct}$ identifies the extent to which the solar-time at location c at time t differs from clock-time. Fig. 1 visualizes the distribution of local sunrise time (at counties' centroids) in two maps. The top panel shows sunrise times on the summer solstice (June 20), the longest day of the year. The bottom panel shows the same for the winter solstice (December 21). Within a time zone, moving from east to west, local sunrise times get later until the next time zone border. Locations that are farther north experience larger differences in sunrise time between the seasons. ϕ_{zbt} are time-zone by latitude-bin by time fixed effects. Thus, the effect of interest is identified from variation in activity timing and sunrise time between locations within the same time-zone and latitude-bin during the same day or week. Latitude bins are one-degree bands. The commute departure analysis using Census data do not have temporal variation, so the fixed effects are only time-zone by latitude-bin.

In each analysis, we also estimate a specification that controls for demographics of the location that might affect how individuals relate to their environmental surroundings, X_c. This includes the percent of the population in urban areas, the percent working in outdoor occupations, the percent in the labor force, and the (log) population of the observational unit.

In the appendix, we also provide results using two different controls for social or economic connectedness across the time zones. Though each of the measures seems to capture important connections of a locations to people in other time zones, neither has a significant impact on activity time or on the impact of sunrise time.

Our analyses omit Hawaii, Alaska, and Arizona. Hawaii and Alaska are not part of our Twitter dataset. Further, Hawaii 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, with the exception of the Navajo Nation which covers much of northeastern Arizona. Our results are very similar when we include Arizona.

A positive β indicates that the timing of the observed activity is responsive to solar-time—not just clock-time. For instance, if eating lunch were the activity, $\beta = 1$ indicates 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—solar-time being the dominant driver for lunch. $\beta = 0.3$ would indicate on average people on the western edge of a time zone eat 0.3 hours (18 minutes) later than people on the eastern edge, 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 following subsections detail how we implement estimation for each of the datasets and then present results. Appendix Table 2 summarizes each dataset.

3.2 Tweets

To use data from the social media platform Twitter (since renamed “X”), we downloaded approximately 2.5 billion geolocated tweets through a connection to Twitter’s Streaming API.[4] From the geolocations, we identify the county in which each tweet occured. For each date in our time period—which ranges from April 2014 through March 2019—we compute the average time (since 4 AM) of the tweets by county.

We then estimate the model

$$\text{Mean(Tweet time)}_{ct} = \beta\ \text{Sunrise}_{ct} + \sum \delta_{1zbt}\ \phi_{zbt} + \varepsilon_{ct}$$

for county c on date t. Sunrise_{ct} is determined by county centroid and date. ϕ_{zbt} are time-zone by one-degree latitude bin by date-of-sample fixed effects. $\text{Mean(Tweet time)}_{ct}$ refers to the average tweet time for all tweets in the dataset for the county-date (or, in the next section, tweets containing a specific key phrase). We weight observations from different counties by the average number of daily tweets for the county; standard errors cluster by state.

The results in column (1) of Table 1 (Panel A) imply that tweets from people located at the west end of a time zone on average occur 0.46 hours (28 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

4. This sample represents the 2% of public tweets for which users permitted geolocation. While these tweets are not a random sample, there is no obvious reason that this sample would bias the 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).

earlier. In other words, for this activity, people have adjusted their behavior by nearly one-half of the solar-time differential between locations that have the same clock-time.

Column (2) shows that the results are almost unchanged when we also include demographic measures for the county.[5]

3.3 Census

The 2000 Census Long Form asked what time during the week prior to "Census Day" (Saturday, April 1, 2000) the respondent typically left for work. For each of the slightly more than 200,000 Census block groups (CBGs), we use the time elapsed between 4 AM and the average reported commute departure time as the primary variable of interest to estimate solar-time's effect on commute decisions.

Unlike the other two datasets we study, the Census data have no time-series variation: they are a cross-sectional snapshot. In addition, departure time is self-reported—potentially including recall-error issues common in self-reported data. Beyond potentially attenuating our results, there is no clear reason recall-related issues would bias our estimation of the impact of solar-time on commute timing. These data also offer a potential advantage in being a 17% sampling of the entire population with very high response rates.

We match individual's reported departure times to their relevant CBGs' sunrise time (at the CBG centroid) on April 1, 2000. The other variables and coefficients follow the Twitter analysis—except at the CBG level, rather than county. We weight this regression by the CBG's population and again cluster standard errors by state. For CBG c,

$$\text{Mean(Commute Departure Time)}_c = \beta\ \text{Sunrise}_c + \sum \delta_{1zb}\ \phi_{zb} + \varepsilon_c$$

The results in Panel B (Table 1) are fairly consistent with the Twitter results. With a one-hour increase in sunrise time, indviduals depart for work 0.37 hours (22 minutes) later (omitting demographic controls in column 1). With demographic controls included in column (2), we estimate that they leave 0.43 (26 minutes) later. As with social-media behavior, commute timing bears strongly follows solar-time.

3.4 Foot Traffic

The cellphone-based foot traffic data from SafeGraph (SafeGraph 2021b) record visits to approximately 6.6 million points of interest (POIs) across the United States. SafeGraph defines a POI 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

5. Appendix Table 5 provides the estimated coefficients for these demographics.

(North American Industry Classification System) codes during our sample period. We focus on visits during 2018 and 2019: 2018 is the earliest year available, and visit patterns for 2020 and 2021 were distorted by the COVID-19 pandemic. Appendix Figure 7 depicts the overall distribution of visits across throughout the day on weekends and weekdays.

This dataset allows us to see the number of visits to a POI by hour of sample, e.g., the number of visits to a specific Walmart from 8–9 AM on March 14, 2019. The data also include each POI's Census block group (CBG). We 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). We also summarize each week's activity by weekdays and weekends.

To identify solar-time's effect on foot-traffic patterns, we estimate

$$\text{Mean(Visit Time)}_{inw} = \beta\ \text{Sunrise}_{cw} + \sum \delta_{1zbw}\ \phi_{zbw} + \sum \delta_{2zn}\ \gamma_{zn} + \varepsilon_{inw}$$

Outcome Mean(Visit Time)$_{inw}$ refers to the average visit time to POI i in NAICS code n during week w, in hours after midnight. Sunrise$_c w$ references the average sunrise time in CBG c during week w; CBG determines time zone and latitude bin for the time-zone/latitude-bin/week-of-sample fixed effect, ϕ_{zbw}. This regression also includes fixed effects for NAICS code by time-zone γ_{zn}.

The results, presented in Panel C of Table 1, again show a substantial and statistically significant adaptation to solar-time and away from pure clock-time, though the estimated effect is smaller than the effects on tweets or comute departure time. Column (1) suggests that people on the west end of a time zone frequent similar points of interest 15 minutes later, on average, than people on the east end of the time zone. Adding CBG demographics (column 2) does not meaningfully change the estimate. Again, we find substantial effects of solart time on human behavior.

4 Heterogeneity in the Clock vs. Solar-Time Tradeoff

We now estimate how the clock- vs. solar-time tradeoff varies across people, places, and activities. Estimates of heterogeneity in the tradeoff are important for predicting how the effect of potential nominal time-shifting legislation would vary across geographic locations and activity choices. For instance, one might expect that activities (or locations) more strongly linked to the outdoors would produce a stronger response to solar-time. The following sections document the effect of solar-time on activity timing in separate regressions across northern and southern locations, demographic categories, and activities that tend to occur at specific times of day.

4.1 Heterogeneity by Location, Demographics, and Activities

Figure 2 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, for instance, compares results for areas north or south of the population-weighted median latitude of the contiguous 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 may adapt to local solar-time more than people who live in the southern part of the country. The pattern is statistically significant at 1% level in the commute departure analysis and very large: a 36 minute adjustment for a 60-minute difference in sunrise time in the north, relative to a 13-minute adjustment in the south. In the Twitter data, the difference is also quite large (37 minutes versus 23 minutes), but the difference is only significant at the 10% level. There is no apparent difference in foot traffic. One possible explanation for this effect in the commute departure time and tweet time analysis is that people living further north are used to adjusting to larger variations in sunrise, sunset, and total sunlight time between the winter and summer—rendering 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 foot traffic adapts significantly (p-value 0.01) more to sunlight in winter months, when sunlight hours are shortest, with the difference implying 6 minutes more time shifting of activities in the winter between the East and West end of a time zone. The Twitter results, however, do not suggest a statistically significant difference. These differences in heterogeneity highlight the potential that our three datasets shed light on somewhat different responses.

The third and fourth panels attempt to document the impact of outdoor activity. Rural areas are typically associated with living closer to natural environments—whether in line of work or choice of leisure activities.[6] Consequently, one might expect greater adaptation to solar-time in more rural locations. Tweet times match this theory—an estimated difference of 21 minutes (p-value 0.01)—but the difference is small and not statistically significant in the foot traffic and commute departure analyses. We also find no statistically significant difference in adaptation to solar-time between counties with above or below median shares of workers engaged in outdoor work.

The fifth panel compares counties by their shares 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 slightly more to solar-time than counties with smaller shares. This difference, however, is only statistically significant in the foot traffic analysis (p-value 0.09) and

6. The Urban variable is very bimodal, with most observations near 0 or 1. We split the sample at 50%, rather than at the sample median, which is close to 1.

not large in any of the datasets.

One might hypothesize that weekend activities—more commonly associated with leisure—are more influenced by solar-time than days typically associated with work. The Twitter-based estimates suggest solar-time effects are 7-minutes larger on weekends (p-value 0.01). However, in the foot-traffic data, weekday and weekend estimates are nearly identical.

Finally, the bottom panel of Figure 2 uses tweets' content—particularly looking at tweets that include the words "breakfast", "lunch", or "dinner". The estimates indicate solar-time adaptation for "breakfast" is the greatest: breakfast-related tweets occur, on average, 36 minutes later for a 60 minute later sunrise time. Tweets about lunch are much less sensitive to solar-time, and not statistically different from zero. Dinner-related tweets between sit between breakfast and lunch—adjusting about 22 minutes across the width of a time zone.

4.2 Heterogeneity by Establishment Type

Figure 3 considers heterogeneity in solar-time adaptation by establishment type. The figure separately estimates the effect of solar-time in the foot-traffic data for each of the 25 most-visited establishment types (six-digit NAICS codes) with at least 5,000 locations. The first 11 establishment types in Figure 3 (in red) are varieties of retail stores (*e.g.*, department, convenience, sporting goods) and indicate a range of adjustments to solar-time with estimates beteen 0.14–0.44 (8–26 minutes across a time zone). Food sellers (orange), like supermarkets and convenience stores, are the most sensitive to solar-time. Restaurants, snack bars, and drinking establishments also exhibit a high degree of adaptation, 16–24 minutes. Perhaps surprisingly, the estimated adaptation for hotels and motels is substantially smaller and not significantly different from zero.

The one business-to-business category in this list (lessors of nonresidential buildings, yellow) has an estimate of 0.28 (17 minutes) and is highly significant. Among the other categories, the lack of adaptation at religious establishments (primarily churches, temples and mosques), and medical care are noteworthy, which suggests more rigid scheduling independent of sunlight. Elementary and secondary schools exhibit a high degree of adaptation to solar-time, while colleges and child day care services do not exhibit adaptation that is statistically significant. Also interesting, fitness and golf establishments and nature parks (blue) appear to adapt to solar-time but less so than restaurants and most retail establishments.

Overall, the results support for the hypothesis that social behavior deviates significantly from clock-time in order to adapt to solar-time. While the level of adaptation clearly varies across activities and industries, a simple explanation for the cross-industry pattern of adaptation is less clear.

5 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 individuals and their behaviors will respond.

We show that individuals and firms systematically adapt their behaviors in response to changes in standardized clock-time. These adaptive behaviors partially offset changes in standardized clock-time. People do not leave for work an hour earlier simply because clock-time advances an hour relative to solar-time. Instead, nearly half of a time-zone's wedge difference clock-time and solar-time is offset by individuals adapting to solar-time. We find similar effects on the timing of individuals' 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 one-quarter of the mismatch between solar-time and clock-time.

Our findings help illuminate the mechanisms underlying previous empirical work. First, the results can rationalize previous mixed evidence of the effect of Daylight Saving Time on energy usage (Kellogg and Wolff 2008; Kotchen and Grant 2011) as partly reflective of differences in sunrise time across these studies' samples—consistent with arguments in Shaffer (2019). Second, findings on electricity usage, vehicle crashes, and crime Smith (2016) and Doleac and Sanders (2015) should be viewed as net of the behavior-shifting effect we observe, since individuals' responses DST shifts are mediated by their natural response to sunlight. 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 2024). 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 demonstrate that people do not ignore environmental factors and operate purely on clock-time. However, clock-time still plays an enormous role in human activity even for activities that are very much influenced by sunlight and weather. These findings demonstrate that policy discussions of clock-time—whether observing daylight saving time or choosing time zones—should recognize that individuals and firms will re-optimize 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.

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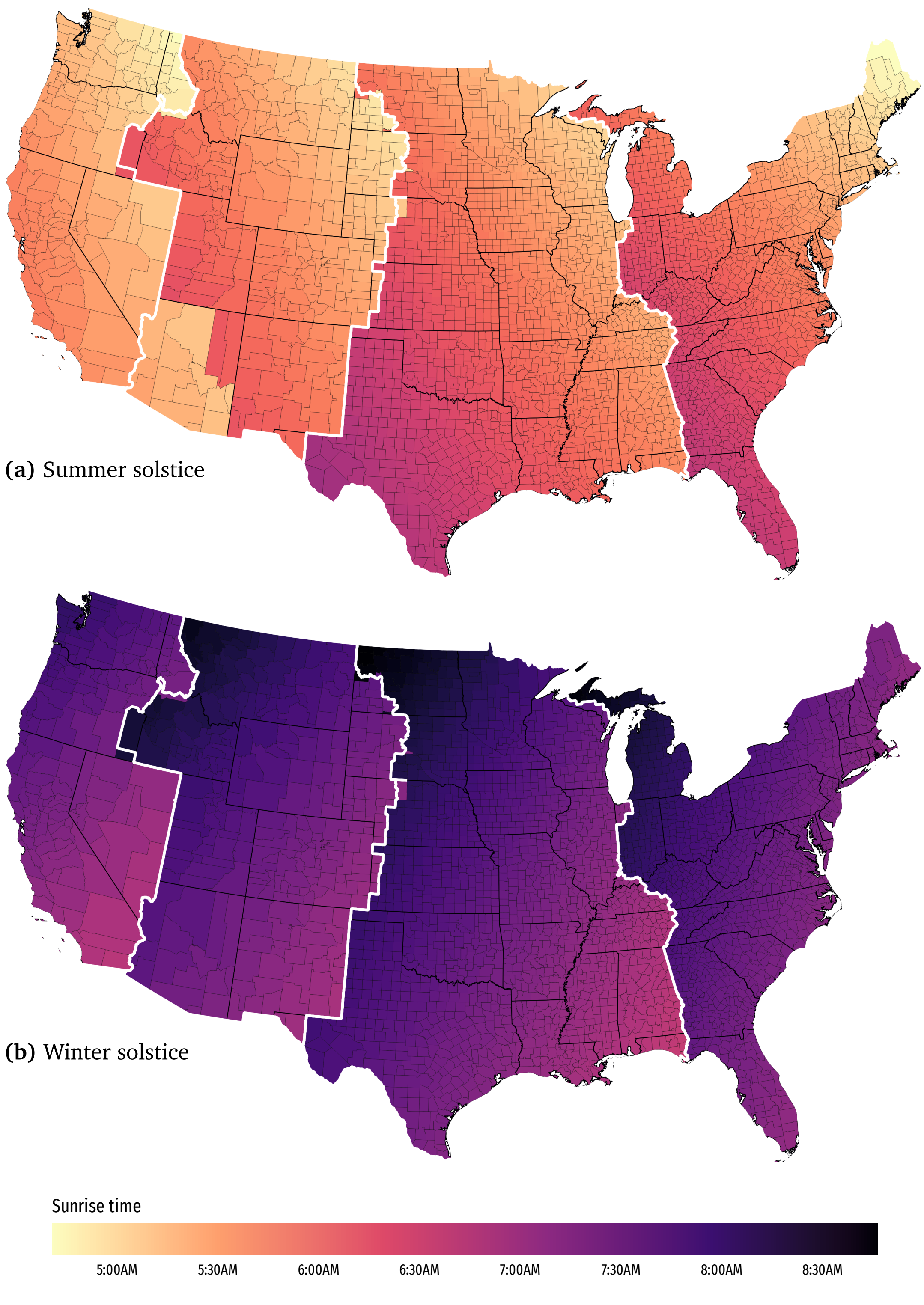
Smith, Austin C. 2016. "Spring forward at your own risk: Daylight saving time and fatal vehicle crashes." *American Economic Journal: Applied Economics* 8 (2): 65–91.

Table 1: The Effect of Sunrise Time on Human Activities

	(1)	(2)
Panel A: *Time of tweet (Twitter)*		
Sunrise	0.461***	0.450***
	(0.088)	(0.082)
TZ × Lat. bin × Day-of-sample FEs	✓	✓
Demographic controls		✓
N obs.	4,184,196	4,181,204
Panel B: *Time left for work (Census)*		
Sunrise	0.369***	0.429***
	(0.054)	(0.070)
TZ × Lat. bin × Day-of-sample FEs	✓	✓
Demographic controls		✓
N obs.	202,748	202,739
Panel C: *Avg. visit time (SafeGraph)*		
Sunrise	0.247***	0.242***
	(0.025)	(0.025)
TZ × Lat. bin × Week-of-sample FEs	✓	✓
TZ × NAICS (6 digit) fixed effects	✓	✓
Demographic controls		✓
N obs. (millions)	159.43	159.08

Notes: Each panel (**A–C**) provides estimated effects of the time of sunrise on a different outcome. Each column (1–2) provides estimates from differing regression specifications. Column (2) includes demographic controls: proportion urban, proportion outdoor, proportion working, and the log of population. Latitude bins cover 1 degree. Cluster-robust (state) standard-errors in parentheses. Significance codes: ***: 0.01, **: 0.05, *: 0.1. **Panel A** estimates the effect of sunrise time on county's average time of tweeting; time of tweet is the average tweet time within a day, where day is defined as starting and ending at 4am. Sunrise time is the time of sunrise in the county on the date. Regressions weight observations (county-dates) by their average number of tweets. Standard errors clustered by state. **Panel B** estimates the effect of sunrise time on the time that respondents (2000 Decennial Census) report leaving for work. An observation represents the average within one Census Block Group (CBG). Sunrise time is the time of sunrise for that CBG on April 1, 2000, when the Census was conducted. Demographic controls are at the CBG level. Regressions weight observations (CBGs) by their population. **Panel C** estimates the effect of sunrise time on a foot-traffic average visit time. An observation is a POI-week (*e.g.*, a specific Walmart location during the week of 2021-03-14). Sunrise time is the average time of sunrise in the POI's CBG during the given week. Demographic controls are at the CBG level.

Figure 1: Local Sunrise Time on the Solstices

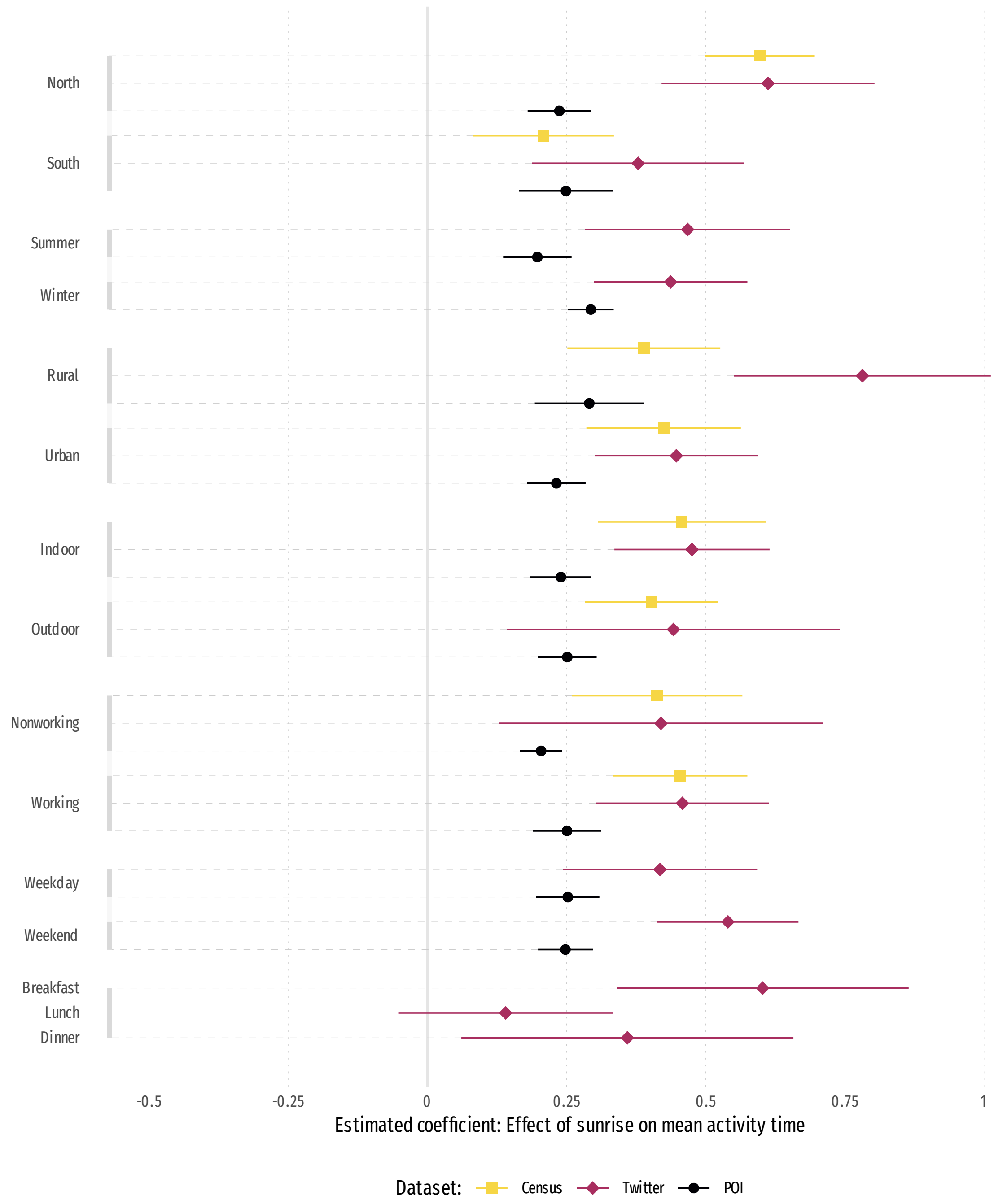


(a) Summer solstice

(b) Winter solstice

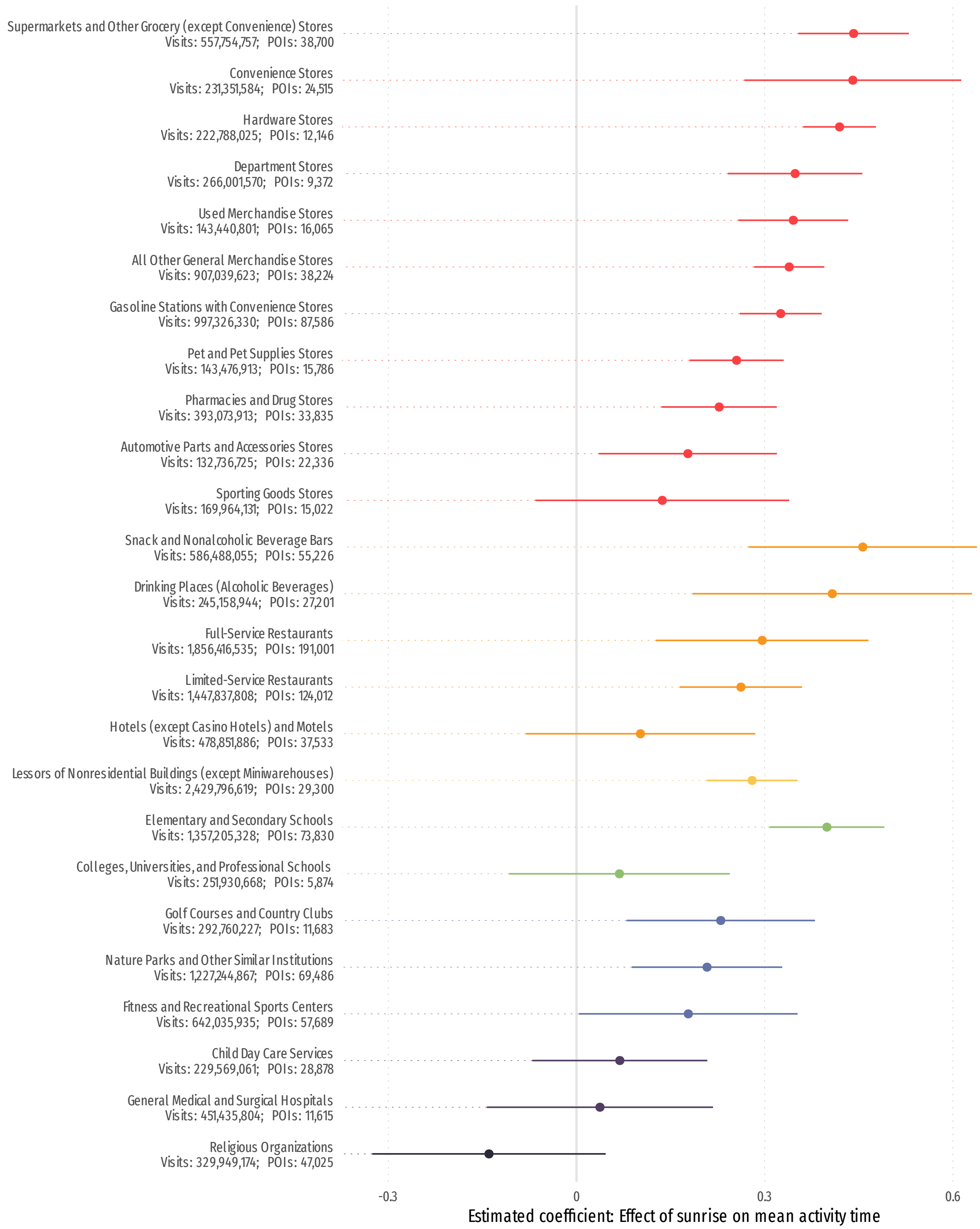
Notes: Figures show the time of sunrise for each county's centroid on June 20 (summer solstice) and December 21 (winter solstice).

Figure 2: The Effect of Sunrise Time on Activity Time (Heterogeneity)



Notes: Figure shows effect of sunrise time on activity time across geographic, temporal, and categories of tweets. Each point-segment pair represents 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 horizontal axis indicates 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 3).

Figure 3: The Effect of Sunrise Time on Visit Time, by Establishment Type

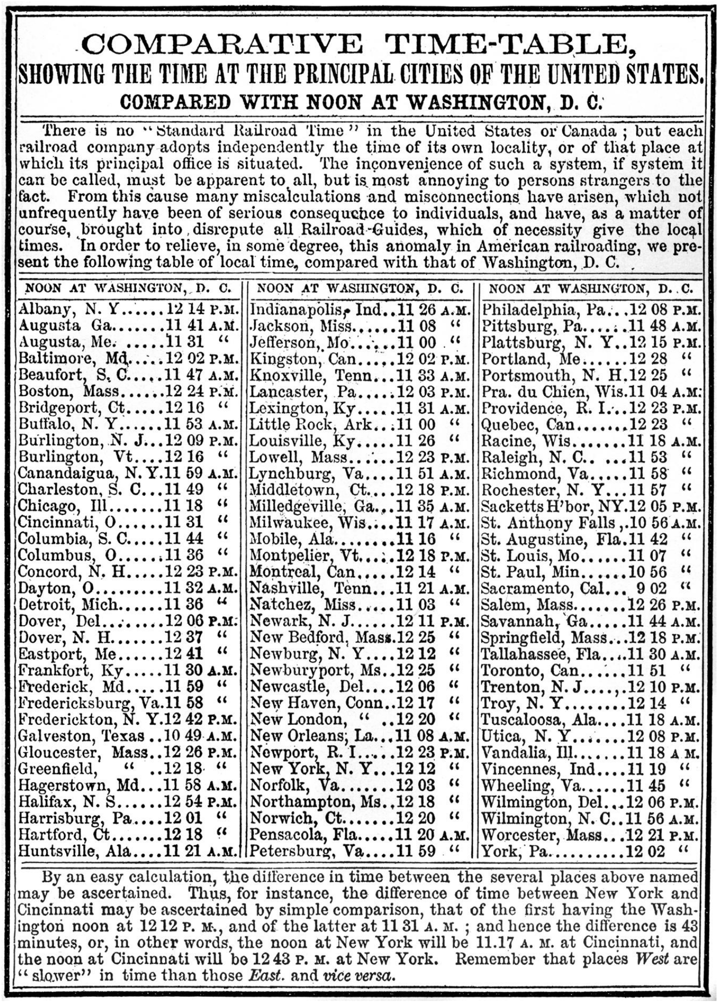


Notes: Figure shows the effect of sunrise on visit time to establishments, split by establishment time. The coefficients in this figure are estimated using 25 separate regressions for each six-digit NAICS code. We group and color the coefficients and confidence intervals (clustering errors at the state) by the industries' two-digit NAICS codes. The twenty-five codes represent the 25 most-visited six-digit NAICS codes in our dataset with more than 5,000 locations.

ONLINE APPENDIX

Appendix A Comparative Time-Table for Railroad Coordination

Figure 4: 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).

Appendix B 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.

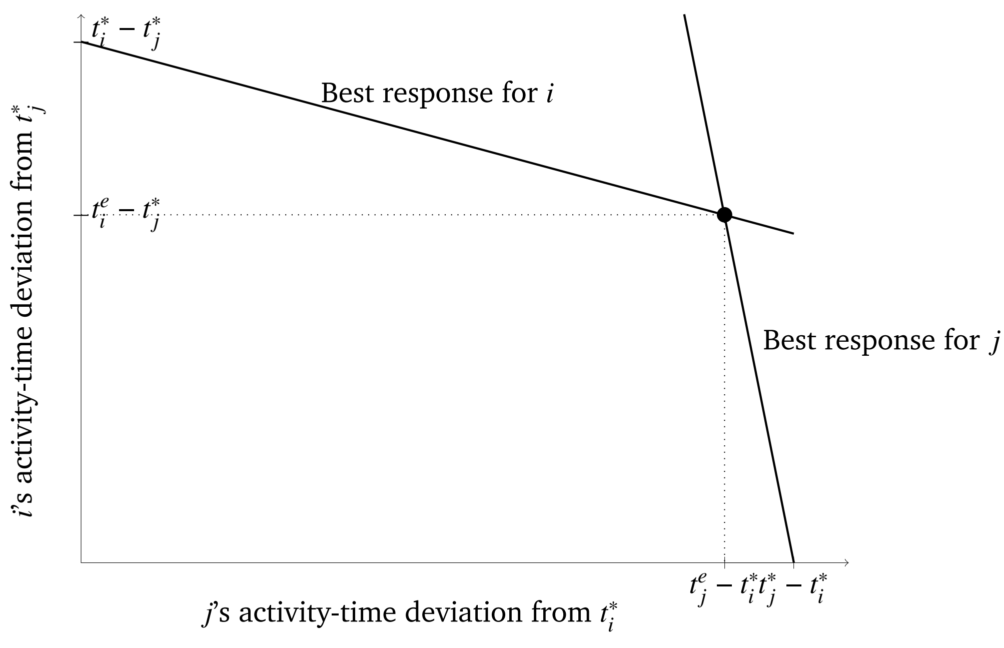
Assume that the utility that individual i gets from a specific activity is a declining function of the deviation of the time of the activity from the individual's own preferred time t_i^* and a declining function of deviation from the time at which another individual, j, engages in the activity,

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

And likewise for individual j,

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

Figure 5: 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.

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.[7] 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 5 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^* 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.

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

Appendix C Descriptive Statistics

Table 2: Summary statistics of demographics

Variable	Mean	Stnd. dev.
Panel A: Twitter		
Tweet time	16.4	2.76
Sunrise (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
	Apr. 2014–Mar. 2019	
Panel B: Census		
Time left for work	8.78	0.830
Sunrise (hr)	5.90	0.284
Urban (prop.)	0.773	0.393
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
	April 2000	
Panel C: SafeGraph foot-traffic		
Visit time (hr)	13.5	1.57
Sunrise (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
	Jan. 2018–Dec. 2019	

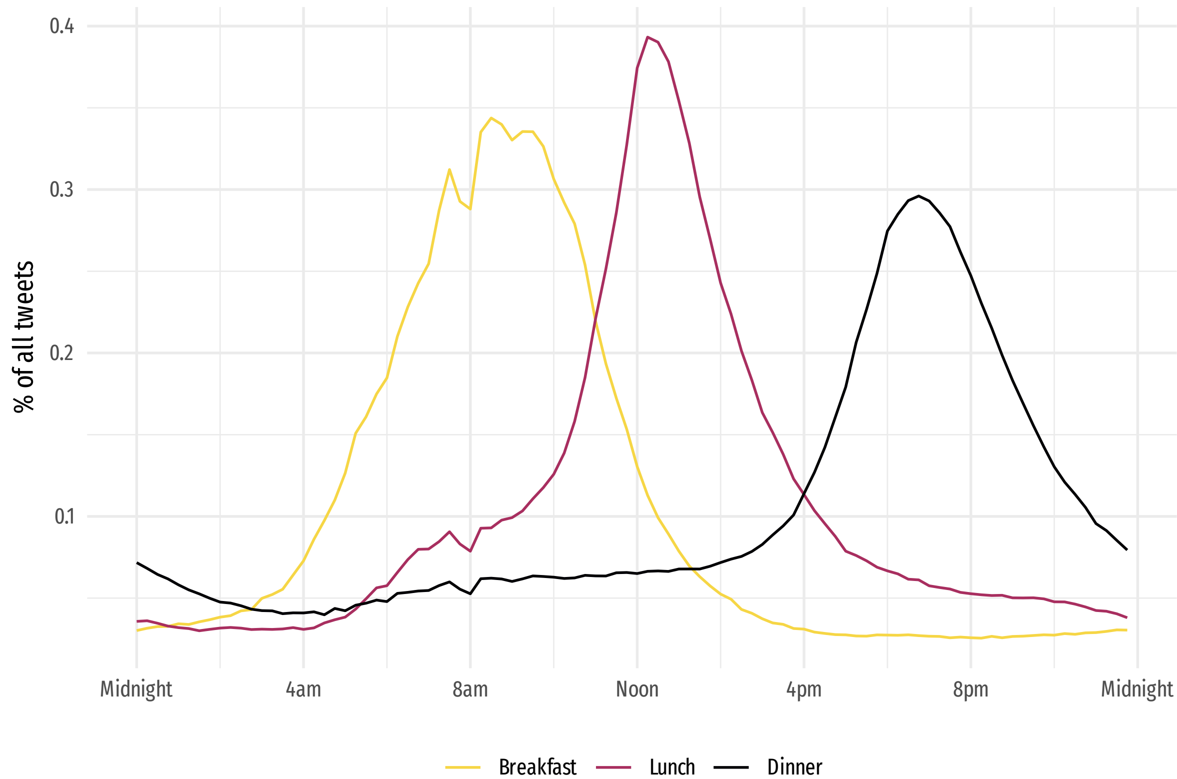
Notes: Table of descriptive statistics for Twitter, Census, and foot traffic (Safegraph) datasets. Demographic variable represent counties for Twitter data and Census Block Groups (CBGs) for the Census and SafeGraph data. Observation counts: 3.9 million observations for Twitter data (2,875 counties; 1,512 days); 189,335 observations for Census data (2,877 counties); 159.4 million observations for foot-traffic data (20.5 billion *visits*; 178,811 CBGs; 3,068 counties; 105 weeks).

Inclusion criteria for the POI dataset: 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,[8] and (3) are not missing location-related data. The resulting dataset includes

8. 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.

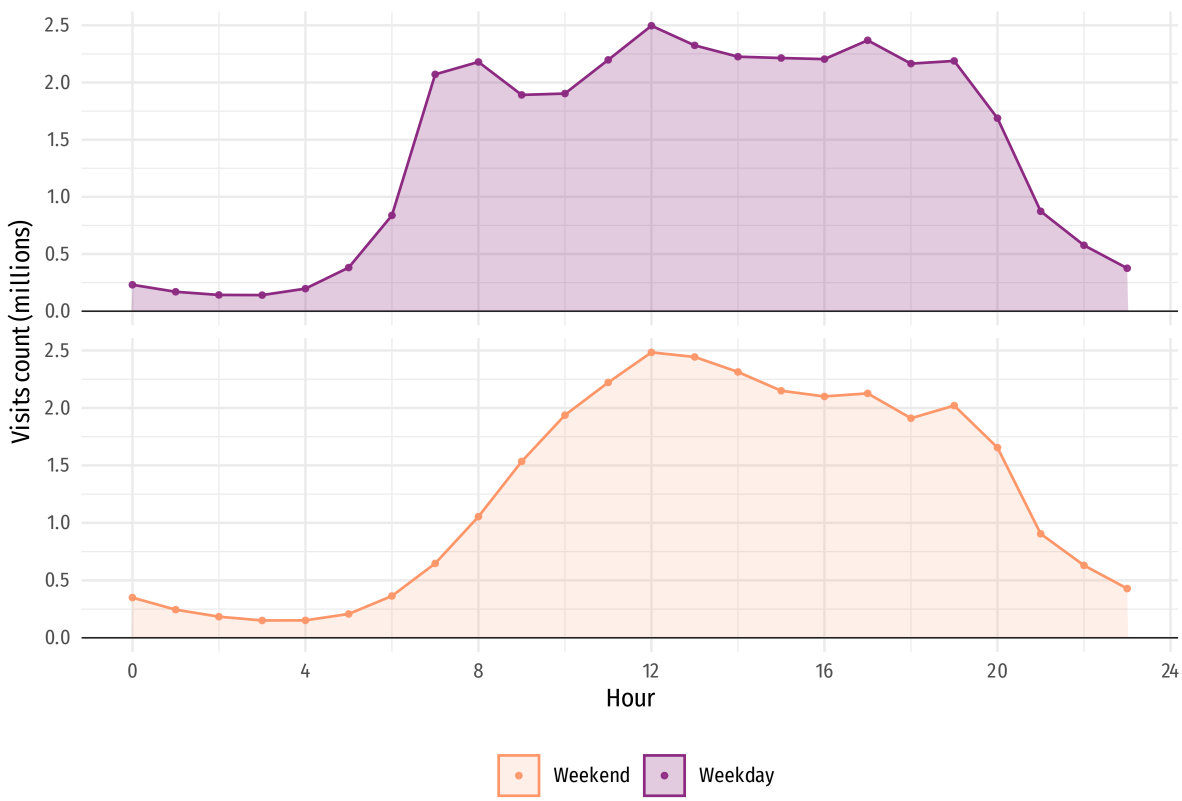
22.4 billion visits (91.6% of all visits in the dataset) to 2.2 million POIs covering 378 six-digit NAICS codes.

Figure 6: 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.

Figure 7: 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.

Appendix D Connectedness

We control for many potential confounders in the main 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.

To control for potential confounding from economic or social connections between nearby cities in different time zones, we also develop a connectedness index from anonymized cellphone data that measures the tendency of a phone that homes in one county to also be detected in other counties.[9]

To measure connectedness, 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.[10]

Table 3 summarizes the measures of connectedness we use.

9. We also estimated 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.

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

Table 3: 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.

The subfigures of Figure 9 illustrate counties' mean offsets using (a) SafeGraph movement data and (b) Facebook connections from Bailey et al. (2018). Counties near time-zone borders tend to spend more time in other time zones.

Subsection D.1 Controlling for Connectedness

Connectedness between individuals living relatively close to one another but in different time zones could also shift the timing of behavior. 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 (in the eastern time zone). 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 their work schedule 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—confounding connections to other time zones with solar-time.

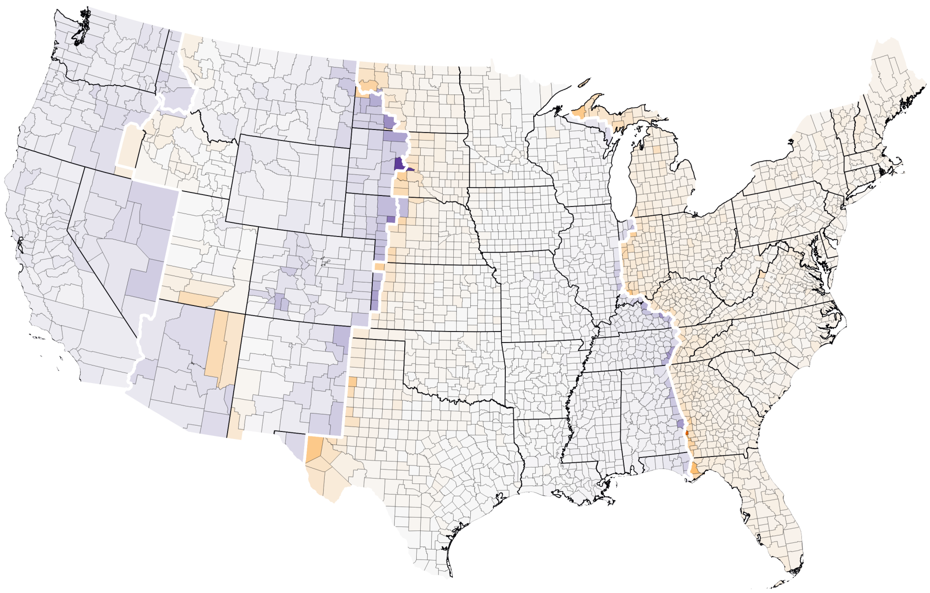
To account for this possibility, we use two separate measures of locations' connections to other time zones.

One measure employs the Social Connectedness Index developed in "Social Connectedness: Measurement, Determinants, and Effects," by Bailey et al. (2018).

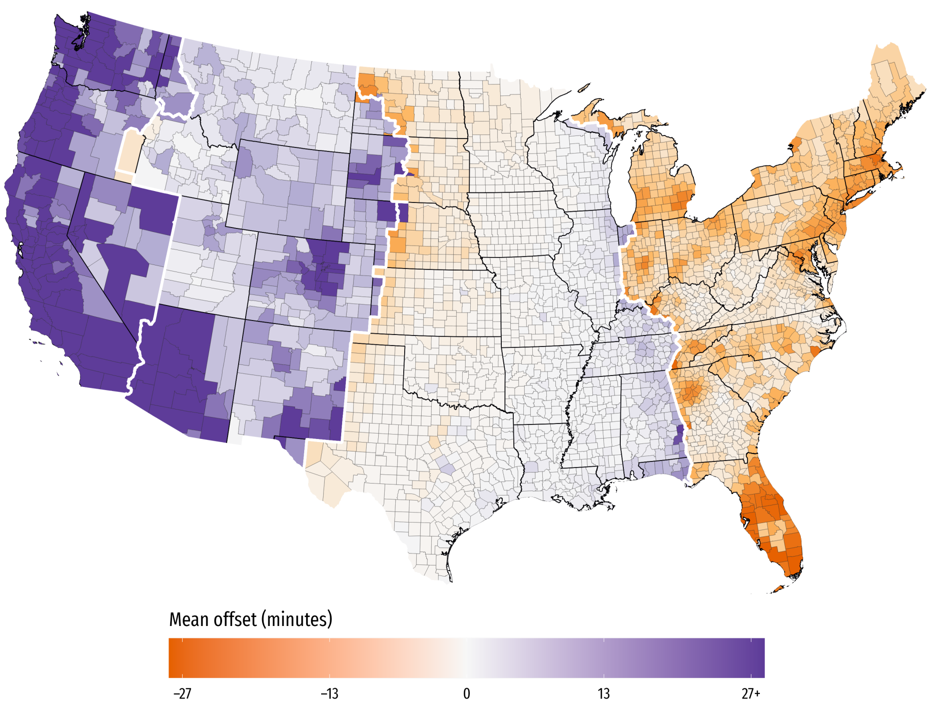
The second measure uses the cellphone-based foot traffic data to construct a variable that measures the proportion of observed visits from residents of each county that occur in other time zones. We describe the construction of this "connectedness" variable in detail in Appendix

Figure 8: Counties' connections to other time zones: Counties' mean offset

(a) Mean offset using SafeGraph foot-traffic for connections



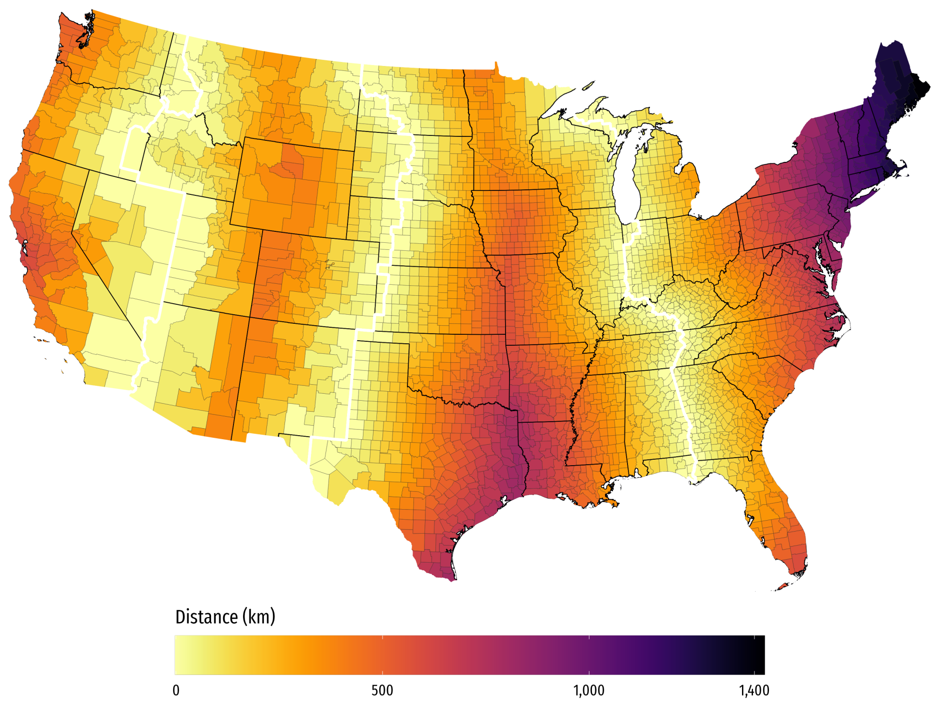
(b) Mean offset using Facebook connections as in Bailey et al. (2018)



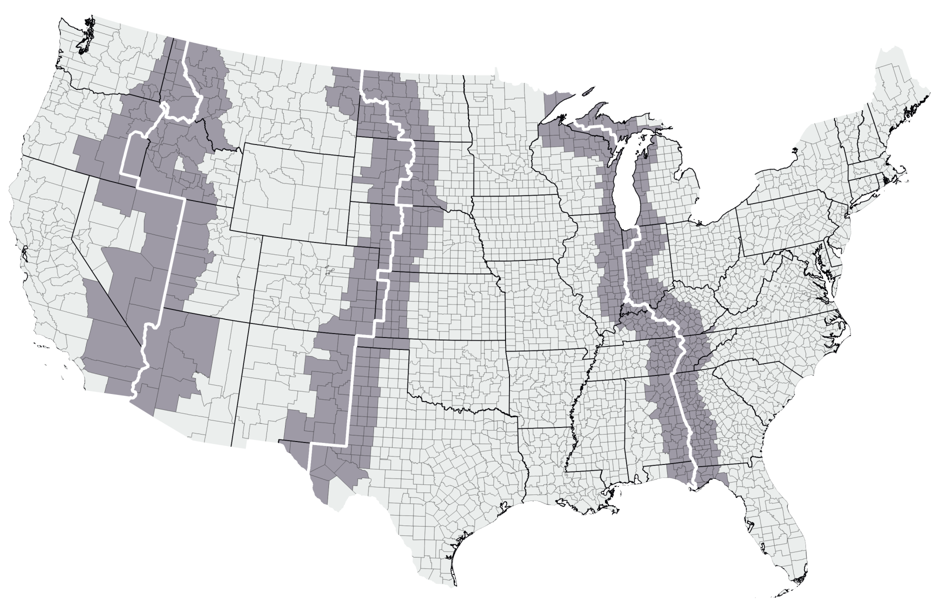
Notes: The subfigures illustrate counties' 'mean offset' due to connections to other time zones. Subfigure (a) uses SafeGraph-based cellphone movement to calculate county-to-county connections; Subfigure (b) relies up Facebook-based connections from Bailey et al. (2018). Subfigure (b) top-codes the Facebook-based connections at approximately 27 minutes for ease of presentation. In the analyses, we do not top code the variable.

Figure 9: Distance to time-zone borders County distances and buffers

(a) Distance to nearest time-zone border (km)



(b) Counties within 100 kilometers of their nearest time-zone border



Notes: The subfigures illustrate counties' distances to the nearest time-zone border. Subfigure (a) depicts the distance in kilometers Subfigure (b) shows the 100-kilometer buffer that we use in the robustness checks shown in Table 4 (darker counties are within 100 kilometers of their nearest time-zone boundary).

Section D. Counties with connections in time zones more to the east of their own will presumably be pulled "earlier" (with respect to their clock-time) into their days. To measure this pull, we calculate the county-level connectedness, $C[h, d]$. We then calculate the average time zone offset for each county—weighting each county's relative offset from each time zone by its connections to the time zone's 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 3 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 occurring in its own time zone), yielding a mean time-zone offset near zero. Appendix Figure 9 illustrates the spatial distribution of these measures. As expected, connectedness to other time zones is strongest for counties near time-zone boundaries.[11]

None of our analyses, however, find evidence that connectedness substantively changes behavior timing. Table 4 provides our main results in column 0 and then compares them to various approaches that account for counties' connectedness. Columns 1 and 2 directly control for counties' connections to other time zones using SafeGraph and Facebook connectedness respectively. Column 3 drops counties within 100 kilometers of a time-zone border, as these counties are presumably most affected by connections to other time zones. For each of the three datasets (Panels A, B, and C) he results of these various approaches do not meaningfully differ from the main results in column 0. Further, if connectedness to other time zones mattered, we would expect the sign of this coefficient to be negative: 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. None of the point estimates are negative. Taken together, connections to other time zones does not appear significant in our setting.

11. 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.

Table 4: Robustness to connections/distances to other time zones

		Control: Connections to other TZs		*Restrict sample:* TZ border dist.
	Main result	SafeGraph	Facebook	> 100 km
	(0)	(1)	(2)	(3)
Panel A: *Time of tweet (Twitter)*				
Sunrise	0.452***	0.479***	0.461***	0.527***
	(0.082)	(0.119)	(0.081)	(0.080)
Mean offset		0.811	0.163	
		(1.973)	(0.145)	
Standard FEs	✓	✓	✓	✓
Dem. controls	✓	✓	✓	✓
N obs.	4,181,204	4,181,204	4,181,204	3,316,718
Panel B: *Time left for work (Census)*				
Sunrise	0.429***	0.537***	0.440***	0.511***
	(0.067)	(0.064)	(0.056)	(0.068)
Mean offset		3.165***	0.413***	
		(0.771)	(0.162)	
Standard FEs	✓	✓	✓	✓
Dem. controls	✓	✓	✓	✓
N obs.	202,739	202,719	202,739	172,570
Panel C: *Avg. visit time (Foot traffic)*				
Sunrise	0.242***	0.306***	0.251***	0.271***
	(0.025)	(0.039)	(0.024)	(0.026)
Mean offset		1.908*	0.147*	
		(1.042)	(0.069)	
Standard FEs	✓	✓	✓	✓
Dem. controls	✓	✓	✓	✓
N obs. (mill.)	159.08	159.08	159.08	134.84

Notes: As with Table 1: Each panel (**A–C**) provides estimated effects of the time of sunrise on a different outcome. Each column (0–4) provides estimates from differing regression specifications. Column 0 provides the 'main' results from Table 1. Columns (1–2) control for the county's level of connection to other time zones using SafeGraph travel (Column 1) and Facebook friends (Column 2). Columns (3–4) restrict the sample to observations farther than 100 kilometers from a time-zone border (Column 3) or within 100 kilometers (Column 4). All regressions include demographic controls (proportion urban, proportion outdoor, proportion working, and the log of population) and fixed effects for one-degree latitude bins interacted with time zone and sample time (day- or week-of-sample). As with the main results in Table 1), Panel C also includes time-zone by 6-digit NAICS fixed effects. Cluster-robust (state) standard-errors in parentheses. Significance codes: ***: 0.01, **: 0.05, *: 0.1. The note in Table 1 provides additional descriptions of the outcomes and level of observation for each panel.

Table 5: Coefficients on demographic controls in Table 1

	Time of outcome (*dataset*)		
	Tweet (*Twitter*) (1)	Left for work (*Census*) (2)	Visit time (*SafeGraph*) (3)
Sunrise	0.452***	0.429***	0.242***
	(0.082)	(0.070)	(0.025)
Prop. Urban	0.517***	0.431***	–0.006
	(0.157)	(0.018)	(0.026)
Prop. Outdoor	4.855***	–1.878***	0.287*
	(1.488)	(0.148)	(0.157)
Prop. Working	–1.619***	–0.968***	0.039
	(0.448)	(0.121)	(0.075)
Log(Pop.)	–0.037*	–0.076***	0.055***
	(0.022)	(0.013)	(0.007)
TZ × Lat. bin × Week-of-sample FEs	✓	✓	✓
TZ × NAICS (6 digit) fixed effects			✓
N obs. (millions)	4.18	0.20	159.08

Notes: This table provides the coefficients on the demographic controls in Column 2 of Table 1 (in addition to the coefficient on *Sunrise*). See Table 1 for a full description of the specification and meaning of the variables. Significance codes: ***: 0.01, **: 0.05, *: 0.1.