Global Warming and the Siesta Effect

September 26, 2023

We are interested in the extent to which firms and individuals adapt to climate change by shifting the time when productive activity takes place. This includes shifting activity across seasons (e.g., decreasing work during the summer and increasing during cooler months); across days (e.g., working less on extremely hot days and more on colder ones, even within seasons); or across hours of the day (e.g., working more in the mornings and evenings, and less during the hottest times of day). We are also interested in the extent to which this time shifting helps mitigate the potential economic damage from rising temperatures.

# Part I: International Patterns

Our first goal is to document the relationship between the climate and major global difference in the timing of productive activity. To do this, we will compile all (??) internationally comparable time use surveys to investigate how time use is related to temperature.

The key sources of data are:

1. Geo-coded temperature data from ERA-Land
2. International time-use surveys [to be filled determined][[1]](#footnote-1)

The exact structure of the empirical analysis will depend a bit about the structure of the surveys.

Important things to determine are:

* Geographic precision: do we know individual locations or just regions/countries?
* Timing: Are there any surveys where individuals are followed over time? Are there surveys where there are multiple rounds, even if not a panel?
* Individual data: what information do we have about respondents? Occupation, age, etc.? • Survey questions: what are the best questions with broad coverage to capture what we’re interested in? Information about start time, breaks during the day, end time, time flexibility...?

## Descriptive Analysis

It would be great to start by visualizing the data. On the temperature side, we should put together global, gridded maps displaying:

1. Average temperature and exposure to extreme temperature (*>*30C)
2. Within-day temperature heterogeneity (SD and IQR)

It will be interesting to see which types of places are hot but with constant temperature and places with a lot of within-day heterogeneity (unsurprisingly, Southern Spain, birthplace of the Siesta, the difference between daily max and min temperatures can be 30 degrees F). This will be very useful to visualize and think through examples.

It will be great to do the same with the survey data on time use as well, once we figure out what those data look like. We will probably end up aggregating to the region or country level and map things like: average start time, average end time, average break during the day, etc. Another idea is to construct something like this ([https://www.printerland.co.uk/blog/ the-daily-routines-of-employees-around-the-world/)](https://www.printerland.co.uk/blog/the-daily-routines-of-employees-around-the-world/), but with our own data.

## Empirical Analysis

We can then investigate systematically how productive time use is related to temperature. Again, the exact structure of the analysis will depend on the survey data, but we have in mind estimating versions of:

TimeShift*i,c* = *βTg*(*i*) + Γ*Xi*′ + *ϵi,c* (1)

where TimeShift*i,c* is some survey-based measure of time use of individual *i* in country *c* (e.g., start time) and *Tg*(*i*) is the temperature of the grid cell *g* in which *i* is located. *Tg*(*i*) could be average temperature or, maybe more accurately, exposure to extreme temperature (days over 30C). We could also estimate a dynamic version of the same specification, to the extent to which we can track individuals or regions over time.

Next, we would expect the extent of time shifting to be greater in places with more scope for time shifting i.e. places with more within-day heterogeneity in temperature. To investigate this, we could estimate:

TimeShift*i,c* = *βTg*(*i*) + *γ*(*Tg*(*i*) × WithinHet*g*(*i*)) + Γ*Xi*′ + *ϵi,c* (2)

where WithinHet*g*(*i*) is the SD or IQR of the within-day temperature distribution. It would also be great to explore heterogeneity across sectors, occupations, etc.

Last, so far this has just focused on within-day time shifting, but we should also look out in the survey data for anything that would let us say something about cross-day or cross-season switching.

# Part II: Firm-Level Evidence from the US

Next, we turn to firm-level evidence to investigate time shifting patterns. Our goals are to (a) document that temperature predicts production timing, (b) show that this is especially true in places with high time shifting “potential” and (c) document that labor supply responds to climate shocks but that this is less true in places with high time-shifting “potential.” The two key sources of data are:

1. Daily geo-coded temperature data from ERA-Land
2. SafeGraph harmonized cell phone data

From the ERA-land data, we extract hourly temperature realizations for all grid-cells in the continental United States from 2018-present. There are two main sets of variables we need to construct. The first is a set of measures of daily temperature. We will likely want both the average temperature in each cell-day, but also measures of extreme temperature (e.g. an indicator if the average temperature is over 30 degrees, etc.). The second is a set of measures of within-day temperature heterogeneity. For each cell-month, we should construct the standard deviation and IQR of within-day temperature.

From Safegrah, we extract both the Places and Patterns Databases from 2018-present (the length that the data exist). We can exclude March 2020-September 2021 in order to avoid using data during major lock downs. There are again two main sets of variables to construct. The first, from the Patterns data, is then umber of unique visitors to each establishment in each day. The second, also from the Patterns data, is the monthly average number of individuals in the establishment in each hour of the day. This can be used to construct our measures of “time shifting” (see below). We will also use the sector associated with each establishment to determine which establishments to include in the sample and which are retail.

The temperature data can be linked to the ERA-Land data using the date and the latitude and longitude of each establishment from the Places data, which we can associate with the nearest ERA-Land cell.

## Temperature and timing

The first goal, mirroring the international analysis, is to simply document that on average, the timing of production is affected by temperature. We can use several potential measures of “morning shifted” production; these include (i) the share of total worker-hours in the morning (8-12, 8-11, 7-11, etc.) and (ii) the approximated start time, captured by the hour at which 90% (or 80% or 70%...) of individuals have arrived at the establishment. We then estimate:

MorningShift*i* = *β* · T*g*(*i*) + *αs*(*i*) + Γ*X*′ + *ϵi* (3)

where *i* indexes establishments, *αs*(*i*) are state fixed effects, and *X*′ is a vector of establishment-level controls. T*g*(*i*) is the average temperature over the sample period of the location of establishment

*i*. If MorningShift*i* is the measure from (i) we hypothesize that *β >* 0 and if MorningShift*i* is the measure from (ii) we hypothesize that *β <* 0.

State fixed effects (*αs*(*i*)) can help zero in on comparisons of geographically proximate counties. The set of controls (*X*′) can include features of geography (latitude, longitude, etc.) or establishment characteristics (sector fixed effects, total employment, etc.).

There is also a dynamic version of the same specification:

MorningShift (4)

where *m* now indexes months and *δi* are establishment fixed effects. Again, if MorningShift*i* is the measure from (i) we hypothesize that *β >* 0 and if MorningShift*i* is the measure from (ii) we hypothesize that *β <* 0. Instead of state fixed effects, we can now experiment with state-by-month fixed effects (*αs*(*i*)*,m*) and time varying controls (*Xi,m*′ ), which may be the same controls as Equation 3 interacted with month fixed effects. The inclusion of firm fixed effects makes this a more extreme test.

## Temperature and timing: High vs. Low Potential

We next investigate whether these patters are especially strong in locations and firms where there is “high time-switching potential.” One thing that increases scope for time switching is the withinday temperature distribution: if there is more within-day temperature heterogeneity, there is more scope to substitute activity toward cooler parts of the day. Using the temperature data, for each month *m* we can construct within-day temperature heterogeneity (standard deviation, IQR, etc.) for each establishment location. We can then estimate augmented versions of Equations 3 and 4, including an interaction term between temperature and within-day heterogeneity:

MorningShift*i* = *β* · T*g*(*i*) + *γ* · (T*g*(*i*) × Within Het*i*) + *αs*(*i*) + Γ*X*′ + *ϵi* (5)

MorningShift*i,m* = *β* · T*g*(*i*)*,m* + *γ* · (T*g*(*i*)*,m* × Within Het*i,m*) + *αs*(*i*)*,m* + *δi* + Γ*Xi,m*′ + *ϵi,m* (6)

Our hypothesis now is that *γ >* 0 if MorningShift*i* is the measure from (i) and *γ <* 0 if MorningShift*i* is the measure from (ii). The places with more within-day heterogeniety are more likely to shift work times, both in the cross section and in response to shocks.

Another source of “switching potential” could be differences across sectors and production processes. There are two strategies for capturing this in the data. The first is to try to construct some direct measure of sector-level “switchability.” This could be done using existing time use surveys or some more creative categorization of production tasks into those that can vs. cannot be shifted across time. A second strategy could be to directly estimate interaction terms between temperature and sector fixed effects in the equation above. This would tell us whether some sectors systematically switch more than others, and ideally we could map these fixed effect estimates back to things that make sense. One way or another, ideally we would develop some measure *Switchj*(*i*) for each sector *j*.

(By the way, another thing to think about is that some types of work might be more responsive because they are more exposed to temperature e.g. work that requires spending time outside or is more physical. Is farming in SafeGraph? How can we measure this?)

## Time Switching and Labor Supply

Next, we investigate how the patterns documented in the previous sections mediate the impact of temperature shocks on labor supply. In particular, we estimate versions of:

V*i,d* = *β*·T*g*(*i*)*,d* +*γ*·(T*g*(*i*)*,d* ×Within Het*i,m*)+*ϕ*·(T*g*(*i*)*,d* ×Switch*j*(*i*))+*αd* +*δi* +Γ*Xi,m*′ +*ϵi,m* (7)

where V*i,d* is the number of visitors to establishment *i* in day *d*. Here, we can include day fixed effects *αd* as well as establishment fixed effects *δi*. We can also include more detailed trends, like state-by-day fixed effects or state-by-month fixed effects, etc. Here, our hypothesis is that *β <* 0 but that *γ,ϕ >* 0. This would indicate that in places with greater “time switching potential,” the direct effect of temperature on overall labor supply is muted.

So far, we have focused on time switching within days. But in principle, switching could also happen across days. I guess the analogy to within-day temperature heterogeneity is cross-day temperature heterogeneity within the week. It would be interesting to know what the geographic distribution of this looks like.

# Part III: Implications for Productivity and Adaptation

Ideally, we would conclude by showing that this mechanism matters for mitigating the productivity consequences of temperature change. The goal would be to show that high temperature reduces firm-level or region-level productivity, but that these effects are muted in locations or industries in which Part II documented there is more scope for time switching. One idea was to do this with the US Census of Manufactures [To discuss: application for restricted use census data].

This could involve estimating some version of Equation 7, where as an outcome we had some measure of productivity. The other challenge is that we will likely not have daily measures of productivity (including in the Census data), so we will have to aggregate to the monthly, quarterly, or yearly level.

1. Two sources that we’ve found are this one: <https://www.timeuse.org/MTUS-User-Guide> and this one: [https: //hdr.undp.org/content/time-use-across-world-findings-world-compilation-time-use-surveys](https://hdr.undp.org/content/time-use-across-world-findings-world-compilation-time-use-surveys) [↑](#footnote-ref-1)