Climate Change and the Economy: The Role of Consumer Demand

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Summary

Climate change is expected to have enormous effects on economic activity, yet the channels through which these materialize are not well-known. Using high-frequency, spatially granular data, our research quantified the effect of temperature fluctuations on consumer demand, as measured by nearly 20 billion visits to a variety of business establishments in the U.S. over a 30-month period – from January 2017 through July 2019. Controlling for seasonality, secular trends, and any unobservable time-invariant location-specific characteristics, findings show that both abnormally warm and abnormally cold days increase same-day establishment visits (relative to a day where temperatures are between 0 and 3 degrees Celsius).

To understand how the demand response will evolve under changing climate conditions, it is necessary to look at how consumer habits may be altered by temperature variances within the local climate. This research indicates that warm temperature fluctuations have only a short-lived impact, while abnormally cold temperatures send consumers shopping more often and for a longer time frame. Specifically, the effect of abnormally warm temperature is short-lived, disappearing within 7 days. The effect of abnormally cold temperatures, however, persists for at least 45 days after the temperature shock and grows with time.

To further understand how the demand response will evolve under changing climate conditions, I then estimate how the demand response to temperature varies with the local climate. Places that have warmer temperatures on average experience a lower increase in establishment visits over 45 days, and places that are sufficiently warm are estimated to experience demand decreases over this time period. In other words, the warmer it gets the more consumer demand appears to wilt with extreme temperatures. Taken together, the results have important implications for how a changing climate may change patterns of economic activity.

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Introduction

Climate change is projected to alter the worldwide distribution of weather, with farreaching implications for many sectors of the economy. Most empirical research on the economic effects of climate change focuses either on aggregate outcomes, such as GDP or income, or on supply-side outcomes, such as agricultural output or labor supply. By contrast, the role of consumer demand in determining economic outcomes in the face of climate change is poorly understood. Quantifying the demand response can help researchers and policymakers better understand the mechanisms through which climate change affects economic output, deepening our knowledge of which sectors will be most affected by climate change. Additionally, climate-related changes in demand represent another source of climate risk for the private sector.

To estimate the effect of daily temperature fluctuations on consumer demand, our research used high-frequency, spatially-granular data that measured visits to a wide variety of business establishments. To consider both immediate (same-day) effects and longer-run (up to 45-day) effects, daily foot traffic data was compiled from SafeGraph and overlayed with daily temperature data from the National Centers for Environmental Information. Using cellular phone data, SafeGraph reports the number of daily visitors to over 4 million diverse establishments across the United States, including retail stores, restaurants, movie theaters, hospitals, schools, and religious establishments. The data span January 2017 through July 2019 and capture nearly 20 billion unique establishment visits across most of the United States. Data was aggregated by ZIP-code-day, and daily foot traffic was correlated to daily temperature fluctuations using a panel approach. To account for possible non-linearities in the effect of daily temperature, indicators for maximum temperatures falling into 3-degree-Celsius bins were used as key independent variables. Examining the demand response to past temperature abnormalities revealed the extent to which changes in demand are permanent. Interacting temperature variables with the local climate traced out the heterogeneity in the demand response across the distribution of climate.

After controlling for ZIP-by-month and date fixed effects, we find that both hot and cold daily maximum temperatures *increase* the same-day number of establishment visits. The lowest relative number of establishment visits occurs when maximum temperatures are between 0 and 3 degrees Celsius. This temperature range is lower than would be optimal for outdoor activities, suggesting that any additional visits are occurring at the expense of activities other than outdoor recreation. The effects of higher maximum temperatures are transient, disappearing in less than a week. This suggests that high temperatures merely shift the pattern of visits over time rather than increase or reduce total consumer activity. By contrast, the effects of cold temperatures grow with time in absolute terms: a day with maximum temperatures between -12 and -15 Celsius increases same-day establishment visits by about 43 visits but increases 45-day establishment visits by about 300 visits. This asymmetry between hot and cold days suggests that the underlying mechanisms through which they affect demand differ, although investigating such differences is beyond the scope of this paper. For example, hot temperatures may only affect the utility from being outdoors, while cold temperatures may also create demand for additional goods and services. Over a 45-day period, the demand increase in response to both abnormally hot and abnormally cold temperatures is estimated to be lower in places that are warmer on average. In areas that are sufficiently warm, demand may even decrease on net in response to temperature anomalies.

Literature on the economic impacts of climate change has focused on income as the main outcome of interest (e.g., Dell et al. 2012; Burke et al. 2015; Deryugina and Hsiang 2017). However, total income is determined by many factors, such as the decision of how many hours to work and, in some industries, by the demand for a firm's product. Additionally, researchers have documented that temperatures can affect a diverse number of outcomes, including sentiment, crime, and suicide (Hsiang et al. 2013; Baylis et al. 2018; Burke et al. 2018; Baylis 2020). Better understanding the mechanisms underlying any aggregate effects can shed light on which sectors of the economy face the highest climate change risks and potentially illuminate some adaptation possibilities.

The effect of weather fluctuations on labor supply has been investigated by several authors (Connolly 2008; Graff Zivin and Neidell 2014; Colmer 2018; Krüger and Neugart 2018). Demand responses, by contrast, have been understudied. It appears that the only study considering how climate change could affect demand patterns is Roth Tran (2020), who estimates the effect of weather fluctuations on sales of a specific apparel and sporting goods brand. Using machine learning, she finds that weather shocks have a relatively small and transient effect on sales, shifting them by about 10 percent over the few weeks following the shock. The effect is lower in areas that have historically high weather variability, suggesting that adaptation will occur in the longer run.

Data

Data on daily establishment visits from January 2017 through July 2019 from SafeGraph aggregate real-time location data from cellular phones to create a measure of daily foot traffic. The database also reports the name and ZIP code of each establishment. In total, over 4.1 million unique establishments are observed during the sample period. Observing establishment names facilitates the classification of establishments into types, albeit imperfectly.

Data on daily maximum and minimum temperatures, as well as precipitation were obtained from weather station data published by the National Centers for Environmental Information (NCEI) of the National Oceanic and Atmospheric Administration (NOAA). The latitude and longitude of each station and of each ZIP code were using to identify weather stations within 20 miles of the ZIP code centroid. We then calculated the inverse-distance-weighted maximum temperature, minimum temperature, and precipitation for each ZIP code-day.

The data reflect 34,710 unique 5-digit ZIP Codes with available weather readings and contain over 35 million ZIP-Code-day observations, reflecting a total of 19.8 billion unique establishment visits. Table 1 shows the summary statistics for the final dataset. The average number of daily establishment visits at the ZIP Code level is 557, but there is a large right tail: the standard deviation is more than twice the mean, and the maximum number of daily establishment visits exceeds 100,000. Maximum temperature averages 19 degrees Celsius and ranges from -44 to 60 degrees.

Notes: unit of observation is ZIP Code-date. Number of observations ranges from 34,752,425 for precipitation to 35,580,982 for the number of visits.

Figure 1 shows the spatial distribution of total establishment visits during the sample period (in thousands), using geospatial representations of ZIP Codes called ZIP Code Tabulation Areas (ZCTAs), produced by the US Census Bureau. The data have excellent spatial coverage, spanning all 50 states (ZIP Codes in Alaska and Hawaii also appear in the sample but are not shown). Each darker red area, corresponding to more densely populated portions of the United States, contains millions of unique establishment visits during the sample period. Lighter colored areas generally correspond to more rural areas of the US. Nonetheless, most of these areas have recorded at least 100,000 visits during the 2.5-year sample period.

Figure 1. Spatial distribution of establishment visits by ZIP Code Tabulation Area (ZCTA). Units are thousands of visits. White areas are either not a part of a ZCTA or have no recorded establishment visits during the sample period. Alaska and Hawaii not shown.

Figure 2 shows the distribution of ZIP Codes' mean maximum temperatures, as observed during the sample period. Half of the ZIP Codes have mean maximum temperatures between about 15 and 22 degrees Celsius; the median ZIP Code has a mean maximum temperature of 18.4 degrees. Almost 99 percent of ZIP Codes have mean maximum temperatures that are below 30 degrees Celsius, and 90 percent of ZIP Codes have mean maximum temperatures that are below 26 degrees Celsius. Note that because these averages are computed over the in-sample period of January 2017 through July 2019, they already reflect some of the effects of climate change. Ongoing climate change will further raise these ZIP Codes' average temperatures, shifting this distribution further to the right.

Figure 2. Distribution of ZIP Codes' mean maximum temperatures. Red line denotes the mean (19.1 degrees Celsius).

Methodology

The most parsimonious analysis of the temperature-demand relationship would be a simple correlation between foot traffic and temperature. However, such a correlation may reflect differences in seasonality (e.g., the holiday shopping season), as well as the current geographic distribution of where people live (e.g., the large US coastal population). To control for these factors, which are unlikely to be informative about the effects of climate change, this research estimates a relationship between establishment visits and temperature that controls for timeinvariant place characteristics, seasonality, as well as changes over time that are common to the entire United States. The basic regression specification is:

$$
Log(visit)_{zt}^{h} = \sum_{b} \beta^{b} 1[Temp_{zt} \in b] + \alpha_{z} + \alpha_{t} + X_{zt}^{h'} \gamma + \varepsilon_{zt},
$$
\n(1)

where $Log(visit)_{zt}^{h}$ is the natural log of all establishment visits in ZIP Code z starting on day t and spanning time horizon h , which ranges from 1 (same-day visits) to 45 (total visits over a 45day period). That is, visits over horizon h include all visits in a given ZIP code on days t through $t + h - 1$. To avoid missing values from zero visits, one (1) was added to the number of visits prior to taking the log.

The set of variables $\{1[Temp_{zt} \in b]\}$ are equal to 1 if maximum temperatures in ZIP Code z on day t fall into temperature bin b and are otherwise equal to 0. The internal temperature bins are constructed to span 3 degrees Celsius (e.g., one temperature bin is 12-15 degrees Celsius). The lowest temperature bin includes all temperatures below -15 degrees Celsius, and the highest bin includes all temperatures above 30 degrees Celsius. The omitted category is 0-3 degrees Celsius. The coefficients of interest are $\{\beta^b\}$, corresponding to the estimated effect of a day with abnormally warm or abnormally cool temperatures on establishment visits over time horizon h, relative to a day with temperatures that are between 0 and 3 Celsius. To account for the fact that temperatures are spatially correlated, standard errors are clustered at the ZIP-3 level (the first three digits of each 5-digit ZIP code).

Considering different values of h allows evaluating the extent to which the effect of a oneday temperature shock on demand persists. Intuitively, if abnormal temperatures merely affect *when* people visit a given establishment, but not the total number of visits, then one would detect a relatively large effect for small values of h (e.g., $h = 1$) but insignificant effects for larger values of h (e.g., $h = 45$). By contrast, if abnormal temperatures have delayed effects, then the estimates will grow with the time horizon. Delayed effects could arise if temperatures create the need for additional goods and services (e.g., if temperatures have delayed health effects or raise the utility from specific goods). To ensure that autocorrelation in temperatures does not confound estimation, controls X_{zt}^h include temperatures on days $t + 1$ through $t + h - 1$, constructed in the same way as contemporaneous temperature bins.

To see whether the effects of temperatures depend on typical temperatures in an area, Equation (1) was augmented to include interactions between the temperature bins and each ZIP Code's mean maximum temperature:

$$
Log(visit)_{zt}^{h} = \sum_{b} \beta^{b} 1[Temp_{zt} \in b] + \sum_{b} \vartheta^{b} 1[Temp_{zt} \in b] \times MeanTemp_{z}
$$
 (2)

$$
+ \alpha_{z} + \alpha_{t} + X_{zt}^{h'} \gamma + \varepsilon_{zt},
$$

where *MeanTemp_z* is the mean maximum temperature in ZIP Code z , as measured during the sample period. All other variables are as in Equation (1). The interpretation of the set of coefficients $\{\beta^b\}$ is that they reflect the effect of temperature bin b in a (hypothetical) ZIP Code with mean maximum temperature of zero degrees. The coefficient set $\{\vartheta^b\}$ then reflects the change in the temperature-visit relationship as average temperatures in a ZIP Code increase. If there is no effect heterogeneity by mean temperature, the estimates of $\{\vartheta^b\}$ should be close to zero and statistically insignificant.

Finally, to see how the effects vary by type of business, a version of Equation (1) was estimated that separately looks at 8 business categories: medical services (including dental and veterinarian services); food and restaurants; education; hospitality and grooming; religious establishments; financial services; professional services; and all others. These classifications were constructed manually from the business name, which sometimes required judgment calls. As such, there is likely some measurement error with respect to the business type, and these results should be interpreted cautiously.

Results

Figure 3 shows the relationship between maximum daily temperatures fluctuations and establishment visits over different time horizons ($h = 1$; $h = 7$; $h = 21$; and $h = 45$), estimated using equation (1). Relative to 0-3 degrees Celsius, both colder and warmer temperatures increase same-day establishment visits. The effects of days with more extreme temperatures are generally larger than those of days with more moderate temperatures. At the ends of the temperature distribution, both really cold ($\lt -15$ Celsius) and really hot (> 30 Celsius) days increase sameday establishment visits by about 4 percent or roughly 30 visits. This increase in demand could be due to establishments providing more comfortable environments compared to other places. Alternatively, or in addition to, extreme temperatures could be increasing the utility from specific goods and services.

The next panel shows the effect of one day of abnormal temperatures on total visits over the subsequent seven days. The effect of really cold days falls to about 2 percent of 7-day visits, but because weekly visits are about 7 times larger than daily visits, the absolute effect is larger, corresponding to an increase of almost 100 visits. The effect of abnormally warm temperatures, however, disappears completely, indicating that the same-day increase in visits caused by abnormally warm temperatures is short-lived. The warm-temperature patterns persist for time horizons of 21 days and 45 days. The absolute effect of cold temperatures, by contrast, continues to grow, with the coldest temperatures causing an increase of over 300 visits over three weeks and an increase of almost 500 visits over 45 days.

Figure 3. Effect of daily maximum temperatures on establishment visits over different time horizons, as indicated in the caption to each subfigure. Ranges indicate 95-percent confidence intervals. Estimates include ZIP Code and month-by-year fixed effects. Standard errors are clustered by 3-digit ZIP Code.

The asymmetry between the longer-run effects of warmer and cooler days suggests that the underlying mechanisms through which colder and warmer temperature affect economic activity are different. Specifically, warmer temperatures appear to merely shift the pattern of economic activity without altering it in the long run. By contrast, colder days appear to generate new demand, not just on the same day but in the following weeks. This could be because of physiological effects of cold days (e.g., delayed health effects) or due to increases in activities that may be habit-forming (e.g., visits to fast food establishments). Understanding the underlying mechanisms in more detail is an important line of inquiry for future research. Because climate change is projected to increase the number of hotter days and decrease the number of colder days, the results in Figure 3 imply that establishment visits will becomes less volatile with climate change, when such visits are aggregated to the weekly or monthly time scale.

To understand how the temperature-demand relationship varies with the local climate, Figure 4 plots the temperature-visit relationships estimated using Equation (2). The left side displays the estimates of $\{\beta^b\}$ over the time horizon indicated in the caption of each panel, while the right side plots the corresponding set of coefficients $\{\theta^b\}$. Recall that the coefficients $\{\beta^b\}$ should be interpreted as reflecting the effect of temperatures on establishment visits in a ZIP Code where the average temperature is 0. Only 11 ZIP Codes have average temperatures that are equal to or are below 0, and these estimates therefore do not have a clear in-sample interpretation. However, the sum $\beta^b + a\vartheta^b$ for various values of a can be used to infer how the effect of temperatures on establishment visits varies by climate.

Figure 4. Effect of daily maximum temperatures on establishment visits by average temperature. The set of figures on the left side shows the estimate effect of abnormal temperatures in a hypothetical ZIP Code where the average maximum temperature is zero. The set of figures on the right side shows how this effect changes as average temperature increases. The time horizon (in days) over which establishment visits are measured is noted in the caption below each figure. Ranges indicate 95-percent confidence intervals. Standard errors are clustered by 3-digit ZIP Code.

As the right-hand side of Figure 4 illustrates, each additional degree increase in average ZIP Code temperature raises the same-day effect of warm temperatures on establishment visits by about 0.5 percent. By using the estimated coefficients β^b and ϑ^b to solve $\beta^b + a^b \vartheta^b = 0$ for a^b , we can calculate approximately how warm a ZIP Code's climate needs to be before warmer temperatures raise, as opposed to lower, demand on net. For same-day establishment visits, these estimates imply that visits increase in response to warm temperatures in all ZIP Codes where mean temperatures are at least 6-14 degrees Celsius, depending on the temperature bin (see Table 2 below), and decrease when mean temperatures are below this value. The average effect of warm days on demand (Figure 3) is positive because most ZIP Codes in the sample have mean temperatures that are above these thresholds (see Figure 2).

For maximum temperatures that are lower than the reference category of 0 to 3 degrees Celsius, the baseline effects are positive and higher average temperatures are estimated to make them less positive. Combining the estimates of β^b and ϑ^b from these cold bins to solve $\beta^b + a^b \vartheta^b = 0$ for a^b indicates that cold temperatures cause a decrease in establishment visits among ZIP Codes whose average temperatures are at least 15-29 Celsius, depending on the bin (see Table 2 below). Correspondingly, the average effect of cold days on demand (Figure 3) is positive because most ZIP Codes in the sample have mean temperatures that are below most of these thresholds (see Figure 2).

Temperature bin	$h=1$	$h=7$	$h = 45$
< -15	15	35	55
-15 to -12	22	18	22
-12 to -9	30	19	21
-9 to -6	27	18	18
-6 to -3	22	17	19
-3 to -0	19	20	-4
3 to 6	14	18	15
6 to 9	14	18	17
9 to 12	13	19	17
12 to 15	11	18	18
15 to 18	9	17	18
18 to 21	8	17	18
21 to 24	7	16	18
24 to 27	6	-175	18
27 to 30	7	24	17
$>=30$	10	23	17

Table 2: Estimated "zero-effect" mean temperatures

Notes: Table shows the estimated average ZIP Code temperature where the total effect of the given temperature bin on establishment visits is zero.

For weekly visits, the change in the effect of days in warm temperature bins as average temperatures rise becomes non-monotonic and most of the estimates are close to zero. For visits over a 45-day period, the baseline effects of both cold and warm temperatures are positive and the changes in the effect as average temperatures increase are almost always negative. The third column of Table 2 shows that the breakeven points for warm temperatures of 17-18 degrees are very close to the sample average of 19 degrees, explaining why the estimated average treatment effect for warm temperatures is close to zero over 45 days. By contrast, the breakeven temperatures for colder bins are generally higher, explaining why the net effect of cold temperatures is positive even over a 45-day period.

The 45-day estimates in Figure 4 and the corresponding "zero-effect" thresholds in Table 2 imply that as climate change increases average temperatures across the United States, the effect of abnormally warm and of abnormally cold temperatures will depress foot traffic compared to the current distribution of temperatures. That is, as areas warm, the effect of both abnormally warm and abnormally cold days will become more pronounced. Of course, the frequency of colder days will decline as well, and the net effect will be spatially heterogeneous, as indicated by Table 2. In relatively cold places (e.g., with mean maximum temperatures of 10 degrees Celsius), extremely warm and extremely cold temperatures will both increase monthly demand. By contrast, in relatively warm places (e.g., with mean maximum temperatures of 25 degrees Celsius), such extremes will decrease demand over the subsequent 45 days.

Finally, Figure 5 shows the estimated effect of temperature fluctuations by establishment type. It is immediately apparent that there is remarkably little heterogeneity in the temperaturedemand relationship across different types of establishment. An important exception is medical establishments, where foot traffic increases by less on abnormally warm days than for other establishment types. This difference is consistent with medical care being less discretionary than other types of services and thus less responsive to weather. At the same time, the fact that foot traffic to medical establishments increases as a result of abnormally warm and abnormally cold days is consistent with the findings that both heat and cold have adverse health effects (Deschênes and Greenstone 2011; Heutel et al 2017).

Figure 5. Effect of daily maximum temperatures on establishment visits by establishment type. The time horizon (in days) over which establishment visits are measured is noted in the caption below each figure. Confidence intervals are suppressed for readability.

Conclusion

Absent substantial adaptation or mitigation efforts, climate change is projected to be costly to society. However, the exact mechanisms by which temperature fluctuations lead to lower income are not yet fully understood. A greater understanding of such mechanisms can enable businesses, governments, and individuals to better plan for the changes ahead.

The analysis of the temperature-demand relationship presented in this paper reveals that both cold and warm temperatures increase establishments' foot traffic. However, the effect of warm days is transient, while the effect of cold days grows with time. Combined with the projected reduction in the number of colder days, the estimates suggest that economic activity may suffer

under climate change on average but also become less variable. Understanding the mechanisms through which temperature fluctuations affect consumer habits is a fruitful area for further research.

Several caveats to this analysis are in order. First, the data do not contain any measure of expenditures. It is possible that spending behaves differently from establishment visits. Relatedly, the research does not account for e-commerce. Finally, the classification of establishments into business types may suffer from measurement errors, and these estimates should, therefore, be viewed as preliminary.

References

Baylis, Patrick, Nick Obradovich, Yury Kryvasheyeu, Haohui Chen, Lorenzo Coviello, Esteban Moro, Manuel Cebrian, and James H. Fowler. 2018. "Weather impacts expressed sentiment." *PLOS ONE*, 13(4): e0195750.

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

Burke, M., Hsiang, S.M. and Miguel, E., 2015. "Global non-linear effect of temperature on economic production." *Nature*, 527(7577): 235-239.

Burke, Marshall, Felipe González, Patrick Baylis, Sam Heft-Neal, Ceren Baysan, Sanjay Basu, and Solomon Hsiang. 2018. "Higher temperatures increase suicide rates in the United States and Mexico." *Nature Climate Change*, 8(8): 723-729.

Colmer, Jonathan. 2018. "Weather, labor reallocation and industrial production: evidence from India." CEP Discussion Paper (CEPDP1544).

Connolly, M., 2008. "Here comes the rain again: Weather and the intertemporal substitution of leisure." *Journal of Labor Economics*, 26(1): 73-100.

Dell, M., Jones, B.F. and Olken, B.A. 2012. "Temperature shocks and economic growth: Evidence from the last half century." *American Economic Journal: Macroeconomics*, 4(3): 66-95.

Deryugina, Tatyana, and Solomon Hsiang. 2017. "The Marginal Product of Climate." No. w24072. NBER Working Paper 24072.

Deschênes, O. and Greenstone, M. 2011. "Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US." *American Economic Journal: Applied Economics*, *3*(4): 152-185.

Graff Zivin, Joshua, and Matthew Neidell. 2014. "Temperature and the allocation of time: Implications for climate change." *Journal of Labor Economics*, 32(1): 1-26.

Heutel, Garth, Nolan H. Miller, and David Molitor. 2017. "Adaptation and the mortality effects of temperature across US climate regions." NBER Working Paper 23271.

Hsiang, Solomon M., Marshall Burke, and Edward Miguel. 2013. "Quantifying the influence of climate on human conflict." *Science*, 341(6151).

Krüger, J.J. and Neugart, M. 2018. "Weather and Intertemporal Labor Supply: Results from German Time‐Use Data." *Labour*, 32(1): 112-140.

Roth Tran, Brigitte. 2020. "Sellin' in the Rain: Adaptation to Weather and Climate in the Retail Sector." Working Paper. Available at SSRN: https://ssrn.com/abstract=3337110 or http://dx.doi.org/10.2139/ssrn.3337110.