The deadly effect of day-to-day temperature variation in the United States

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Keywords: climate change, mortality, temperature variability

Abstract
Recent research has found anthropogenic forcing to also affect day-to-day variability of temperatures. For many people, the climate is not only becoming hotter but also more volatile. Based on the new climate-economy literature, I explore the historical impact of day-to-day temperature variation on mortality in the United States over a 35-year period. I find that an extra +1 °C of daily temperature variability caused an additional 0.206 deaths per 100 000, equal to a 0.28% increase in the average monthly mortality rate. There is, however, evidence of adaptation to daily temperature variability as income and access to air-conditioning have increased and as people have become accustomed to large seasonal variation in temperatures. Given the deadly effect of day-to-day temperature variation, falling average daily temperature variability in the US since 1970 could have resulted in as many as 1400 and 1600 premature deaths avoided every winter and summer, respectively. In comparison, the increase in the number of days with a mean temperature above 35 °C could have caused an additional 655 premature deaths every year. These back-of-the-envelope calculations show that current estimates of the social cost of carbon are omitting an important channel for the mortality impact of climate change by not considering this additional effect of temperature volatility.

1. Introduction
A large body of empirical research has focused on estimating the social and economic impacts of climate change. Rising temperatures are projected to have profound impacts on almost all aspects of social and economic life, such as agricultural yields [1, 2], labor productivity [3–5], economic growth [6–8], conflicts [9–13] and mortality [14–18]. Climate change, however, will be especially costly in terms of human lives [19–21]. Almost a third of the world’s population is already exposed to at least 20 days a year with potentially deadly climate conditions, and in absence of drastic mitigation it is projected that this share will increase to three quarters of the population by the end of the century [22]. Despite the relatively modest increase in the global mean temperature so far, over a third of all heat-related deaths in summers can already be attributed to anthropogenic climate change [23].

It has been argued that several of the recent extreme temperature events have been too extreme to be explained by a simple increase in mean temperatures only [24–26]. While anthropogenic forcing is causing a general increase in seasonal mean temperatures [27], there is less certainty regarding its effect on daily temperature variability. Recent observational studies, however, have detected an increased spatial polarization in recent decades, with daily temperature variability increasing at low to mid latitudes [28] and decreasing at northern mid to high latitudes [29, 30]. This polarization of daily temperature variability can largely be attributed to anthropogenic greenhouse gas emissions [28, 30]. There is also seasonal heterogeneity in the effect of anthropogenic forcing on temperature variability, with large parts of Europe having experienced increased daily temperature variability in summers but decreased variability in winters [28]. For most of North America, however, temperature
variability has decreased in both summers [31] and winters [32].

While studies assessing the social and economic impacts of climate change have focused mainly on the impacts of rising mean temperatures [19, 33, 34], others have emphasized the importance of the potential impact of climate change on the variability of temperatures as well [35–38]. Humans are nature’s ‘generalist specialist’ species—although we can adapt to a wide range of climates, even extreme ones, we are still vulnerable to changes in our current climate [39].

Increased temperature variability will expose us more often to temperatures that deviate from the seasonal means that we have adapted to, and can therefore have additional social and economic consequences that are not properly accounted for in the literature.

There is currently only a handful of studies that have estimated the social and economic impacts of increased daily temperature variability. The literature has so far documented a harmful impact of temperature variability on agricultural production [40, 41], economic growth [42], and mortality [43–45]. Previous studies have found an association between exposure to day-to-day temperature variation and mortality risk among those with predisposing diseases [45], the elderly [44], and in several communities around the world [43].

Here I extend this emerging literature by exploring the historical impact of exposure to daily temperature variability on mortality for the full population in the contiguous United States over the period 1970–2004. This study builds upon the new climate-economy literature that uses panel data models with a rich set of fixed effects to isolate the variation in temperature exposure that stems from the stochastic nature of the weather [33].

To identify the causal effect of temperature variability on mortality it is important to separate between the direct and indirect effect of a change in variability. Figure 2 illustrates the temperature probability distribution for when there is only an increase in the mean temperature and for when there is also an increase in daily temperature variability. In both cases, there is an increase in the expected number of hot days. However, the increase in the expected number of hot days is largest for when there is also an increase in daily temperature variability. I isolate the direct effect of temperature variation on mortality by simultaneously estimating the impacts of exposure to increased daily temperature variability and exposure to extreme daily mean temperatures on mortality. The estimated impact on mortality from exposure to increased temperature variability can thus be interpreted as the additional effect on mortality that is separate from that of exposure to more days in the tails of the temperature probability distribution.
2. Methods and data

2.1. Data

Based on death certificates, the multiple cause-of-death (MCOD) files contain information about all deaths occurring on US territories [46]. Mortality rates are constructed by combining death counts with population estimates from the National Cancer Institute [48]. The monthly mortality rate is defined as the number of deaths that occurred in a county in a month per 100 000. In addition, age-specific mortality rates are constructed by counting the number of deaths per 100 000 in different age groups. Starting in 1989, county information is suppressed for deaths occurring in counties with less than a 100 000 people, and after 2004, all geographic information is suppressed in the public MCOD files.

Temperature data is extracted from the Global Historical Climate Network daily (GHCN-daily) database, maintained by the National Oceanic and Atmospheric Administration [47]. The GHCN-daily database contains daily summaries from a selection of land surface stations in countries all around the world with each station subjected to a common set of quality assurance checks. The variables of interest in the summaries are the daily maximum and minimum temperatures. Although the database contains almost 60 000 weather stations in the contiguous US, data is extracted only from stations that report a daily summary of the variables of interest for each day within a year to reduce the measurement bias from stations going online and offline [49]. If a station does not fulfill this criterion, then all observations from that station in that year are dropped from the sample. In addition, stations with an elevation above 2000 meters, or with missing information on elevation, are dropped from the sample. On average, there are almost 3000 stations that fulfill these criteria in any given year.

In the exploration of potential modulators of the effect of day-to-day temperature variability on mortality, observations on real income per capita and penetration rates of air-conditioning are used. Annual real income per capita for each county is taken from the Bureau of Economic Analysis [50], while the annual share of households with air-conditioning for each state is taken from [51]. The final data set contains monthly observations on mortality, temperatures, air-conditioning and income for 3101 unique counties from 1970 to 2004. Because of the restrictions on geographic information for deaths occurring in small counties after 1988, only 397 of these counties are observed throughout the full sample period.

2.2. Temperature variables

All temperature variables are constructed at the level of the weather station. The variables are aggregated to the county level by taking a weighted average of observations from all weather stations within a 300 km radius of the county centroid. The weights given are the inverse of the squared distance between the station and the centroid, hence giving a higher weight to closer stations and a lower weight to stations more likely to being located in a neighboring county. Day-to-day temperature variation is measured as the standard deviation of daily mean temperatures within a month, with the daily mean temperature calculated as the average of the daily maximum and minimum temperature.

To isolate the effect of temperature variability from that of exposure to extreme temperatures, a 4th order polynomial in the daily mean temperature is constructed. First, the daily mean temperature observed at each station is raised to the \( n \)th power. Second, the \( n \)th polynomial is aggregated to the county level by taking a weighted average across all stations as described above. Lastly, the \( n \)th polynomial is summed across all days in a month for each county. Under the assumption that weather events are additive, this aggregation of the daily mean temperature to the monthly level preserves the nonlinear
relationship between mortality and temperature that occurs on the day-to-day level [52].

A potential modulator of the relationship between mortality and daily temperature variability is the extent that people are accustomed to temperature variation throughout the year. I therefore follow [42] and calculate the seasonal temperature difference, which is calculated as the difference between the highest and lowest daily mean temperature observed in a county in a year, averaged across all the years in the sample for each county.

### 2.3. Regression models

The impact of daily temperature variability on mortality is estimated by exploiting the variation in temperatures and mortality within counties over time. In the main analysis, I use ordinary least squares regression to estimate the parameters of following regression model

\[
y_{\text{cym}} = \beta_0 + \beta_1 \sigma(T)_{\text{cym}} + \gamma_{\text{cym}} \text{TIME}^2 + \epsilon_{\text{cym}}
\]

where \(y_{\text{cym}}\) is the number of deaths per 100,000 in county \(c\), year \(y\) and month \(m\). In some specifications, \(y\) is the age-specific mortality rate. The regression model estimates the marginal effect of day-to-day temperature variation, \(\sigma(T)_{\text{cym}}\), which is measured as the monthly standard deviation of daily mean temperatures. To isolate the direct effect of day-to-day temperature variation from that of exposure to days with extreme temperatures, the model controls for the latter. This control is captured by \(f(T)_{\text{cym}}\), which is a 4th order polynomial in the sum of daily mean temperatures: \(\omega_1 \sum_d T_{\text{cym}} + \omega_2 \sum_d T_{\text{cym}}^2 + \omega_3 \sum_d T_{\text{cym}}^3 + \omega_4 \sum_d T_{\text{cym}}^4\) where \(T_{\text{cym}}\) is the mean temperature on day \(d\) raised to the \(n\)th power as explained in the previous section.

One concern to causal interpretation is the presence of county characteristics that are correlated with both mortality rates and temperatures, e.g. income. A spurious relationship could also arise from the strong seasonality in both mortality rates and temperatures. To address these concerns, the model includes a county-by-month fixed effect, \(\alpha_{\text{cym}}\), and a year-by-month fixed effect, \(\rho_{\text{ym}}\). The first effect absorbs unobserved but permanent differences in mortality between counties in each month of the year. The second fixed effect absorbs the seasonality in the variables of interest and time shocks that are common to all counties. In addition, the model includes a quadratic time trend, \(\delta_{\text{cym}} \text{TIME}^2\) and \(\gamma_{\text{cym}} \text{TIME}^2\), that is interacted with a county-by-month identifier to allow each county a unique trend in seasonal mortality rates and temperatures.

Although exposure to high temperatures is associated with an increase in mortality in the near term, some of this increase is counteracted by a lower mortality rate than expected in the following days and weeks [14, 53]. This phenomenon is known as ‘harvesting’, where exposure to extreme temperatures is expediting the deaths of people that are severely ill. The aim of this analysis, however, is to explore whether exposure to increased daily temperature variability is associated with meaningful changes in life expectancy. Since equation (1) is estimated on the monthly level rather than the daily level, it is less likely that the estimated marginal effects of temperature exposure are driven by a simple short-term displacement of deaths. Nevertheless, longer exposure windows could still be necessary to explore the long-term effect of temperature exposure on mortality [16, 18, 51].

I explore harvesting by expanding the model in equation (1) with lagged temperature variables

\[
y_{\text{cym}} = \sum_{l=0}^{L} (\beta_l \sigma(T)_{\text{cym}-l} + f(T_{\text{cym}-l})) + \alpha_{\text{cym}} + \rho_{\text{ym}} + \delta_{\text{cym}} \text{TIME} + \gamma_{\text{cym}} \text{TIME}^2 + \epsilon_{\text{cym}}
\]

where \(\beta_{l=0}\) is the impact on mortality from an increase in day-to-day temperature variation this month, while \(\beta_{l=1}\) is the effect from an increase in day-to-day temperature variation in the previous month. If an (unexpected) increase in temperature variability is mostly expediting the deaths of the already ill, we expect to see that an increase in daily temperature variability this month has a negative effect on future mortality, i.e. \(\beta_{l=1} < 0\). The long-run impact of temperature variability on mortality after \(L\) months is thus given by the sum of the coefficients, \(\sum_l \beta_l\).

Adaptation to daily temperature variability is explored by expanding the model in equation (1) with interactions between the temperature variables and potential modulators

\[
y_{\text{cym}} = M \times (\phi_0 + \phi_1 \sigma(T)_{\text{cym}} + \phi_2 f(T_{\text{cym}})) + \alpha_{\text{cym}} + \rho_{\text{ym}} + \delta_{\text{cym}} \text{TIME} + \gamma_{\text{cym}} \text{TIME}^2 + \epsilon_{\text{cym}}
\]

where \(M\) contains a single or multiple modulators of the temperature-mortality relationship. The modulators include the log of real income per capita in a county in a year, air-conditioning penetration rates in state in a year, and county-specific seasonal temperature differences. Equation (3) allows the marginal effects of daily temperature variability and extreme temperatures to vary as linear functions of these modulators.

In all regressions, observations are weighted by the population in county \(c\) in year \(y\), and standard errors are clustered on the county level to

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1 Although cumulative weather events such as e.g. heat waves, could have a particular harmful impact on human health; because the regression models in the new climate-economy literature tend to be very demanding on the data it is common for papers in the literature to assume additivity.
allow for arbitrary within-unit auto-correlation in the disturbance term $\epsilon_{\text{sym}}$.

3. Results

Over the sample period, 1970–2004, the average American was exposed to a monthly standard deviation of daily mean temperatures of 3.58 $^\circ$C (table A6). By exploiting the within-county variation in daily temperatures over time, I find that exposure to increased day-to-day temperature variation has had a deadly effect in the United States. Figure 3 shows the estimated relationship between day-to-day temperature variation and mortality from estimating the regression model in equation (1). Using the full sample from 1970 to 2004, I find that exposure to a $+1$ $^\circ$C increase in the standard deviation of daily mean temperatures during a month caused an additional 0.206 deaths per 100 000 in a county (95% confidence interval: [0.151, 0.261]). Given that the average monthly mortality rate was 73.3 deaths per 100 000 in the sample, the marginal effect of daily temperature variability translates to only a 0.31% increase in the base rate ($0.206/73.3 \times 100$). The deadly impact of daily temperature variability found in the full sample is not driven by the unbalanced nature of the data. Limiting the sample to only the 397 counties that were observed in all years returns a marginal effect similar to the one estimated in the full sample (0.213 vs. 0.206).

3.1. Heterogeneity and robustness

Heterogeneity in the impact of day-to-day temperature variation on mortality is explored by estimating equation (1) for different subsets of the data. A $+1$ $^\circ$C increase in the monthly standard deviation of daily mean temperatures caused an additional 1.351 deaths per 100 000 among those aged 65+. However, because of the high average mortality rate in this age group, the marginal effect of daily temperature variability translates to only a 0.31% increase in the base rate ($1.351/438.9 \times 100$). Exposure to increased temperature variability did not have a statistically significant effect on mortality among those 45 years and younger.

There has also been a large decline in the marginal effect of exposure to day-to-day temperature variation over time, which is similar to the decline previously found for the US in the marginal effect of exposure to days with extreme temperatures [51]. Over the sample period, the marginal effect of an additional $+1$ $^\circ$C in the monthly standard deviation of daily mean temperatures fell from 0.351 deaths per 100 000 in the 1970s to 0.108 deaths per 100 000 in the early 2000s.

To explore whether exposure to increased daily temperature variability is more or less harmful when natural temperature variability is higher, equation (1) is estimated separately for summer months (June, July and August) and winter months (December, January and February). Although a deadly impact of exposure to increased daily temperature variability is found in both summers and winters, the impact of a $+1$ $^\circ$C increase in the monthly standard deviation of daily mean temperatures is found to be more than twice as deadly in summer months (0.604) than in winter months (0.268) when natural temperature variability is higher.

The estimates presented so far have been the effect of exposure to increased daily temperature variability on mortality within the same month. To explore whether exposure to increased day-to-day temperature variation in a month is followed by reduced mortality in the following month, I estimate the distributed lag model in equation (2) with a one-month lag. Figure 3 reports both the contemporaneous and lagged marginal effects of daily temperature variability, and the cumulative effect over the two-month exposure window. I find little evidence of harvesting in the deadly impact of day-to-day temperature variation. To the contrary, the coefficient on the one-month lag of daily temperature variability is positive (albeit not statistically significant) and the cumulative effect over the two-month exposure window is slightly higher than the baseline estimate from equation (1) (0.239 vs 0.206). This indicates that the deadly impact of daily temperature variability represents a meaningful change in life expectancy rather than a short-term displacement of deaths. In fact, a deadly impact can be observed until nine months after the initial exposure to increased daily temperature variability (figure A3).

3.2. Adaptation to daily temperature variability

The observed decline in the marginal effect of exposure to extreme temperatures on mortality has largely been attributed to rising income levels [20], and especially to increased penetration of residential air-conditioning [51]. I investigate the effect of income and residential air-conditioning on the deadly effect of day-to-day temperature variation by estimating equation (3) that expands the baseline model in equation (1) with interactions between these potential modulators and daily temperature variability. Figure 4 shows the marginal effect of a $+1$ $^\circ$C increase in the monthly standard deviation of daily mean temperatures as a linear function of the log of real income per capita in a county and the share of households with air-conditioning in a state. Although the interactions are not statistically significant, both modulators are associated with a decrease in the deadly effect of daily temperature variability.

Over the sample period, the median county experienced an increase in real income per capita from 12 160 to 36 330 dollars (in 2012 dollars), and went from being located in a state where only 44% of households had access to air-conditioning to a state with full penetration of residential air-conditioning. Using the estimates from the regression model that
Figure 3. Heterogeneity and robustness in the marginal effect of daily temperature variability. The table shows the marginal effect of a $+1\, ^\circ\text{C}$ increase in the monthly standard deviation of daily mean temperatures from estimating the model in equation (1) with different samples, and from estimating the distributed lag model in equation (2) with a one-month lag on temperature exposure. Nobs. is the number of observations used for estimating each of the models, while Base rate is the average mortality rate in the specific sample.

| Sample          | Nobs. | Base rate | Estimate (95% CI) |
|-----------------|-------|-----------|-------------------|
| Full sample     | 787752| 73.3      | 0.206 (0.151, 0.261) |
| Balanced sample | 164220| 74.1      | 0.213 (0.159, 0.268) |
| < 1 yr          | 787524| 100.6     | 0.146 (-0.171, 0.462) |
| 1-44 yrs        | 787524| 9.6       | 0.012 (-0.008, 0.033) |
| 45-64 yrs       | 787524| 73        | 0.153 (0.073, 0.234) |
| > 64 yrs        | 787524| 438.9     | 1.351 (0.996, 1.707) |
| 1970-1981       | 442848| 75        | 0.351 (0.281, 0.42)  |
| 1962-1993       | 284304| 73.3      | 0.192 (0.113, 0.272) |
| 1994-2004       | 60600 | 71.4      | 0.108 (0.02, 0.197)  |
| Summer months   | 196938| 69.6      | 0.604 (0.481, 0.728) |
| Winter months   | 196938| 78.8      | 0.268 (0.163, 0.373) |
| Current month   | 784651| 73.3      | 0.215 (0.17, 0.259)  |
| Lagged month    | 784651| 73.3      | 0.024 (-0.039, 0.086) |
| Current + lagged| 784651| 73.3      | 0.239 (0.15, 0.326)  |

Includes both modulators simultaneously (column (3) in table A5), these increases are associated with a 52% reduction in the marginal effect of a $+1\, ^\circ\text{C}$ increase in the monthly standard deviation of daily mean temperatures (from 0.211 to 0.102), bringing the marginal effect close to the estimate observed at the end of the sample period in figure 3.

Previous research on the temperature-mortality relationship has found an important modulator to be the extent that people are expecting to be exposed to extreme temperatures [20, 51]. This could be the reason why the marginal effect of daily temperature variability was found to be substantially lower in winters when within-season temperature variability is high (figure 3). In addition, I explore the effect of between-season temperature variability on adaptation by allowing the marginal effect of day-to-day temperature variation to vary as a linear function of the average seasonal temperature difference in a county. There is substantial variation in the average seasonal temperature difference across counties in the US, ranging from $20\, ^\circ\text{C}$ to $55\, ^\circ\text{C}$ (figure A4).

A higher average seasonal temperature difference is associated with a reduction in the deadly effect of day-to-day temperature variation (column (4) in table A5). By combining the regression result with the county-specific seasonal temperature differences, figure 5 shows county-specific marginal effects of a $+1\, ^\circ\text{C}$ increase in the monthly standard deviation of daily mean temperatures. There is a distinct spatial pattern in the marginal effect of daily temperature variability on US mortality in the period 1970–2004. A deadly effect is mainly found in areas along the West coast and in the South, whereas in areas in the Midwest, where the population is accustomed to large between-season temperature variation, exposure to increased daily temperature variation had little to no effect on mortality.
4. Discussion and conclusion

By using methods from the new climate-economy literature, this study has explored the deadly effect of exposure to day-to-day temperature variation on the population in the United States over a 35-year period. I find that a $+1$ °C increase in the monthly standard deviation of daily mean temperatures caused an additional 0.206 deaths per 100,000 over the sample period 1970–2004. This deadly effect of daily temperature variability is the direct effect of daily temperature variability on mortality that comes in addition to that of exposure to extreme temperatures. There has, however, been substantial adaptation to daily temperature variation, both over time as income and access to air-conditioning have increased, and across space as areas with a large seasonal temperature difference have grown accustomed to variation in temperatures.

Previous research has detected a reduction in day-to-day temperature variation in both summers and winters in large parts of North America \[31, 32\]. That means that although I find a deadly marginal effect of day-to-day temperature variation,
the total effect of falling temperature variability in North America could in fact have been to reduce temperature-related mortality in the United States over the period of study. To quantify this potential reduction in temperature-related mortality from reduced daily temperature variability, I fit a linear trend to the annual and seasonal average monthly standard deviation of daily mean temperatures over the period 1970–2020 (section A.4 in supplementary data). According to the linear trends, the average American has since 1970 experienced a 0.54 °C reduction in average daily temperature variability in winters and a 0.26 °C reduction in average daily temperature variability in summers (figure A5).

Using the season-specific estimates from figure 3 and assuming a US population of 330 million people, the estimated reductions in winter and summer temperature variability translate to approximately 1400 premature deaths avoided each winter and almost 1600 premature deaths avoided each summer. In comparison, the average American experienced over the same period an additional 0.575 days with the mean temperature above 35 °C (figure A6). Using the estimated 4th order polynomial in daily mean temperatures (figure A2), this increase in the number of hot days translates to an additional 655 premature deaths every year. While mean temperatures will continue to increase [27], climate change could cause even further reductions in daily temperature variability in the US in the future [28].

These back-of-the-envelope calculations underline the importance of also considering the deadly effect of temperature variability when estimating the mortality cost of climate change. It is projected that if emissions levels continue to rise undeterred, daily temperature variability can double in low latitudes while decreasing by up to 40% in high latitudes by the end of the century [28]. Since current estimations only consider the effect of rising mean temperatures they may severely underestimate the mortality cost in areas with rising temperature variability, while overestimating the mortality cost in areas with declining temperature variability. However, in the long run, people will most likely grow accustomed to a more volatile climate, which could mitigate some of the deadly impact of increased daily temperature variability.

Although the focus here has been on the United States, the deadly effect of day-to-day temperature variation documented in this study may offer some broader insights. For instance, not all areas in the United States have experienced falling daily temperature variability (figure A7). In some areas, temperature variability has instead increased, causing an increase in the number of temperature-related premature deaths (figure A8). The effect of anthropogenic forcing on day-to-day temperature variability could deepen current inequalities between rich and poor areas. If the observed polarization of seasonal temperature variation between high and low latitude areas continues, then poor countries in the South will not only continue to bear the burden of heat-related mortality [20, 23], but they will also bear the burden from increased day-to-day temperature variation. In addition, low income and seasonal temperature difference might make it even more difficult for these countries to adapt to a potentially more volatile climate.

Data availability statement
The data that support the findings of this study are available upon reasonable request from the authors.

Acknowledgment
This work was supported by the Norwegian Research Council through the Centre for Research-Based Innovation ‘Climate Futures’, project number 309562.

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