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

Patrick Baylis, Severin Borenstein, and Edward Rubin*

June 13, 2024

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 times (Census), and foot traffic (SafeGraph). A one-hour change in the wedge between solar time and clock time shifts behavior 10–32 minutes, with larger effects in northern latitudes and for activities occurring closer to sunrise.

*Baylis: Vancouver School of Economics, University of British Columbia, patrick.baylis@ubc.ca; Borenstein: Haas School of Business and Energy Institute at Haas, University of California, Berkeley, severinborenstein@berkeley.edu; Rubin: Department of Economics, University of Oregon, edwardr@uoregon.edu. For excellent research assistance, we thank Sara Johns. We have received valuable comments from Hunt Allcott, Jacob LaRiviere, Sam Norris, and seminar audiences at the Association of Environmental & Resource Economists annual meeting, UC Berkeley, and UC Santa Cruz. An earlier version of this paper circulated under the title, "When We Change the Clocks, Do the Clocks Change Us?".

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 personal preferences or environmental constraints.

Technological advances in the US during the 19th 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.[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 become 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, such as 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, in this case by reducing energy use.

Debates regarding the appropriate balance between synchronization of time across locations and alignment of activities with sunlight began with the introduction time zones and DST and continue to this day (Latson 2015). Between 2020 and 2022, at least 33 states considered legislation to change their use of daylight saving time or to change their time zone, either of which also requires federal action.[2] 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 (Metzger 2022). Policy debates over daylight saving time and changing time zones are very similar, because choosing to live on standard time or daylight saving time 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 assumed

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), as 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 daylight saving time legislation here: https://www.ncsl.org/transportation/daylight-saving-time-state-legislation.

that individuals will continue to engage in activities at the same clock time regardless of how it synchronizes with solar time.[3]

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 when activities occur. When such coordination occurs across distant locations, however, it is more likely to move the timing of activities away from the choices people would make based purely on solar time.

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—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? In Appendix Section B, we provide 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 focus on different behavior and have been collected in different ways. First, we examine data from Twitter, focusing on when individuals tweet. Second, we use data from the 2000 US Census Long Form regarding 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 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 consistent across all three datasets. Within the same time zone, locations where sunrise occurs an hour later have an average tweet time that is 20 minutes later, a finding that is insensitive to the inclusion of various demographic controls and after accounting for potential social or economic connections to places in other time zones. The estimates using time left for work in the Census are larger, with more than a 30-minute difference of departure time in response to a one-hour difference in sunrise time. The timing of visits to retail establishments is the least sensitive to sunlight time but still strongly statistically significant, with visit time shifting by 10 minutes in response to an hour difference in sunrise time.

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

The solar time versus clock time trade-off could also differ depending on the activities that an individual is engaging in on a given day. We document how the clock vs. solar-time tradeoff differs between weekend and weekday activities, outdoor-oriented versus indoor-oriented activities, rural versus urban communities, and other factors. We also show how visits to business establishments vary by sector. The pattern of heterogenous responses suggests that the length of daylight and the proximity of the activity to sunrise both matter: northern locations respond more than southern locations, summer responses are larger than winter responses, and tweets about breakfast are more response than tweets about lunch or dinner. Certain types of establishments are also more responsive than others; for example, visits to department and convenience store are more sensitive to sunlight than visits to hospitals or religious organizations.

A small body of literature examines the relationship between time and economic behavior. We highlight key findings here and provide a more complete accounting of the literature in Appendix Section C. In general, economic studies of time and behavior have uncovered several important relationships: daylight saving time switches do not consistently lead to significant electricity savings (Kellogg and Wolff 2008; Kotchen and Grant 2011; Rivers 2018; Shaffer 2019), and the timing of sunlight time can alter safety (Barnes and Wagner 2009; Doleac and Sanders 2015; Smith 2016), educational outcomes (Heissel and Norris 2018; Jagnani 2018), and even long-run earnings by disrupting sleep patterns (Gibson and Shrader 2018). 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.

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 conditions restrain that response. Assessing the potential impact of changing time conventions on energy use and human activity requires a deeper understanding of how and how much departures of clock time from solar time matter. This paper provides the first direct measurement of the clock vs. solar-time tradeoff using a detailed investigation across three different large-scale datasets on human activity timing.

2 Estimating the Clock- vs. Solar-Time Tradeoff

This section describes the empirical estimation in the paper. Section 2.1 provides the overall empirical approach, Section 2.2 documents the construction of the control for connectedness of areas across time zone boundaries, and Sections 2.3 to 2.5 describe the data and estimate the clock- vs. solar-time tradeoff for the Twitter, Census, and foot traffic datasets.

2.1 Empirical Approach

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

Let i denote location and t the observed day or week; our general specification is

$$\text{Mean(Activity Time)}_{it} = \;\; \text{Sunrise}_{it} + \;\; \text{Connectedness}_i + \;\; {}^{TZ} + X_{it} + \text{"}_{it} \tag{1}$$

The outcome $\text{Mean(Activity Time)}_{it}$ is the average local clock time of the activity aggregated across observations in location i during time interval t. For the Twitter and Census analyses, we measure time in hours after 4 AM, as 4 AM 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 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, complicating comparisons between weekdays and weekends. Further, in aggregate, observed foot traffic between midnight and 4 AM is very low and fairly constant (e.g., Appendix Fig. 7).

Sunrise_{it} is the main variable of interest: the time of sunrise at location i on time t. Given a latitude, a day, and a time zone, Sunrise_{it} identifies the extent to which the solar time at location i on date 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 during the summer solstice (June 20), the longest day of the year. The bottom panel shows the same for the winter solstice (December 21). In both maps, moving from west to east, local sunrise times increase until the next timezone border. Between the maps, locations that are farther north experience larger differences in sunrise time between the seasons. Our specifications, which include time-zone by latitude-bin fixed effects, rely on comparisons of activity and sunrise time between locations within the same time zone and latitude band. The specifications using Twitter and foot traffic data, which include temporal variation across the year, also incorporate comparisons across seasons.

Connectedness_i controls for the degree to which a location is connected to other areas with different clock times. We discuss the motivation and construction of Connectedness_i in detail in the next subsection. ^{TZ} represents a set of time zone dummy variables that allow different baseline clock times for the activity in different time zones—absorbing differences in average activity times across 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 (discussed below).

A positive 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, $= 1$ 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, $= 0$ would indicate that the activity follows clock time alone, ignoring solar time differences. $= 0{:}4$ 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 our Twitter data. 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.

The definition of an observation—and its implied level of aggregation—differs across the datasets. The following subsection discusses connectedness; the subsequent three subsections detail how we implement estimations for each of the three datasets. Appendix Table 2 summarizes each dataset.

2.2 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. 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.

To account for this possibility, we use 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 Section E. 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 Figures 8 and 9 illustrate the spatial distribution of these measures. As expected, connectedness to other time zones is strongest for counties near time-zone boundaries.[4]

2.3 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.[5] 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. Appendix Figure 6 documents the occurrence of each phrase throughout the day: "good morning" occurs earliest in the day, followed by "breakfast", "lunch", "dinner" and "good night" (which actually peaks in the early morning hours). Aggregate tweeting activity peaks around the middle of the day. Using tweets' geolocations, we identify the county in which each tweet occurs. We then compute the average time of tweet—as well as tweets with each activity

4. 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 signi cantly changing behavior timing.

5. 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 our estimation of the impact of clock time versus solar time. Further, our Twitter-based results are consistent with our Census results, which come from a random sample with substantial coverage of the US population. A more comprehensive description of the methods by which these data were obtained, stored, and processed can be found in Baylis (2020).

phrase—by county and date.

We then estimate the model

$$\text{Mean(Tweet time)}_{ct} = \ \text{Sunrise}_{ct} + \ \text{Connectedness}_{c} + \ _{c} + \ _{t} + "_{ct}$$

for county c on date t. Sunrise_{ct} is determined by county centroid and date, Connectedness_{c} is the average connectedness offset for the county described in Section 2.2, $_{c}$ are time zone by one-degree latitude bin xed effects, and $_{t}$ is a date-of-sample xed effects. $\text{Mean(Tweet time)}_{ct}$ refers to the average tweet time (measured in hours after 4 AM) for all tweets in the dataset for the date-county (or, in the next section, tweets containing a speci c key phrase). Observations from different counties are weighted by the average number of daily tweets for the county, and 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 0.357 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, 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) show that connectedness of a county to locations in other time zones does not signi cantly affect when a person tweets. In fact, we would expect the sign of this coef cient to be negative to the extent that greater connectedness with people in a “later” (further east) time zone would cause one to engage in activities earlier as measured in local clock time. Controlling for connectedness has very little effect on the estimated effect of sunrise time. In column (3), we also include demographic measures that might affect how individuals relate to their environmental surroundings—the percent of respondents in urban areas, the percent working in outdoor occupations, the percent in the labor force, and the (log) population of the observational unit, in this case, the county. The effect of sunrise time is virtually unchanged, while the coef cient on connectedness is now negative, though still far from statistically signi cant.

2.4 Census

We use the 2000 Census to estimate solar time's effect on the clock time that individuals leave for work. The 2000 Census Long Form asked what time during the week prior to “Census Day” (which was Saturday, April 1, 2000) the respondent typically left for work. For each of slightly more than 200,000 Census block groups (CBGs), we use the time elapsed between 4 AM and the average reported departure time as the primary variable of interest. We also analyze the mean time of arrival at work with nearly identical results. [6]

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 common to self-reported data. 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.

Sunrise time 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. For CBG c,

$$\text{Mean(Departure time)}_c = \;\; \text{Sunrise}_c + \;\; \text{Connectedness}_c + \;\; _c + \varepsilon_c$$

The results in column (1) of Panel B (Table 1) are consistent with the Twitter data results: 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 in column (3) is larger, but the implied effect is still quite small—indicating that a one standard deviation increase in connectedness causes one to leave for work about 5 minutes later. Adding the demographic and connectedness controls also has a substantial effect on the impact of solar time. 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 (where the sun rises 60 minutes earlier), offsetting more than half of the change in the solar time/clock time mismatch.

2.5 Foot Traffic

To analyze the effects of time measurement on human mobility, we use cellphone-based foot-traffic data from SafeGraph (SafeGraph 2021b). These data record visits to approximately 6.6 million points of interest (POIs) across the United States. SafeGraph defines a point of interest

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

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 the facts that (1) 2018 is the earliest year available and (2) data for 2020 and 2021 were distorted by COVID. The overall distribution of visits across the day on weekends and weekdays is given in Appendix Figure 7.

This dataset 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 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.

We estimate the model

$$\mathrm{Mean(Visit\ time)}_{inw} = \mathrm{Sunrise}_{cw} + \mathrm{Connectedness}_{c} + {}_{c} + {}_{w} + {}_{nz} + "_{inw}$$

for POI i in 6-digit NAICS category n during week w. CBGs, c, determine time-zone by latitude-bin fixed effects, as well as the sunrise time during 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 $_{nz}$. The Mean(Visit time) refers to the average visit time to i during week w, in hours after midnight.

The results, presented in Panel C of Table 1, again show a statistically significant adaptation to solar time and away from purely following clock time. However, the effect estimated in this case is less than half as large as the results from the Twitter or Census data. Column (1) 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 with the Twitter and Census results, adding the connectedness variable—column (2)—does not meaningfully change the estimated impact of solar time. Column (3) adds Census Block Group (CBG) demographics. The sunrise time coefficient is similar, and when all controls are included we measure a 10-minute visit time effect of a one-hour shift in sunrise time.

3 Heterogeneity in the Clock vs. Solar-Time Tradeoff

It's likely that the trade-off between operating on standardized clock time and local solar time varies depending on people, places, and activities. This heterogeneity could correlate with residents' demographics, but it could also vary with tweets' content or by the types of businesses and associated activities in the foot traf c 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 several demographic and activity categories and report the estimated effect of earlier sunrise on the timing of the activities.

3.1 By Location, Demographics, and Activities

Figure 2 presents separate point estimates and 95% con dence 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 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 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 signi cant at 1% level in the Census data and statistically signi cant at 5% level in the Twitter data.[7] One possible explanation for this result 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-traf c data suggest visits to points of interest adapt signi cantly 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 signi cant 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. This difference in heterogeneity highlights the potential that our three datasets shed light on somewhat different responses.

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.[8] Consequently, we might expect greater adaptation to solar time in more rural loca-

7. The p-value for the north-south difference in the foot-traf c data is 0.12.
8. The Urban variable is very bimodal, with most observations near 0 or 1, so we split the sample at 50%, rather than at the sample median, which is close to 1.

tions. However, we see no significant difference. The same is true in the next panel, where counties with larger shares of outdoor workers do not differ statistically from those with smaller shares for any of the activity measures.[9]

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).

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). Perhaps surprisingly, 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 2 uses 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.

3.2 By Establishment Type

Figure 3 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 3 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,

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

the lack of adaptation at religious establishments (primarily churches, temples and mosques), colleges and universities, medical care, and child daycare are noteworthy—suggesting more rigid scheduling independent of sunlight. Also interesting, tness 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 signi cantly from clock time in order to adapt to solar time, we do not see a consistent pattern across the types or locations of behavior.

4 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 show that individuals and rms systematically change their behaviors in response to changes in standardized clock time. These adaptive behaviors partially offset changes in standardized clock time. 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. 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 nd slightly smaller effects on the timing of individuals' tweets; shifting solar time one hour later causes tweeting to occur about 20 minutes later. In looking at foot traf c around stores and other locations open to the public, we nd a smaller, but still strongly statistically signi cant, offsetting about one-sixth of the mismatch between solar time and clock time.

Our ndings help illuminate the mechanisms underlying previous empirical work. First, the mixed evidence of the effect of daylight saving time on energy usage (Kellogg and Wolff 2008; Kotchen and Grant 2011) can be rationalized as partly re ective of differences in sunrise time across these papers' samples, consistent with arguments in Shaffer (2019). Second, both the above ndings on electricity usage and the ndings of increased vehicle crashes and decreased crime in Smith (2016) and Doleac and Sanders (2015) should be viewed as net of the shifting effect we observe, since the response of individuals to a daylight saving time shift is 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 2018). Our ndings 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 operate purely on clock time, ignoring environmental factors. 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 focused on observing daylight saving time or locations choosing time zones—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.

References

Bailey, Michael, Rachel Cao, Theresa Kuchler, Johannes Stroebel, and Arlene Wong. 2018. "Social connectedness: Measurement, determinants, and effects." Journal of Economic Perspectives 32 (3): 259–80.

Barnes, Christopher M, and David T Wagner. 2009. "Changing to daylight saving time cuts into sleep and increases workplace injuries." Journal of applied psychology 94 (5): 1305.

Baylis, Patrick. 2020. "Temperature and temperament: Evidence from Twitter." Journal of Public Economics 184:104161.

Bokat-Lindell, Spencer. 2021. "It's Time to Change the Clocks Again. Why Do We Do This to Ourselves?" The New York Times (November 4, 2021).

Doleac, Jennifer L, and Nicholas J Sanders. 2015. "Under the cover of darkness: How ambient light influences criminal activity." Review of Economics and Statistics 97 (5): 1093–1103.

Farrell, Diana, Vijay Narasiman, and Marvin Ward Jr. 2016. "Shedding Light on Daylight Saving Time." J.P. Morgan Chase & Co. (November).

Gibson, Matthew, and Jeffrey Shrader. 2018. "Time use and labor productivity: The returns to sleep." Review of Economics and Statistics 100 (5): 783–798.

Giuntella, Osea, and Fabrizio Mazzonna. 2019. "Sunset time and the economic effects of social jetlag: evidence from US time zone borders." Journal of health economics 65:210–226.

Hamermesh, Daniel S, Caitlin Knowles Myers, and Mark L Pocock. 2008. "Cues for timing and coordination: latitude, letterman, and longitude." Journal of Labor Economics 26 (2): 223–246.

Heissel, Jennifer A, and Samuel Norris. 2018. "Rise and shine the effect of school start times on academic performance from childhood through puberty." Journal of Human Resources 53 (4): 957–992.

Ingraham, Christopher. 2019. "How living on the wrong side of a time zone can be hazardous to your health." The Washington Post (April 19, 2019).

Jagnani, Maulik. 2018. "Poor sleep: Sunset time and human capital production." Mimeo.

Kellogg, Ryan, and Hendrik Wolff. 2008. "Daylight time and energy: Evidence from an Australian experiment." Journal of Environmental Economics and Management 56 (3): 207–220.

Kotchen, Matthew J, and Laura E Grant. 2011. "Does daylight saving time save energy? Evidence from a natural experiment in Indiana." Review of Economics and Statistics 93 (4): 1172–1185.

Latson, Jennifer. 2015. "When Daylight Saving Time Was Year-Round." Accessed May 27, 2024. https://time.com/3695333/daylight-saving-time-wwii/.

Metzger, Bryan. 2022. "Upset the sun sets so early? Blame the House for not voting to make daylight savings time year-round." Accessed May 27, 2024. https://www.businessinsider.com/house-failed-vote-daylight-savings-time-permanent-sunshine-protection-act-2022-12.

Prerau, D. 2009. Seize the Daylight: The Curious and Contentious Story of Daylight Saving Time. Basic Books.

Rivers, Nicholas. 2018. "Does daylight savings time save energy? Evidence from Ontario." Environmental and Resource Economics 70 (2): 517–543.

SafeGraph. 2021a. Social Distancing Metrics.

———. 2021b. Weekly Patterns.

Shaffer, Blake. 2019. "Location matters: Daylight saving time and electricity demand." Canadian Journal of Economics/Revue canadienne d'économique 52 (4): 1374–1400.

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)	(3)
Panel A: Time of tweet (Twitter)			
Sunrise	0.357	0.361	0.343
	(0.062)	(0.098)	(0.072)
Connectedness		0.251	0.286
		(3.051)	(1.705)
TZ Lat. bin (1 deg.) fixed effects	X	X	X
Day-of-sample fixed effects	X	X	X
N obs.	3,879,339	3,879,339	3,876,347
Panel B: Time left for work (Census)			
Sunrise	0.372	0.428	0.535
	(0.054)	(0.057)	(0.064)
Connectedness		1.744	3.227
		(0.866)	(0.830)
TZ Lat. bin (1 deg.) fixed effects	X	X	X
N obs.	188,246	188,246	188,237
Panel C: Avg. visit time (SafeGraph)			
Sunrise	0.154	0.165	0.166
	(0.026)	(0.030)	(0.030)
Connectedness		0.488	0.640
		(0.886)	(0.872)
TZ Lat. bin (1 deg.) fixed effects	X	X	X
Week-of-sample fixed effects	X	X	X
TZ NAICS (6 digit) fixed effects	X	X	X
N obs. (millions)	159.43	159.43	159.08

Notes: Each panel (A–C) provides estimated effects of the time of sunrise on a different outcome. Each column (1–3) provides estimates from differing regression specifications. 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. Column (3) includes demographic controls: proportion urban, proportion outdoor, proportion working, and the log of population. 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 POI's (point of interest) 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 coef cient and its 95% con dence 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 coef cient. The dimensions of heterogeneity: North/South (split at the 38.5^{th} latitude); Summer/Winter (summer: April–September); Rural/Urban (split at 50% urban), Indoors/Outdoor (split at median share employed in farming/ shing/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 xed effects corresponding to the appropriate dataset (see Section 2).

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 coef cients in this gure are estimated using 25 separate regressions for each six-digit NAICS code. We group and color the coef cients and con dence intervals (clustering errors at the state) by the industries' two-digit NAICS codes. The twenty- ve codes represent the 25 most-visited six-digit NAICS codes in our dataset.

ONLINE APPENDIX

Appendix A Comparative Time-Table for Railroad Coordination

Figure 4: Comparative Time-Table for Railroad Coordination (1857)

Notes Figure reproduces the time-table from Dinsmore'sAmerican 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, rm, 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.

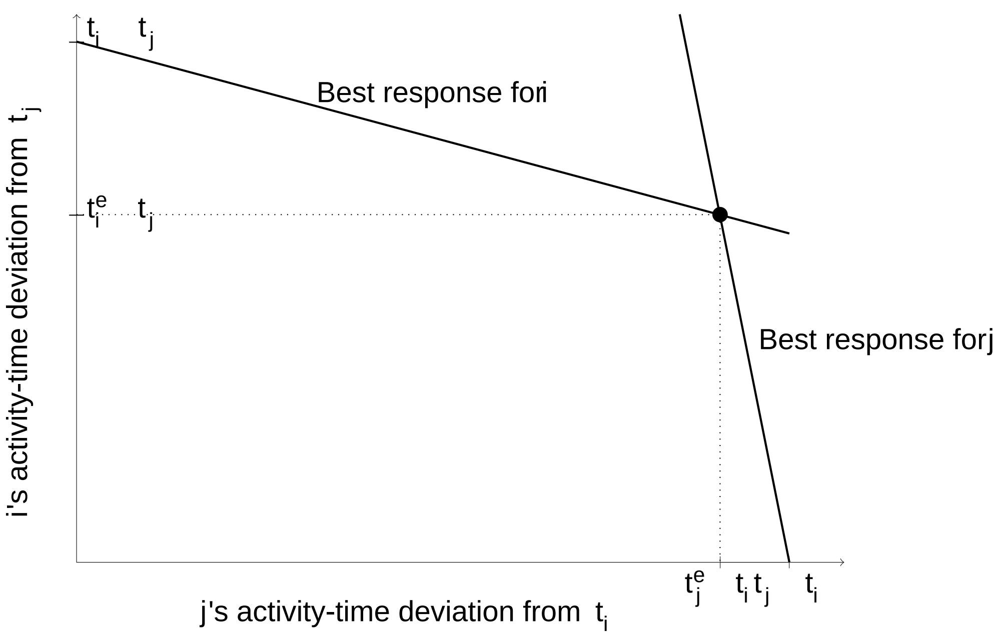
Assume that the utility that individual i gets from a speci c activity is a declining function of the deviation of the time of the activity from the individual's own preferred time t_i and a declining function of deviation from the time at which another individual, j, engages in the activity,

$$U_i = U_{0i} \quad f_i(|t_i \quad t_i|) \quad g_i(|t_i \quad t_j|):$$

And likewise for individual j,

$$U_j = U_{0j} \quad f_j(|t_j \quad t_j|) \quad g_j(|t_i \quad t_j|):$$

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 $f(0) = 0$, $f^{0}() > 0$ and $f^{00}() > 0$, and $g(0) = 0$, $g^{0}() > 0$ and $g^{00}() > 0$ for both i and j.[10] 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 $f_i^0 + g_i^0 = 0$. Conversely, j's best response to i's choice of t_i is $f_j^0 - g_j^0 = 0$. Under the assumptions on $f(\,)$ and $g(\,)$, 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.

10. To assure an interior equilibrium, we also assume that $f_i^0 > g_i^0$ and $f_j^0 > g_j^0$ for all t.

Appendix C Existing Literature

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, nd 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 nds 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 nd 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) nd that 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 nd 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.[11]

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

Appendix D 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-traf c		
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	

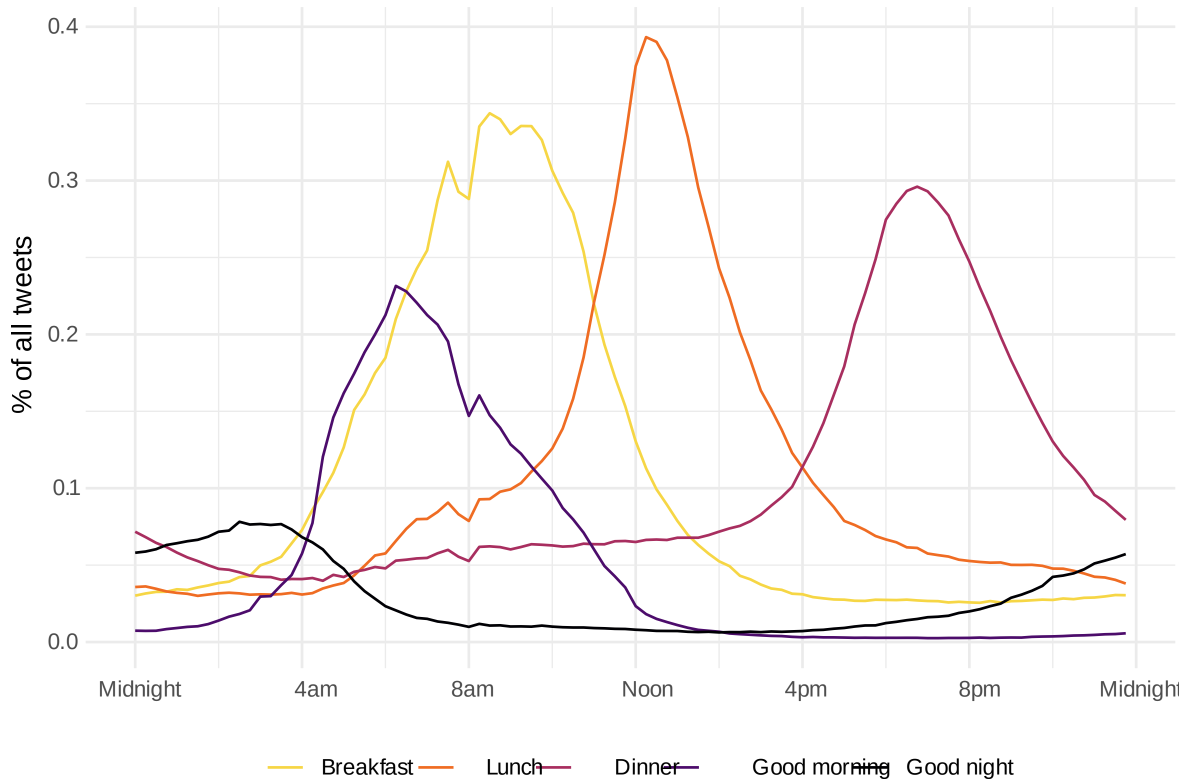
Notes Table of descriptive statistics for Twitter, Census, and foot traf c (Safegraph) datasets. Demographic variable represent counties for Twitter data and Census Block Groups (CBGs) for the Census and SafeGraph data. Observation counts: 3.9 million observations for Twitter data (2,875 counties; 1,512 days); 189,335 observations for Census data (2,877 counties); 159.4 million observations for foot-traf c 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,[12] and (3) are not missing location-related data. The resulting dataset includes

12. 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.

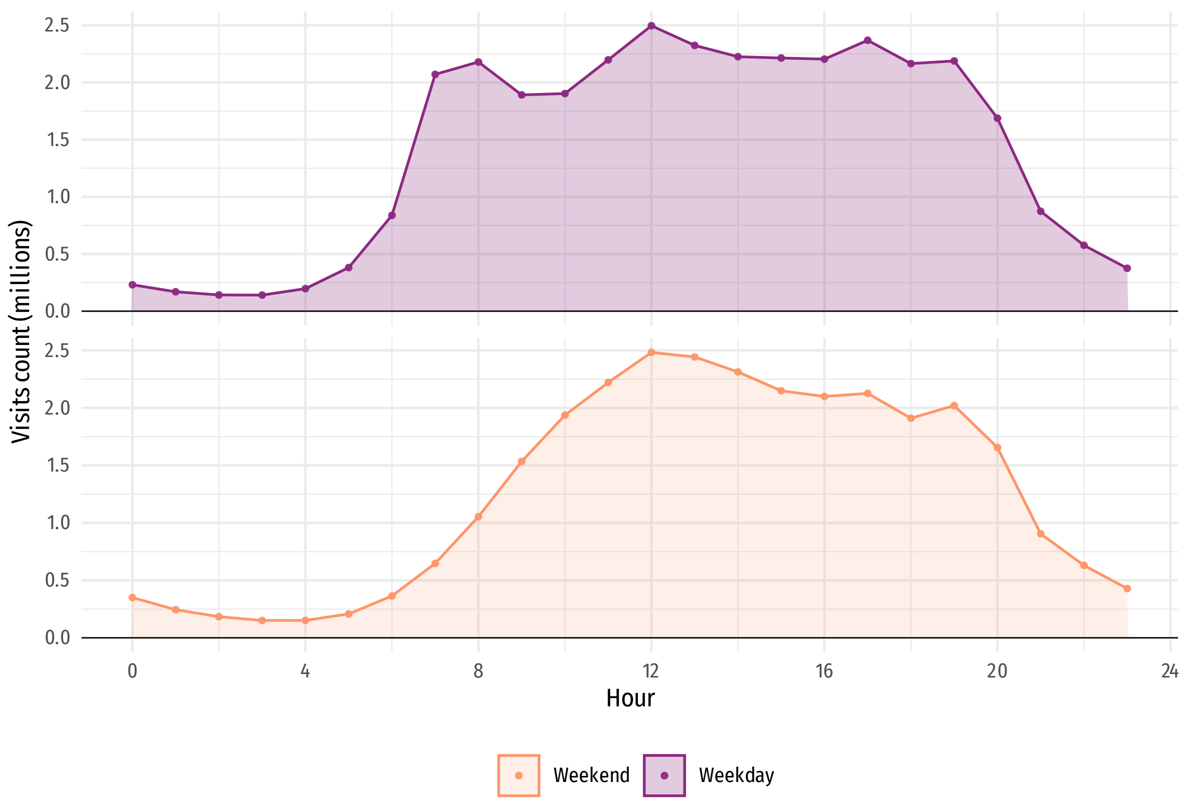
22.4 billion visits (91.6% of all visits in the dataset) to 2.2 million POIs covering 378 six-digit NAICS codes.

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 E 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.[13]

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., $V[h; \ ]$. We define this ratio as county h's connectedness to county d: $C[h; d] = V[h; d]=V[h; \ ]$, i.e., the share of visits from residents of county h that are to county d.[14]

Table 3 summarizes the measures of connectedness we use.

13. 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.

14. 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.

Figures 8 and 9 illustrate counties’ (1) mean offsets and (2) connectedness to their own time zones (along with state and time-zone borders). Counties near time-zone borders tend to spend more time in other time zones.

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.