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EXTREME WEATHER EVENTS, MORTALITY AND MIGRATION

Olivier Deschenes
Enrico Moretti

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ABSTRACT

We estimate the effect of extreme weather on life expectancy in the US. Using high frequency mortality data, we find that both extreme heat and extreme cold result in immediate increases in mortality. However, the increase in mortality following extreme heat appears entirely driven by temporal displacement, while the increase in mortality following extreme cold is long lasting. The aggregate effect of cold on mortality is quantitatively large. We estimate that the number of annual deaths attributable to cold temperature is 27,940 or 1.3% of total deaths in the US. This effect is even larger in low income areas. Because the U.S. population has been moving from cold Northeastern states to the warmer Southwestern states, our findings have implications for understanding the causes of long-term increases in life expectancy. We calculate that every year, 5,400 deaths are delayed by changes in exposure to cold temperature induced by mobility. These longevity gains associated with long term trends in geographical mobility account for 8%-15% of the total gains in life expectancy experienced by the US population over the past 30 years. Thus mobility is an important but previously overlooked determinant of increased longevity in the United States. We also find that the probability of moving to a state that has fewer days of extreme cold is higher for the age groups that are predicted to benefit more in terms of lower mortality compared to the age groups that are predicted to benefit less.

Olivier Deschenes
Department of Economics
2127 North Hall
University of California
Santa Barbara, CA 93106
olivier@econ.ucsb.edu

Enrico Moretti
University of California, Berkeley
Department of Economics
549 Evans Hall
Berkeley, CA 94720-3880
and NBER
moretti@econ.berkeley.edu

1. Introduction

Through the twentieth century, the United States population has experienced an unprecedented increase in life expectancy. The economic value of such increase is enormous, exceeding, by some calculations, the value of the growth in all non-health goods and services (Nordhaus, 2002). While the determinants of the increase in life expectancy are numerous and complex, it appears that economic growth, public health measures and especially science and technology were important determinants. Cutler, Deaton and Lleras-Muney (2006) provide a recent survey of the importance of the various determinants and their interplay.[1]

In this paper we focus on the relationship between weather and mortality in the US. Specifically, we estimate the effect of episodes of extreme heat and extreme cold on longevity. We use these estimates to provide new evidence on the underlying causes of long-run increases in life expectancy experienced by the US population over the past several decades.[2]

Extreme weather events generate enormous interest in the public. Each summer, the popular press devotes significant coverage to the impact of heat waves on mortality. Heat waves are claimed to kill scores of people, especially among the poor and the elderly. Recent examples include the 2006 heat wave in California (400 deaths), the 2005 heat wave in Arizona (100 deaths), and the particular deadly heat wave in France in 2003, which according to the French National Institute of Health and Medical Research caused 18,000 deaths. Cold waves are also claimed to increase mortality. The clamor that is associated with these events sometimes results in drastic and costly policy changes. For example, following the 1995 heat wave which reportedly caused 800 deaths in Chicago, Mayor Richard M. Daley put in place an articulated policy of response to extreme weather events that includes the mobilization of thousands of emergency personnel to contact, provide supplies to and, in some cases, relocate elderly citizens.[3]

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[1] See Costa (2003) for historical evidence.

[2] While considerable attention has been devoted to effect of weather on economic outcomes in developing countries (for example, Miguel, 2005; Acemoglu, Simon and Robinson, 2003; Oster 2004), less attention has been devoted to the effect of weather in the US.

[3] In addition to the immediate impact of extreme weather on mortality, there is now increasing concern that higher temperatures and incidence of extreme weather events caused by global warming could create major

While it is clear that mortality spikes in days of extreme hot or cold temperature, the significance of those deaths in terms of reduction in life expectancy is much less clear. The number of deaths caused by extreme temperatures on a given day could be compensated for by a temporary fall in mortality in the subsequent days or weeks, if extreme temperature principally affects individuals whose health is already compromised. This could happen if extreme temperature precipitates the health condition of individuals who are already weak and would have died even in the absence of the shock. In this case the only effect of the weather shock is to change the *timing* of mortality, but not the number of deaths. Such temporal displacement is sometimes referred to as the "harvesting" effect. Thus, the excess mortality observed on cold and hot days does not necessarily imply significant permanent reductions in life expectancy.[4]

Unlike much of the previous literature, our estimates of the effect of extreme weather events on mortality allow for a flexible dynamic relationship between weather shocks and mortality, and therefore account for the possibility of near-term mortality displacement. We base our analysis on data that include the universe of deaths in the United States over the period 1972-1988. We match each death to weather conditions in the day of death and the county of residence. The use of high-frequency data and the fine geographical detail allow us to estimate with precision the effect of cold and hot temperature shocks on mortality, as well as the dynamics of such effects.

Our results point out to widely different impacts of cold and hot temperature on mortality. Consistent with accounts in the media, we find that hot temperature shocks are indeed associated with a large and immediate spike in mortality in the days of the heat wave. As expected, this effect is particularly large for elderly individuals. Remarkably, however, almost all of this excess mortality is explained by near-term displacement. In the weeks that follow a heat wave, we find a marked *decline* in mortality hazard. This

public health problems in the future. A growing literature analyzes that, and related questions (Deschenes and Greenstone 2007, Kalkstein 1993, Tol 2002). In this paper, however, we leave these issues aside and focus on the impact of extreme temperature on realized longevity.

[4] On the other hand, the opposite may also be true. Consider for example, the case where unusually low temperature today results in increased mortality over the next few days or weeks, because some respiratory conditions take time to fully develop and spread. This lagged response would imply that the long run effect of extreme weather is larger than the short run effect.

decline completely offsets the increase during the days of the heat wave. As a consequence, there is virtually no lasting impact of heat waves on mortality.

In contrast, we find that the cold temperature days have a significant and long-lasting impact on mortality rates. Cold waves are associated with an immediate spike in mortality in the days of the cold wave, but there is no offsetting decline in the weeks that follow. The cumulative effect of 1 day of extreme cold temperature during a 30-day window is an increase in daily mortality by as much as 10%. As such, the deaths attributable to cold temperature represent significant reduction in life expectancy. This impact of cold weather on mortality is mostly attributable to increased mortality due to cardiovascular and respiratory diseases. When we stratify by income, we find that the impact of extreme cold temperature is significantly larger in low income areas. In particular, the effect for counties in the bottom income decile is 66% larger than the effect for counties the top income decile. Not surprisingly, infants and older adults are more affected by cold temperature than prime-age adults.[5]

The aggregate magnitude of the impact of extreme cold on mortality in the US is large. We estimate that the number of annual deaths attributable to extreme cold temperature in the white population is 27,940, or almost 700 deaths per cold day. This roughly corresponds to 1.3% of deaths in the United States. We interpret this figure as a remarkably large number. For example, this total exceeds the annual deaths due to leukemia, homicide, and chronic liver disease / cirrhosis. Of course, there are sizable differences across cities in the incidence of cold-related deaths. Minneapolis, Detroit, Cleveland, and Chicago are the most affected, with estimates ranging from 1.5% to 3.3% of annual deaths that could be delayed by changing the exposure to extreme cold days.

Our findings have important implications for explaining improvements in life expectancy of the U.S. population. We estimate that a significant fraction of the increase in longevity experienced by the US population over the past thirty years can be attributed to reduced exposure to cold days induced by geographical mobility. Geographical mobility affects longevity because it modifies the exposure of individuals to extreme temperatures. As a whole, the U.S. population has moved from cold Northeastern states

[5] In contrast, cold temperature *reduces* mortality for young adults (aged 20-34) through a marked reduction in motor-vehicle accidents fatalities.

to warm Southwestern states. For each individual in the US who lives in a state different from the state of birth, we compare the exposure in the state of residence with the counterfactual exposure that that individual would have experienced in the state of birth.

We calculate that each year 5,400 deaths are delayed by the changing exposure to cold temperature due to mobility. The average number of years of life gained per delayed death is 9.1 years, a sizable increase in life expectancy. As a consequence, the average individual experiences an increase in longevity of 0.02-0.03 years per calendar year as a result of the lower exposure to cold weather. We compare this figure to the annualized increase in longevity experienced in the United States over the past thirty years, which has been 0.25 years per calendar year. Thus, our estimates indicate that 8%-15% of the gains in longevity experienced by the US population over the past three decades are due to the secular movement toward warmer states in the West and the South, away from the colder states in the North. This evidence on mobility-induced changes to cold weather exposure identifies an important but previously overlooked explanation for increased longevity in the United States.

Finally, we test whether mobility decisions of individuals are sensitive to the health benefits associated with avoiding extreme cold. We find that the probability of moving to a state that has fewer days of extreme cold is higher for the age groups that are predicted to benefit more in terms of lower mortality compared to the age groups that are predicted to benefit less.

The paper is organized as follows. In the next section, we review the existing literature on the link between extreme weather and mortality. In Section 3 we describe the data. In Section 4 we present the estimates of the effect of heat and cold waves on mortality. In Section 5, we quantify the effect of cold waves on longevity and the effect of geographical mobility on longevity. Section 6 concludes.

2. Background

Within certain limits, healthy individuals can cope with thermal stress caused by increases or decreases in ambient temperatures through thermoregulatory responses. For example, exposure to both high and low temperatures generally triggers an increase in the heart rate in order to increase blood flow from the body to the skin. Thus in periods of prolonged exposure to excessive cold or hot temperatures the increase cardiovascular stress results in mortality for some individuals.

The relationship between excessively high or low temperature and mortality has been well-documented since the early 1900s (see Grover 1938 for an early example), though most of the emphasis is on the effect of elevated temperature. In fact, most of the first and second-generation studies consisted of case studies of particular heat waves. Since then, the focus has shifted somewhat to studying the longer-term relations between weather and mortality. Basu and Samet (2002) offer a comprehensive overview of the literature on heat-related mortality.

Mechanisms. The prominent causes of death in periods of elevated temperatures are cardiovascular diseases, respiratory diseases, and cerebrovascular diseases. Similarly, cold-related mortality is also mostly attributable to cardiovascular diseases. The main mechanism underlying the increased mortality in periods of excessive temperature is the additional stress imposed on the cardiovascular and respiratory systems by the demands of body temperature regulation. These additional demands can be particularly taxing on individuals with limited physical ability to adapt like the elderly. The mechanisms linking mortality to cold temperature also stem from increased burden on the cardiovascular system. Exposure to excessively cold temperature can lead to increase cardiovascular stress because of vasoconstriction and increased blood viscosity. Less is known as to which groups of the population are more likely to be affected by such effects.

Behavioral risk factors. The literature has identified several risk factors associated with heat-related mortality, though the identification strategies used is sometimes questionable. Most of the risk factors appear to be related to socioeconomic status. For example, multiple studies have showed that access to air-conditioning greatly reduces mortality risks during period of elevated temperatures. While socioeconomic factors are strong predictors of heat-related mortality, other factors also appear important. Klinenberg (2003) documents the effect of the 1995 Chicago heat wave on mortality. He argues that the reason why elderly mortality seems be more sensitive to heat waves than mortality of other age groups is isolation. In addition, persons living in densely population urban areas have high risks than those living in rural or suburban areas of because of the phenomenon known as the “urban heat island effect” (Landsberg 1981). Unfortunately, there is much less evidence available on the risk factors associated with cold-related mortality.

Indirect effects. A smaller literature has also established that weather fluctuations can also affect human health through indirect channels. For example Bhattacharya, DeLeire, Haider and Currie (2002) examine the effects of cold weather periods on family budgets and on nutritional outcomes in poor American families. They find that poor families increase fuel expenditures and reduce food expenditures in response to cold weather. Weather events also have important impacts on the incidence of motor-vehicle accidents. Eisenberg and Warner (2005) found that on snow days there were more nonfatal accidents than on dry days, but less fatal crashes. They also found evidence of behavioral adjustment in the sense that the first snowy day of year was associated with substantially higher accident risk than subsequent snow days.

3. Data and Preliminary Analysis

The mortality data is drawn from the Multiple Causes of Death (MCOD) files for 1972-1988. Data are obtained from certificates filed for deaths occurring in each state.[6] The key variables for our analysis are the cause and age of death, exact date of death, and county of occurrence.[7] Throughout the analysis we pool males and females together and estimate the models separately for 10 age groups. For each of these groups, we construct a balanced panel of mortality totals for each day between 1972 and 1988. Each of those panels has 18,487,710 observations.[8] The balanced MCOD data are then combined with county-level population totals by age groups to calculate daily-level mortality rates that we will use in the analysis.[9]

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[6] Since 1968, the MCOD files provide information on all deaths occurring in the United States. However, information on *exact* date of death is only available in the public-use data for 1972-1988. After 1988, only the month of death and the weekday of death (e.g. Monday, Tuesday, etc) are reported in the public-use files.

[7] We exclude 130 counties from the analysis because they either changed name or FIPS over the course of the study period. The majority of those are from Virginia.

[8] There has been 6,210 days between 1972 and 1988, so for the 2977 counties in our sample, this amounts to 18,487,710 observations.

[9] The population data are from the 1968-88 Compressed Mortality Files.

The weather data are drawn from the National Climatic Data Center Summary of the Day Data (TD-3200). The data are daily measurements from 24,833 weather stations that were operational in the United States at some point over the sample period. The station-level data is aggregated at the county level by matching stations to the closest county. Matches are based on the exact longitude and latitude of the weather station and the longitude and latitude of the county centroid. For the period 1972-1988, we obtain a panel of 12,534,615 county-day observations with non-missing information on daily temperature and precipitation.

Table 1 shows the average daily mortality rates per 100,000 population by age group and for selected causes of death.[10] Row 1 reports that the average daily mortality rate for all age groups is 2.54 per 100,000 population. Thus on average during the period 1972-88, there are 2.54 deaths per 100,000 on a typical day in the United States. Importantly, our estimates of the average daily mortality rate are consistent with the average annual mortality rates reported by the National Center for Health Statistics.[11]

The typical age-profile of mortality is apparent when examining the columns of Table 1. For all-cause mortality, infant mortality rates are higher than any age group younger than the 55-64 group. Then, beginning with the 55-64 age group, mortality rates increases exponentially with age, peaking at 44.3 deaths per 100,000 in the 85 and above age group (our last category). In addition to all-cause mortality we also consider 7 mortality causes: infectious disease, neoplasms, cardiovascular disease, respiratory disease, motor-vehicle accidents, suicides, and diabetes.[12] Together, these 7 causes explain 86% of the overall mortality rate. As is well-known, mortality due to cardiovascular disease is the single most important cause of death in the population as a whole. The figures in column 1 suggest that on a typical day, there are 1.30 deaths per 100,000 attributable to cardiovascular disease. However, the relative importance of each cause of death differs by age. For example, respiratory disease is the most frequent cause of infant death, while motor-vehicle accidents is the most important in explaining mortality up to age 44. Finally, for the population aged 45 and above---where the

[10] All statistics reported in this paper are weighted by the county population in relevant year and age group.
[11] For example, in 1980 the annual mortality rate was 878.3 per 100,000, which roughly corresponds to the daily-level estimate we report in Table 1 ($2.54 \times 365 = 927.1$).
[12] Together, these 5 causes of death explain approximately 80% of the overall mortality rate.

mortality rates increase exponentially with age---cardiovascular disease and neoplasms are the two primary causes of mortality.

Seasonal patterns in mortality. Panel B in Table 1 documents the seasonality of mortality patterns for each age group. For simplicity, we present all-cause daily mortality rates by season of occurrence. The well-documented seasonality in mortality (see e.g. Alderson 1985, McKee 1989) is apparent in column 1. For the population as whole, mortality is highest in the winter months, followed by fall, spring and summer. The same seasonal pattern is observed for infants and for age groups 45-54 and above. Interestingly the pattern is reversed for children and young adults (under the age of 45): for these groups, daily mortality rates are highest in the summer, followed by spring, fall and winter.

The seasonal pattern of mortality is even more evident in the panels of Figure 1, which shows the full seasonal patterns of all-cause and cause-specific mortality rates. On the horizontal axis is each day of the year, starting at 1 for January 1 and ending at 365 for December 31 (for simplicity we excluded February 29 in leap years). Each line in the figure represents the average mortality rate per day for all age groups over the period 1972-1988. We removed the mean of each series in order to have a common scale for each series. Panel A shows the overall mortality rate. Again, the pervasive seasonality in all-cause mortality is apparent: mortality rates essentially follow a U-shaped pattern, with the peaks in January and December, and lowest points in the mid-July to mid-August period. Similarly, cardiovascular mortality, displayed in panel B also follows U-shaped pattern. However, the season trend of all-cause mortality is not mirrored in all the specific causes. For example, there is essentially no seasonality in mortality due to neoplasms, as seen in panel C. Finally, panel D shows that respiratory disease mortality is also concentrated in the winter months.

Seasonal patterns are not same everywhere. Figure 2 documents the geographical variation in the seasonal patterns of mortality. To this end we compare Suffolk County, MA (which includes the city of Boston) and San Diego County, CA (which includes the city of San Diego). These counties were chosen because of the marked difference in their winter climate, and because of the similarity of their summer climate and other characteristics, such as per capita income.

Again, we removed the mean of each series in order to have a common scale for each figure. In order to emphasize the main trends, the series were smoothed using a 7-day moving-average. Panel A in Figure 2 shows the average daily all-cause mortality rates of all age groups for Suffolk, MA (full line) and San Diego, CA (dashed line). For both counties we observe that mortality rates follow the U-shaped seasonal patterns showed in Figure 1, but also with geographical differences. For example, it is apparent that the mortality rate is higher in Suffolk than in San Diego in the winter months (days 1-90). Panels B-D of Figure 2 further document the seasonal differences in mortality rates between San Diego and Suffolk by examining mortality rates for specific causes of death.

Table 2 quantifies these differences by reporting estimates from a simple "difference-in-difference" model where the coefficient of interest is the interaction term between winter months and Suffolk County, MA. That is, we pool our data on daily mortality rates for the two counties and estimate a linear regression model of the daily mortality rate on a dummy for Suffolk County, a dummy for winter months, and an interaction between Suffolk and winter months. The first column in Table 2 reports the estimated coefficients on the interaction term, winter dummy and Suffolk County dummy (winter and Suffolk dummies are only reported for all cause mortality). The excess winter average daily mortality rate per 100,0000 in Suffolk relative to San Diego is 0.2433 with a standard error of 0.0349. In column 2 we report difference-in-difference estimates based on age-adjusted mortality rates to the 1980 Standard Population. This approach normalizes the age difference in the populations of San Diego County and Suffolk County, and thus the estimates are not confounded by secular age differences. Again, we find evidence of excess winter mortality in the coldest county. The difference in average winter daily mortality rates per 100,000 between Suffolk County and San Diego County is 0.1419 (std error = 0.0333).

Panel B of Figure 2 indicates that cardiovascular mortality shows the same pattern as overall mortality, with excess mortality rates in Suffolk during the winter days. For that cause, the estimated excess mortality rate is 0.1319 in column 1 and 0.0688 in column 2 (standard errors are 0.023 and 0.021 respectively). Neoplasms, which are depicted in Panel C show essentially no seasonal patterns for both counties, as was the case in Figure 1. This is also apparent in Table 2 where the interaction terms for neoplasms are small in magnitude and statistically insignificant. Panel D shows the seasonal patterns of mortality due to respiratory disease, and while the data in the figure are noisier, the difference-in-difference estimates of excess mortality in Table 2 are positive and statistically significant. There is also little evidence of significant difference of excess winter mortality due to diabetes, and external causes. Finally, we note that the difference in the magnitude of the estimates in columns (1) and (2) underlines the importance of using age-adjusted mortality rates to avoid confounding differences in population age-structures across counties. Any subsequent estimates for the overall population are therefore based on age-adjusted mortality rates. In practice, however, the estimates of the extreme temperature effects based on crude mortality rates and age-adjusted mortality rates are very similar when we analyze the 2,279 counties in our sample.

4. Estimates of the Effect of Extreme Weather on Mortality

In this section we present static estimates of the effect of weather shocks on mortality. We begin in Subsection 4.1 by presenting estimates of the contemporaneous effect of heat and cold waves on mortality. In Section 4.2 we consider a more general model that includes the effect of heat and cold waves on mortality not only in the days of the extreme weather event, but also in the days and weeks following it. This model allows us to calculate the long run effect of the event, net of any harvesting and accounting for any delayed impacts in the effect. In Subsection 4.3 we differentiate the effect by cause of death. Finally, in Subsection 4.4 we investigate whether the effect depends on county income and relative exposure.

4.1 Contemporaneous Effect

To quantify the contemporaneous effect of extreme temperature on mortality in any given day and location, we estimate a simple linear model relating the daily mortality rate in a county, Y_{cdt}, to a daily temperature measurement for this county (T_{cdt})[13]:

$$(1)\ Y_{cdt} = \alpha + \beta T_{cdt} + \lambda_{cmt} + u_{cdt}$$

where c denotes county, d denotes day of the year (1-365, except in leap years where d ranges from 1-366), m (1-12) denotes month, and t denotes year (1972-1988). In order to account for seasonality and geographical differences in mortality patterns documented in the previous section, we include a series of county-by-year-by-month effects, λ_{cmt}. With 16 years of data and 2,279 counties, there are approximately 400,000 such effects. We also include a quadratic in daily precipitation. Since weather and mortality are likely to be serially correlated over time within county, all standard errors reported in this paper are clustered at the county level.

Under the assumption of a linear additive model, the county-by-year-by-month effects non-parametrically account for all the determinants of mortality that vary across counties and months over time, as well as for the monthly level seasonality in mortality. This is important since seasonality in mortality has been known to confound estimates of the temperature-mortality relationship (Mackenberg et al. 1992). As such, the temperature effect on mortality is identified from county-by-year-by-month deviations in temperature. Since the daily mortality in low-population counties may exhibit sizable day-to-day variation, we also weight the all regression models by county population.

We experimented with several possible specifications of the temperature effects. We begin in Table 3 by reporting the estimates where T_{cdt} is a dummy equal to 1 if the mean temperature in county c, day d and year t is below or above a predetermined threshold. Mean temperature in a given day is defined as the simple average of the minimum and maximum temperature that day. Since the underlying model relating weather and mortality is unknown, we examine several possible thresholds,

[13] Since the literature is unclear as whether mortality is more related to daytime or nighttime temperatures, we use the 24-hour average temperature for each day.

corresponding to cold and heat-related mortality.[14] Panel A presents results from models with dummy variables corresponding to “cold” temperature, where the daily mean temperature is below 10°F, 20°F, and 30°F respectively. Panel B presents results from models with dummy variables corresponding to “hot” temperature, that is, where the daily mean temperature is above 70°F, 80°F, and 90°F respectively.

The first row of Table 3 shows the fraction of days in our sample where the mean temperature falls below or above a given threshold. For example, 1% of all days have a mean temperature below 10°F, while 0.6% of all days have a mean temperature above 90°F. The estimates for the cold weather models indicate that there is a small immediate increase in mortality on cold days. For example, the all-cause mortality rate increases by 0.0252 on days where the mean temperature falls below 10°F. This impact corresponds to a 1% effect, compared to the mean daily mortality rate reported in Table 1. The standard error corresponding to the point estimate is 0.012, indicating a statistically significant impact. The other contemporaneous impacts of “cold” temperature are similar in magnitude, although the percent effect appears to decline slightly when we use 20°F or 30°F as thresholds.

The remaining rows are organized by mortality cause. Examination of the cause-specific estimates reveals two significant patters: First, the estimated cold weather effect is entirely driven by excess cardiovascular mortality on cold days. Second, mortality due to external causes is lower on cold days, in particular for motor vehicle accidents. Presumably this is due to the fact that fewer people leave their houses and drive in extreme cold, also there is evidence that snowfall is associated with fever fatal crashes (Eisenberg and Warner 2003). However, the magnitude of the impact on external causes is small relative to the average daily mortality rate.

Unlike the moderate impacts of cold temperature days on mortality rates, the estimates for hot temperature in Panel B are much larger in magnitude. The all-cause mortality rate increases by 0.1011 (std error = 0.0122) on days where the mean temperature goes above 80°F, corresponding to a 4% effect. Similarly, mortality rates are

[14] Other aspects of daily weather such as humidity and wind speed could influence mortality, both individually and in conjunction with temperature. Importantly for our purposes, there is little evidence that using wind chill factors (a non-linear combination of temperature and wind speed) perform better than simple temperature levels in explaining daily mortality rates (Kunst et al. 1994).

approximately 2.5-3.7% higher on days where the average temperature goes above 70°F or 90°F. Turning to specific causes of death, the entries in Table 3 suggest that hot weather excess mortality is mostly attributable to cardiovascular diseases, and, to a lesser extent, to an increase in neoplasms. The immediate impact of heat on cardiovascular diseases and neoplasm mortality has been reported elsewhere (see e.g. Braga et al. 2002 and Huynen et al. 2001).

In conclusion, the evidence in Table 3 is thus suggesting that mortality rates are significantly higher on both cold and hot weather days, but that the excess mortality on hot days is substantially larger (e.g. 3-6 times larger) than on cold days. This evidence is consistent with the popular notion that "heat waves" (and, to a lesser extent, cold waves) significantly increase mortality, and with the dramatic characterization of these events found in the popular press.

4.2 Dynamic Effect

The results reported so far do not take into account the potentially dynamic relationship between temperature and mortality. It is possible that deaths resulting from extreme temperature could constitute near-term mortality displacement. In other words, extreme temperatures may simply anticipate the death of individuals whose health is already compromised and who would have died a few days later even in the absence of the event. In this case the weather shock only effect is to change the *timing* of mortality, but not the number of deaths. Such temporal displacement is sometimes referred to as the "harvesting" effect. If this is the case, extreme temperatures could have no significant permanent effect on life expectancy and the contemporaneous estimates reported in Table 3 could grossly overstate the mortality effect of cold and hot temperature shocks.

On the other hand, it is also possible that the presence of dynamic effects may have the opposite effect. This could happen, for example, if an unusually low temperature today results in increased mortality over the next few days or weeks, because some respiratory conditions take some time to fully develop and spread. This lagged response would imply that our estimates in Table 3 underestimate the true long run effect.

Ultimately, whether the long run effect is larger or smaller than the short run effect is an empirical question. We investigate this possibility by including a distributed lag structure in our models:

$$(2) \qquad Y_{cdt} = \alpha + \sum_{j=0}^{J} \beta_j T_{cdt-j} + \lambda_{cmt} + u_{cdt}$$

This model allows for the effect of temperature up to J days in the past to affect mortality today. In equation (2), the total effect of temperature on mortality rates--also called dynamic causal effect--is obtained by summing the coefficients on the contemporaneous and lagged temperature variables, $\sum_{j=0}^{J} \hat{\beta}_j$.[15] The dynamic causal effect measures the combined effect of temperature today, yesterday, and so forth, on mortality rates today. Different lag structures will potentially generate different estimates of the dynamic causal effect. In our context, the relationship between the dynamic causal effect and the lag length is informative about the extent of mortality displacements attributable to temperature shocks. If temperature shocks lead to temporal displacement of mortality (e.g. harvesting), then there should be a negative relationship between the estimated dynamic causal effect and the lag length. In other words, if there is harvesting, then the immediate increase in mortality in the first few days following a hot or cold shock (implying a positive dynamic causal effect for short lag lengths) should be followed with a corresponding compensatory effect where mortality in the weeks following the shock declines relative to trend (implying a negative dynamic causal effect for medium to long lag lengths).

The richness of our data and our large sample sizes, allows us to control for the independent effect of temperature in each of the 30 days preceding a given recorded death. We choose 30 days for our base specification because it is unlikely that weather shocks have significant lagged effects after one month. Later, we estimate models with

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[15] This dynamic causal effect is sometimes referred to as the "cumulative dynamic multiplier". See Stock and Watson (2003) for an insightful discussion of dynamic causal effects. Consistent estimation requires that $E[u_{cdt} \mid \lambda_{cdt}, W_{cdt}, W_{cdt-1}, ..., W_{cdt-J}] = 0$.

60 and 90 days lags, and find that, consistent with this assumption, the results do not change significantly.

In Table 4, each row reports the independent effect of lagged temperature variables, estimated in a model where 30 lags are included. The coefficients in the first row (the "0" lag independent effect) measure the contemporaneous effect of today's temperature on today's mortality, conditional on the temperature for the last 30 days. The coefficients in the second row (the lag "1-2" independent effect) measure the combined effect of the temperature in the two preceding days on today's mortality, conditional on today's temperature and on the other lags. In terms of equation (2), this corresponds to $\hat{\beta}_1 + \hat{\beta}_2$. The interpretation of the coefficients in the other rows is similar. Finally, the 30-day dynamic causal effect in the last row is the sum of the coefficients on the contemporaneous temperature dummy variables and the coefficients on all lagged temperature dummy variables: $\sum_{j=0}^{30} \hat{\beta}_j$. This measures the long-term effect of the temperature shock.

Examining the results in Table 4, it is clear that the contemporary effect of temperature is vastly different for hot and cold days. The estimates for hot temperate indicate that on hot days, there is an immediate increase in mortality, as was shown in Table 3. For example, on days where the average temperature raises above 80°F, the death rate increase by 0.0904 deaths per 100,000 (std error = 0.0068). Panel A in Table 4 shows that there is no such immediate relationship for cold days: The estimates for the three cold temperature thresholds are either negative or statistically insignificant.[16] The effect of lags 1 and 2 measures the cumulative effect of 1 day of cold or hot temperature in the last 2 days affects the mortality rate today. Again, there is a remarkable difference between cold and heat effects: The 1-2 day lag effects for heat are attenuated compared to the contemporaneous, while the cold estimates are larger than the contemporaneous ones. For example, the cumulative effect of 1 day with temperature above 80°F in the last 2 days raises today's mortality rate by 0.0481 points, while temperature below 30°F in the last 2 days raises today's mortality rate by 0.0796 points.

[16] The negative cold effect for contemporaneous temperature has been found elsewhere as well (see e.g. Huynen et al. 2001), but the epidemiology literature has yet to explain it.

At longer displacements, the divergence between the heat and cold temperature effects on mortality is even more apparent. The effect of days with mean temperature below 30°F is positive and significant at all displacements considered. However, for heat-related mortality, the effect of temperature at longer displacements is negative, though the particular lag at which the effect becomes negative varies with the temperature threshold. Thus, the initial increase in mortality following a hot day is compensated for with a decline in mortality in the subsequent days, consistent with the harvesting hypothesis. For all definition of hot temperature considered in Panel B, all of the increase in mortality at lags 0,1, and 2 is compensated for by decreases in mortality in the longer lag periods.

We show the 30-day total effect in the last row. This corresponds to the sum of the reported effects of the different lag displacements in the rows above. The results are striking. The long-term effect of 1 cold temperature day raises the daily mortality rate by 0.16 – 0.23 points, corresponding to percentage effects of 6.1 – 9.1%. For example, the 30-day cumulative effect of 1 day of temperature below 30°F is an increase in daily mortality rates by 0.2273 points, corresponding to a 8.9% effect. The estimates are precise, with t-statistics ranging from 5.1 to 19.4. No significant effect is discernible for extreme hot temperature above 80°F or 90°F. Extreme heat shocks seem to precipitate the health condition of individuals who are already weak and would have died even in the absence of the shock. The only effect of a heat shock is a minor change in the timing of mortality.

The models in Table 4 include only 30 lags, and therefore implicitly assume that any effect occurs within a month of the weather shock. We have also estimated models with longer lag structures in order to capture dynamic effects of longer horizons. When we estimated models with temperature lag windows of 60 and 90 days, we find that the magnitude of the dynamic causal effect does not change significantly. For example, for the case of temperature below 30, the model with a 60 days window produces an estimate (std error) of 0.2361 (0.0161), while the model with a 90 days window produces an estimate of 0.2711 (0.0218) (not in the Table). While both these estimates are larger in magnitude than the baseline estimate (0.2273), the differences are small when compared to the difference in sampling errors. Thus it appears that the full impact of a cold day on mortality occurs within 30 days, and consequently that the dynamic responses in Table 4 are well-specified.

Overall, the evidence in Table 4 points to an important conclusion of this paper. Increases in heat-related mortality observed during heat waves appear to be an artifact of harvesting, and completely disappear within weeks. In other words, the immediate effect of heat on mortality is mostly driven by temporal displacement. By contrast, there is no evidence of harvesting associated with cold-related mortality. The immediate increase in mortality caused by extreme cold weather is not followed by a reduction in the following weeks. As a consequence, it is a long lasting effect that has the potential of inducing significant changes in a person's longevity. In Section 5 and 6 we will quantify the effect on longevity.

4.3 Dynamic Estimates by Age and Cause of Death

We now turn to estimates of the effect of cold temperature on mortality by age group and cause of death. This exercise provides valuable information about the pathways between cold weather and mortality. Each column in Table 5 corresponds to an age group (adjusted to the 1980 population standard), and each row corresponds to a specific cause of death. We report the 30-day total effect corresponding to days with temperature below 30°F.

The results are remarkable. Essentially all of the cold-related excess mortality is attributable to increase cardiovascular and respiratory disease mortality. There is some evidence that infectious disease also significantly contribute to the excess cold-related mortality, but the magnitude of the impact is small. The effect on cardiovascular is by far the most important, explaining 67% of the impact on all-cause mortality. As reported earlier, the effects for external causes are *negative*. That is, cold weather leads to less mortality due to motor-vehicle accidents and suicides.

Column 2 shows estimates for infant deaths (less than 1 year olds). The dynamic causal effect for all-cause mortality is positive (0.1194), but imprecisely estimated. In fact, the only significant impact in column 2 is for respiratory disease: accounting for any temporal displacement, cold temperature days raise infant mortality due to respiratory disease by 0.0449 points. An interesting finding in Table 4 is that for teenagers and young adults (the 10-19 and 20-34 categories), the dynamic causal effect for all-cause mortality is negative and statistically significant. For example, in column 5, the dynamic causal effect reported is –0.0257, corresponding to a 8.2% reduction in daily mortality rates for that age group. This impact is mostly attributable to a causal effect between cold temperature and lower rates of motor vehicle accident mortality. Remarkably the point estimates and standard errors for both the 10-19 and 20-34 age groups are similar (–0.0174 vs. –0.0177). One explanation for this finding is that snowfall is more likely on colder days, and that snowfall has been shown to be associated with fewer fatal car accidents (Eisenberg and Warner 2005). In general, however, few estimates are statistically significant for the relatively young age categories, possibly because of sample size: the number of deaths in a county of a given cause for a given age group in a given day is likely to be rather noisy, especially in small and medium-size counties.[17]

For prime-aged adults there is strong evidence of excess mortality as a result of cold days. The estimates of the cumulative effect of 1 cold day on daily mortality rates are positive and precisely estimated. The magnitude of the excess mortality caused by cold temperature increases with age, from 0.0779 per 100,000 for the 45-54 age group, to 8.8723 per 100,000 for the 85+ age group. Since mortality rates also increase with age this result may be misleading. However, the same pattern is observed when report the estimates as percentage effects relative to the age-specific average mortality rates. The percent effect increases from 5.3% for the 45-54 age group to 20.0% for the 85+ age group. To the best of our knowledge we are the first to document this finding for narrowly-defined age groups.[18]

For all prime-aged groups, there is significant evidence that cold spells cause increases in cardiovascular mortality. A similar pattern is observed for mortality due to infectious and respiratory diseases, though the magnitudes of the impacts are smaller. There is no evidence of a connection between neoplasms and cold temperature. Finally, with the exception of the last age group (85+), there is no significant relationship between external causes of death and cold weather.

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[17] Importantly, the measurement error in the dependent variable is likely uncorrelated with the temperature variables on the right-hand side conditional on the county-by-month-by-year fixed effects.

[18] There is some evidence in the previous literature that elderly are more sensitive to temperature fluctuations. However it is not always easy to interpret these estimates because they are based on less transparent research designs and on much broader age categories.

Taken as a whole, the evidence in Table 5 indicates that the cold temperature effect is stronger for older age groups, and is mostly concentrated in excess cardiovascular mortality. The estimated impacts are not attributable to temporary displacement of deaths, and thus represent a potentially significant reduction in longevity.

4.4 Dynamic Effect by Income and Relative Exposure

In Table 6, we show the estimates from alternative specifications. We first look at models where the effects of cold temperature are interacted with income. We are interested in investigating whether the effect of a cold day is larger in counties that are poorer. We then provide two tests of the acclimatization hypothesis, which in essence suggest that the temperature-mortality relationship may vary across geographic areas. First we examine whether the cold temperature effects differ with the average exposure to cold days for the county. Second, we quantify the impact of exposure relative to the county normal rather than the impact of absolute temperature thresholds. The idea is that one day below 30F in Florida and Minnesota might not have the same effect on mortality, and or, that the cold temperature thresholds vary across geographic areas because human bodies get acclimatized to cold or hot temperatures (see e.g. Eurowinter Group 1997).

The first row in Table 6 reproduces the baseline all-age estimates from Table 5. Following Table 5, the temperature variables are modeled using simple indicators for days where the mean temperature falls below 30F. The estimates in the second row pertain to different income subgroups of the sample. In order to gauge the impact of income on the impact of cold temperatures on mortality, we stratify the analysis for 3 different groups of counties. The regression models were estimated separately on the 10% poorest counties in our sample (based on real per-capita income), the 10% richest counties, and the remaining 80% of counties whose per-capita income falls between the 10^{th} and 90^{th} percentiles of the national distribution. The estimates indicate that the mortality impacts are larger in the poorest counties. For these counties, one day of cold temperature increases the daily mortality by 0.3696 deaths per 100,000 residents. The impact for the richest counties is the smallest at 0.2174 deaths per 100,000, while the impact for the remaining counties is slightly larger at 0.2320. Thus, it appears that there are differences in the impact of cold temperatures on mortality due to income and that the relationship is non-monotonic as the impact in the richest counties is practically the same as among the counties in $10^{th} - 90^{th}$ percentile range.

In row 3 we consider models that are estimated separately for counties that exposed to few or many cold days in the typical year. In particular, we consider counties that experience 10 or fewer cold days per year, and 90 or more cold days per year (the national average is 40 days per year in which daily mean temperature falls below 30F). This allows us to investigate the acclimatization hypothesis, which predicts that the mortality impacts should be smaller in counties that face more cold days per year, because residents and public authorities are better prepared to deal with cold weather. The evidence under row 3 suggests to some extent that individuals get acclimatized to cold temperatures. The mortality impact of cold temperature is remarkably larger in counties that experience 10 or less cold days per year---on such days the mortality rate is increased by 0.6238 deaths per 100,000. The impact is markedly smaller in counties that are exposed to at least 90 cold days per year in the typical year. Nevertheless, the impact of cold temperature on mortality is sizable and significant. The point estimate indicates that on such cold days in the highly exposed counties, the mortality rate per 100,000 is elevated by 0.1569 points (std error=0.0331). We note that the difference between this impact and the impact calculated using all counties is not statistically significant at the 5% level.

The last rows of Table 6 examine consider the possibility that relative exposure (as opposed to absolute exposure) is what matters in the temperature-mortality relationship. So far the models we considered specify an "absolute" relationship between temperature and mortality. In other words, in the specification analyzed in Table 3-5, cold temperature is defined independently of counties. This could be inappropriate under the hypothesis that there is acclimatization. In that case exposure relative to the county normal could be a better predictor of mortality. Moreover, areas with relatively warm climates with low fluctuations in temperatures, such as Southern California, will contribute little or no identifying variation to the models.[19] In order to take this possibility into account, we define cold days as those where the temperature falls 10 or 20

[19] For example, over our sample period 1972-1988, San Diego county had no days where the mean temperature fell under 30°F.

Fahrenheit degrees below the county mean for the month of observation. For example, in the case of 10 degree variation, the temperature variables used in the regressions are defined as T_{cdt} = ($Temperature_{cdt}$ – Mean $Temperature_{cm}$ < 10). The results from this "relative" effect model obtained estimating the fixed-effect model in equation (3) with these new temperature variables are reported under row 6 of Table 6. Remarkably, the estimates appear similar or even larger than the baseline estimates. For example, the 30-day cumulative effect of 1 day where the temperature is 10°F below the county mean for the month of observation increases daily mortality rate by 8.8%, which is slightly below what we estimate from the "absolute" effect models. When we consider the relative effect model with deviation of 20°F, the estimated dynamic causal effect increases significantly to 0.4678 (std error = 0.0324), which corresponds to a 14.5% effect. The remarkable similarity between the estimates from the "absolute" and "relative" models is greatly reassuring since it implies that our baseline estimates in Tables 3-5 are not driven by the choice of a particular model of the temperature-mortality relationship.

5. The Effect of Cold Weather on Life Expectancy

In Section 4 we have shown that episodes of extreme cold are associated with permanent increases in mortality. In this section we ask the following question: how large is the effect of cold temperature exposure on life expectancy? [20] In particular, in sub-section 5.1, we ask what would happen to life expectancy in the absence of exposure to extreme cold episodes. We answer this question both for the US as a whole, and for some selected cities. Second, in the sub-section 5.2, we ask what fraction of the gains in life expectancy experienced by the US population over the last 30 years can be attributed to lower exposure to extreme cold due to the secular movement of the US population from cold states toward warm states. Finally, in sub-section 5.3 we test whether mobility decisions of individuals appear to be sensitive to the longevity benefits associated with avoiding extreme cold.

5.1 Years of Life Lost Due to Cold Weather

[20] We focus only on cold-related mortality since our results suggest that hot temperature only causes near-term displacement of mortality, therefore not leading to significant reductions in life expectancy.

In Table 7 we calculate the number of annual deaths caused by cold weather and the corresponding years of life lost (YLL) per death. We begin by multiplying the white population in that age group in 2000 (column 1) by the age-specific estimate of the effect of 1 cold day on mortality (column 2).[21] The product of column 1 and 2 is then multiplied by 40, which is the annual number of cold days for the typical county (defined as days where the mean temperature falls below 30F) to obtain an estimate of annual deaths associated with cold shocks (column 3).[22] Not surprisingly, the implied number of deaths is positive for young and old ages, and is negative for ages between 20 and 44. The estimates range from –474.3 for the 20-34 age group to 13,468.2 for the 85+ age group.[23]

As a whole, there are 27,940 annual deaths attributable to cold temperature in the United States, which corresponds to approximately 1.3% of annual deaths (based on the 2000 mortality total for whites). We interpret this figure as a remarkably large number. For example, this total exceeds the annual deaths due to leukemia, homicide, chronic liver disease / cirrhosis and other important causes of death.

The next column (column 4) displays the years of life lost per death in each age group, based on the 2000 life tables for whites. Based on this, a person dying between the ages of 10 and 19 looses 64.1 years of life on average, while a person dying between the age of 65 and 74 looses only 14.4 years of life.[24] We multiply these years of life lost (column 4) by the number of implied deaths in each age group (column 3). The resulting figure (column 5) corresponds to the total number of years of life lost caused by cold temperature. The age group most affected is the group 75-84, which loses 74,476 years of life because of cold temperature. One caveat to this calculation is that it may overstate the loss in life years, because the affected individuals may have been negatively drawn from the health distribution. In order words, affected individuals are likely to have shorter life expectancies than the average person in their age group.

Finally, we divide YYL in column 5 by the total number of deaths attributable to cold temperature to obtain the number of years of life lost per death caused by cold temperature (YYL per death). The estimate is substantial: the average person who died

[21] These estimates are from Table 5.
[22] For simplicity, this estimate assumes uniform distribution of population across all counties.
[23] As we demonstrated in Section 4, the negative effect or middle age individuals is mostly driven by a reduction in car accidents.
[24] These data are available at: http://www.cdc.gov/nchs/data/lt2000.pdf .

because of cold temperature lost 9.1 years of potential life. This simple calculation highlights the fact that cold temperature cause non-trivial reductions in expected lifetime. Even for the population aged 65+---the age groups that are the most affected by fluctuations in temperature---the years of life lost per death are 7.6 years, arguably a large loss.

Of course, this effect varies tremendously depending on geography. Table 8 examines cold-related deaths by city among the elderly. In this table we focus on the population of age 65 and above since it is the most affected by cold temperature. Since most individuals in this population are retired, they face less constraints in their mobility decisions that prime-aged adults. We focus on the 20 largest MSA in terms of elderly white population[25]. The Chicago MSA is the largest with an elderly population of 562,627 and the Houston MSA is twentieth, with a population of 205,557. The second column shows the total annual deaths for each MSA. Interestingly, the total mortality rankings do not exactly correspond to the population rankings. For example, the New York has the largest mortality total in the white elderly group (39,414) while it ranks third in population.[26] The next column shows the average annual number of cold days in each metropolitan area (as before, defined as days where the mean temperature falls below 30F). For example, Chicago is exposed to 57 cold days per year on average, while the Philadelphia faces only 31. The city with the strongest exposure is Minneapolis, with an average of 109 cold days per year. Several cities experience no or few cold days, including Los Angeles, Tampa Bay, Phoenix, and San Jose.

A simple counterfactual exercise is to ask how many deaths would be delayed if all the elderly in a "cold" city moved to a city where they would not be exposed to cold temperature (for example: Los Angeles). The answer is provided in column 4, which shows the implied annual deaths due to cold temperature in each metropolitan area. This is obtained by the product of columns 1 and 3 (the exposure) multiplied by 1.74, the estimated impact of 1 cold temperature day on deaths per 100,000.[27] The Chicago MSA

[25] We use data from the 2000 Census.

[26] Of course, these differences cannot be interpreted causally, as they might reflect differences in the age distribution above 65 or socio-economic and racial differences across cities.

[27] This estimate is obtained from estimating our distributed lag regression (3) for the population aged 65 and above. It roughly corresponds to a population-weighted average of the age-specific estimates reported in Table 5.

has the most annual cold-related deaths, 557, followed by Minneapolis (462) and Detroit (440). For the twenty MSA as a whole, 3,294 deaths--or 0.8% of all deaths in these cities--could be delayed by moving individuals to areas not exposed to cold temperature. The last column shows the city-specific impacts in percentage terms. This is obtained by taking the ratio of implied deaths to total deaths. The results show that for some city, cold-related deaths represent a sizable fraction of actual deaths. For example, in the Minneapolis MSA, our estimate of cold-related mortality corresponds to 3.3% of all deaths. Other impacted MSA are Detroit (1.9%), Chicago (1.5%) and Cleveland (1.6%).

5.2 Gains in Life Expectancy Due to Secular Trends in Mobility

We now turn to geographical mobility. Over the last half a century, the U.S. population has moved from the Northeastern and Midwestern states to Southwestern states. This movement has resulted in a diminished exposure to cold weather. We compute how much of the observed increase in life expectancy can be attributed to the secular movement of the US population from cold areas in the North to warmer areas in the South West.

Over that 30 years period, the average age of death in the white population increased by 8.1 years for females and 6.3 years for males. How much of this improvement can be attributed to lowered exposure to extreme cold caused by geographical mobility? We look at all US born individuals who live in a state different from the state of birth. For each of these movers, we compare the exposure in the state of residence with the counterfactual exposure that that individual would have experienced in the state of birth.[28]

Our estimates indicate that on net 5,400 deaths are delayed by the changing exposure to cold temperature each year. This figure is the *net* effect of mobility, because it is the difference between the lower mortality experienced by those who moved from cold states to warm states and the higher mortality experienced by those who moved in the opposite direction. We calculate this difference for each state pair and age group.

[28]To identify movers, we use Census data. Since we only know the state of birth, but not the county of birth, we compute the change in exposure as the difference between the number of cold days in the state of residence minus the number of cold days in the state of birth, thus ignoring within-state differences in weather.

When we multiply this difference by the estimated number of years of life lost associated with a cold day for the relevant age group, we find that the average age of death (or longevity) increased by 0.02 to 0.03 years per calendar year as a result of lower exposure to cold weather due to migration. In other words, US residents gained about 10 days of extra life per calendar year because of mobility. The details of the calculation are presented in the appendix.

We compare this figure to the annualized increase in longevity in the United States over the period 1970-2000. In annual terms, the average age of death in the white population has increased by 0.20-0.25 years per calendar year, over the last 30 years. Assuming that the age distribution of movers across states is constant over time, we can compare our estimated longevity effect of mobility to the annualized increased in overall longevity in the United States between 1970 and 2000. Our estimate of the longevity effect of mobility corresponds to approximately 8-15% of these annual gains in overall longevity. We view this as a remarkably large effect.

5.3 The Decision to Move and Cold Weather

We now test whether individual mobility decisions appear to be affected by the desire to avoid exposure to cold weather shocks. If individuals living in colder regions are aware of the effect of cold weather on life expectancy, they may decide to move to warmer areas, and this effect should be larger the larger the benefit in terms of higher life expectancy.

Table 9 shows estimates of the impact of differential exposure to cold weather on the probability of moving, by age. The dependent variable is a dummy equal one if the relevant individual in the 2000 Census resides in a state different than their state of birth.[29] The main independent variable is the interaction between the difference in the number of cold days and the relevant age group. Weather is measured at the state level. The first entry in column 1 indicates that the probability of moving between two locations increases if the difference in the number of cold days declines. This probably simply reflects the secular movement toward warmer locations.

[29] We only include white males and females, born in the 48 continental states and the District of Columbia.

What is more interesting is that the magnitude of this effect is different across age groups. In particular, column 2 indicates that such magnitude increases with age (in absolute value), after controlling for age dummies. For example, for individuals 33-44, the probability of mobility is only marginally affected by the difference in exposure to cold. A one day decline in the number of annual cold exposure is associated with an increase in the probability of mobility by .0008. By contrast, the effect is four times larger for individuals above 75: a one day decline in the number of annual cold exposure is associated with an increase in the probability of mobility by more than 3 tenths of a percentage point. The key point here is that the pattern of the age-specific coefficients mirrors differences across age groups in the effect of cold weather on mortality uncovered in Table 5.

In column 3 to 6, we include an increasing number of controls. In column 3 we add a full set of demographic variables, including sex, educational attainment, marital status, family size, work disability, weeks worked, and total income. All of these are controlled for using a series of unrestricted dummy variables. In column 4 we include dummies for state of birth, and in column 5 we also include dummies for state of residence. The model in column 5 is close to be fully saturated and it fully accounts for permanent differences across states of births and state of residence, as well as age dummies and demographics. The coefficients on the interactions are generally lower. Notably, the differences across age groups persist. The coefficient for the groups above 75 remains about four times larger than the coefficient for the age group 35-44. Based on this finding, we conclude that individual mobility decisions appear to be affected by the desire to avoid exposure to cold weather shocks, even after controlling from where they were born and where they live.

6. Conclusion

Our findings indicate that increases in mortality caused by cold temperature are long lasting. We find evidence of a large and statistically significant permanent effect on mortality of cold waves. By contrast, the increases in mortality associated with heat waves are short lived. The increase in mortality that occurs in the days immediately following heat waves appears entirely driven by temporal displacement.

The aggregate effect of extreme cold on mortality is large. We estimate that the number of annual deaths attributable to cold temperature is about 1.3% of actual deaths in the United States. This effect is significantly larger in low income areas.

The main contribution of this paper is to document the importance of a previously unrecognized determinant of gains in life expectancy in the United States. Over the past several decades, the U.S. population has moved from the Northeastern states to the Southwestern states. This secular trend has resulted in a diminished exposure to cold weather. We calculate that every year, 5,400 deaths are delayed by the changing exposure to cold temperature. Such effect on longevity accounts for 8%-15% of the overall increase in longevity experienced by the US population over the last 30 years.

We also find that individuals seem to take the longevity benefit into consideration in their mobility decisions. Exposure to extreme cold is an important determinant of mobility decisions, especially for the age groups that are most affected by cold-induced mortality.

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Appendix: Calculation of longevity gains

In order to better describe our procedure, we define some notation. To begin, let N_{ajk} denote population of age a, residing in state j, born in state k. The differential exposure to cold weather shocks is defined as S_{jk} = number of annual cold weather days in state j – number of annual cold weather days in state k. Note that by construction, $S_{jj} = 0$.

(i) Death rates and conditional mortality probabilities

Since the mobility patterns are tabulated from the 2000 Census, we also compute mortality rates and probability from the 2000 Multiple Cause of Death Files. We estimate the age-specific death rates for each state as:

$$R_{aj} = \frac{D_{aj}}{\sum_{k=1}^{49} N_{ajk}} \qquad a = 0, 1, \ldots, 100$$

Where D_{aj} is the number of deaths occurring at age a in state j. In other words R_{aj} is simply the ratio of the number of deaths at a given age, to the population of that age in a state. In the case where the age*state specific death rate is exactly zero (which occurs when no deaths occur at a given age in a state), we use the national death rate for that age.[30] Conditional mortality probabilities are also computed from the data in the 2000 MCOD file. We consider ages 0-100, and compute the probabilities at the national level. Let D_a denote the number of deaths at age a. The share of total deaths at age a, F_a, is defined as:

$$F_a = \frac{D_a}{\sum_{a=0}^{100} D_a} \qquad a = 0, 1, \ldots, 100$$

Given survival to age m, the conditional probability of dying at age a (a>m) is given by:

$$P_{a|m} = \frac{F_a}{\sum_{i=m+1}^{100} F_i}$$

Note that for a given survival age m, $\sum_a P_{a|m} = 1$. By construction $P_{a|m} = 0$ for $a \le m$. For the last age group (when m=100), this probability is not defined, so we assume that no one lives past 100.

(ii) Affected number of migrants

First, we calculate the "expected" annual number of migrants deaths at age a. This is obtained by multiplying the number of migrants of age a in state j by the age-specific death rate in state j (so that we are assuming that the same death rate apply to both migrants to state j, and to residents born in state j):

[30] For the 49 states and the 101 ages in our data, imputation is required for 36 of 4,949 state*age pairs

$$E_{aj} = \sum_{k=1}^{49} R_{aj} * (N_{ajk} - N_{ajj})$$

Where E_{aj} = expected annual number of migrant deaths in state j, at age a. For the U.S. as a whole, there were approximately 700,000 expected migrant deaths in 2000. There is substantial variation across states in the expected number of migrant deaths, which reflects differences across states in the number and age distribution of migrants, and in the age-specific mortality rates. For example, the unadjusted standard deviation in the number of annual expected migrant deaths is 19,100. The states with the highest totals are California and Florida, while the states with the lowest totals are Washington DC and North Dakota.

From this, we calculate the "affected" number of migrant deaths---the annual number of migrant deaths attributable to (mobility-induced) differential exposure to cold weather shocks:

$$A_{aj} = \sum_{k=1}^{49} E_{aj} * \beta_a * S_{jk} / 365.25$$

Where β_a is the dynamic causal effect of a cold weather day on daily mortality rates for age group a, taken from Table 5. Since we calculate the affected number of migrants deaths by single year of age, we assign β_a accordingly to the age groups. Note that we divide by 365.25 because the mortality regressions are at the day level, so dividing by 365.25 converts this effect back in annual terms.

Our estimates suggest that the total number of affected migrant deaths is -5,402, so that on the net, (mobility-induced) differential exposure to weather shocks delayed mortality for 5,402 migrants. Again, there is important variation across states in both the sign and magnitude of the affected number of migrant deaths. At the two extremes are California and Michigan: In conjunction with differential exposure to cold weather days, mobility to California delayed the mortality of 1,834 people in 2000, while mobility to Michigan accelerated the mortality of 149 people.

(iii) Counterfactual distribution of longevity, with implied effect on average of death

We implement this by calculating the actual share of death at age a (F_a, see step (i)) and the counterfactual share of death at age a, $\hat{F}_a$. The average age of death in the "affected" group of migrants is changed by mobility. This, in turn changes the average age of death in the population as a whole. Depending on the age group, mobility may accelerate death (positive β_a) or delay mortality (negative β_a). The counterfactual age of death distribution is obtained as follows:

$$\hat{D}_a = \sum_{j=1}^{49} \sum_{m=a+1}^{99} [1(\beta_a < 0) * P_{a|m} * A_{aj} + 1(\beta_a > 0) * a]$$

Where $\hat{D}_a$ is the counterfactual number of deaths at age a. For the age groups for which mobility decreases longevity (positive β_a), the counterfactual age of death is simply the given age. For the age groups for which mobility increases longevity (negative β_a), the counterfactual age of death is obtained from the conditional probabilities of death.

To obtain the counterfactual share of death at age a, we simply divide $\hat{D}_a$ by the total number of deaths in the counterfactual distribution:

$$\hat{F}_a = \frac{\hat{D}_a}{\sum_{a=0}^{100} \hat{D}_a + NA_a} \qquad a = 0, 1, \ldots, 100$$

Where NA_{aj} is defined as $NA_{aj} = D_{aj} - A_{aj}$. The mean effect on longevity is computed as follows:

$$= \sum_{a=0}^{100} (\hat{F}_a - F_a) * a$$

Based on our estimates, this number is 0.025 year, or 9.13 days. To put this number in perspective, we compare it to the annualized increase in longevity in the United States over the period 1970-2000. In annual terms, the average age of death in the white population has increased by 0.20-0.25 years per calendar year, over the last 30 years. Assuming that the age distribution of movers across states is constant over time, we can compare our estimated longevity effect of mobility to the annualized increased in overall longevity in the United States between 1970 and 2000. Our estimate of the longevity effect of mobility corresponds to approximately 8-15% of these annual gains in overall longevity. We view this as a remarkably large effect.

Figure 1. Average Daily Mortality Rates for All-Cause and Cause-Specific Mortality, 1972-1988, Per 100,000 Population [deviations from day-specific averages]

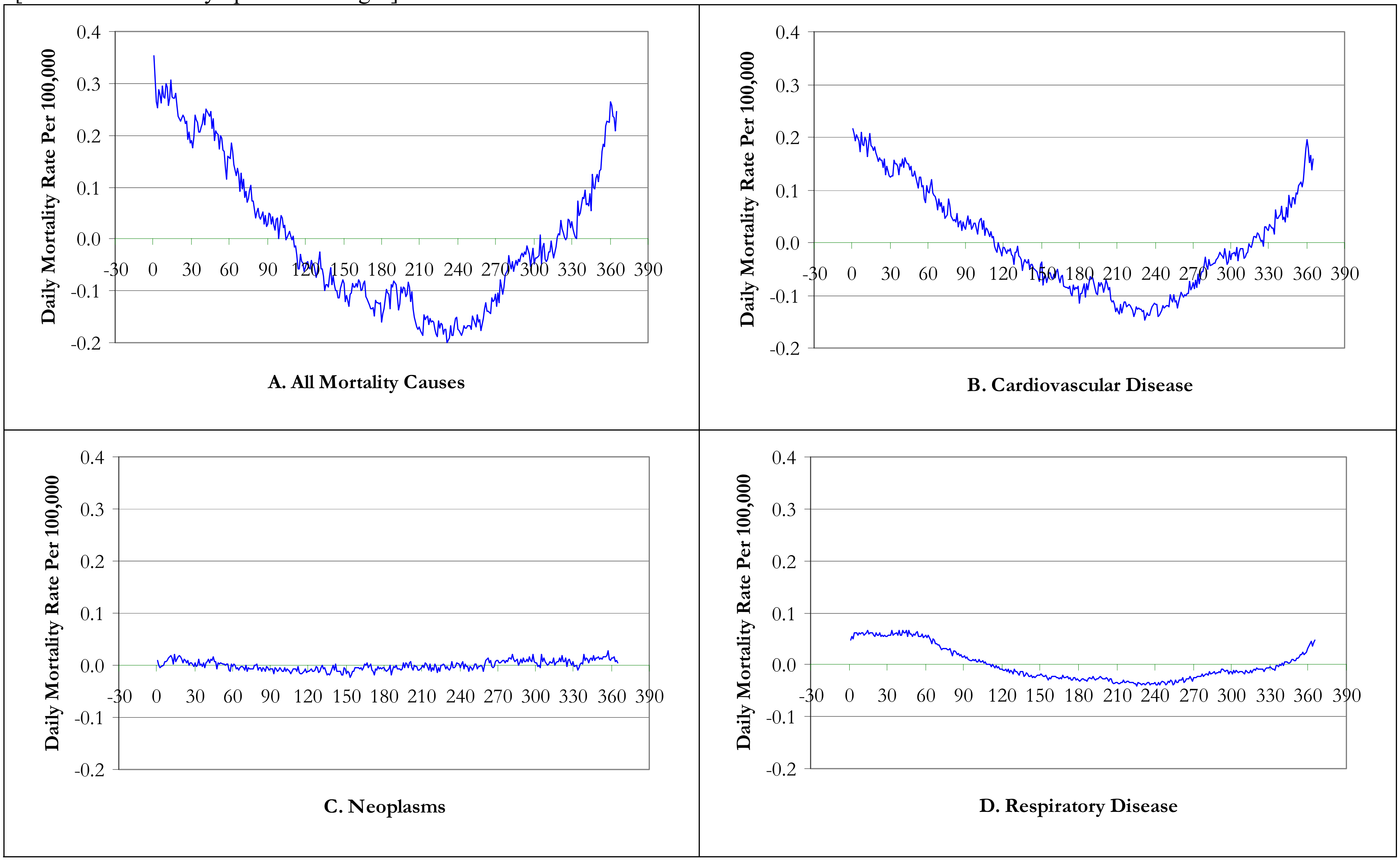

Figure 2. Average Daily Mortality Rates For Suffolk County, MA and San Diego County, CA, 1972-1988, Per 100,000 Population [deviations from county*day specific averages]

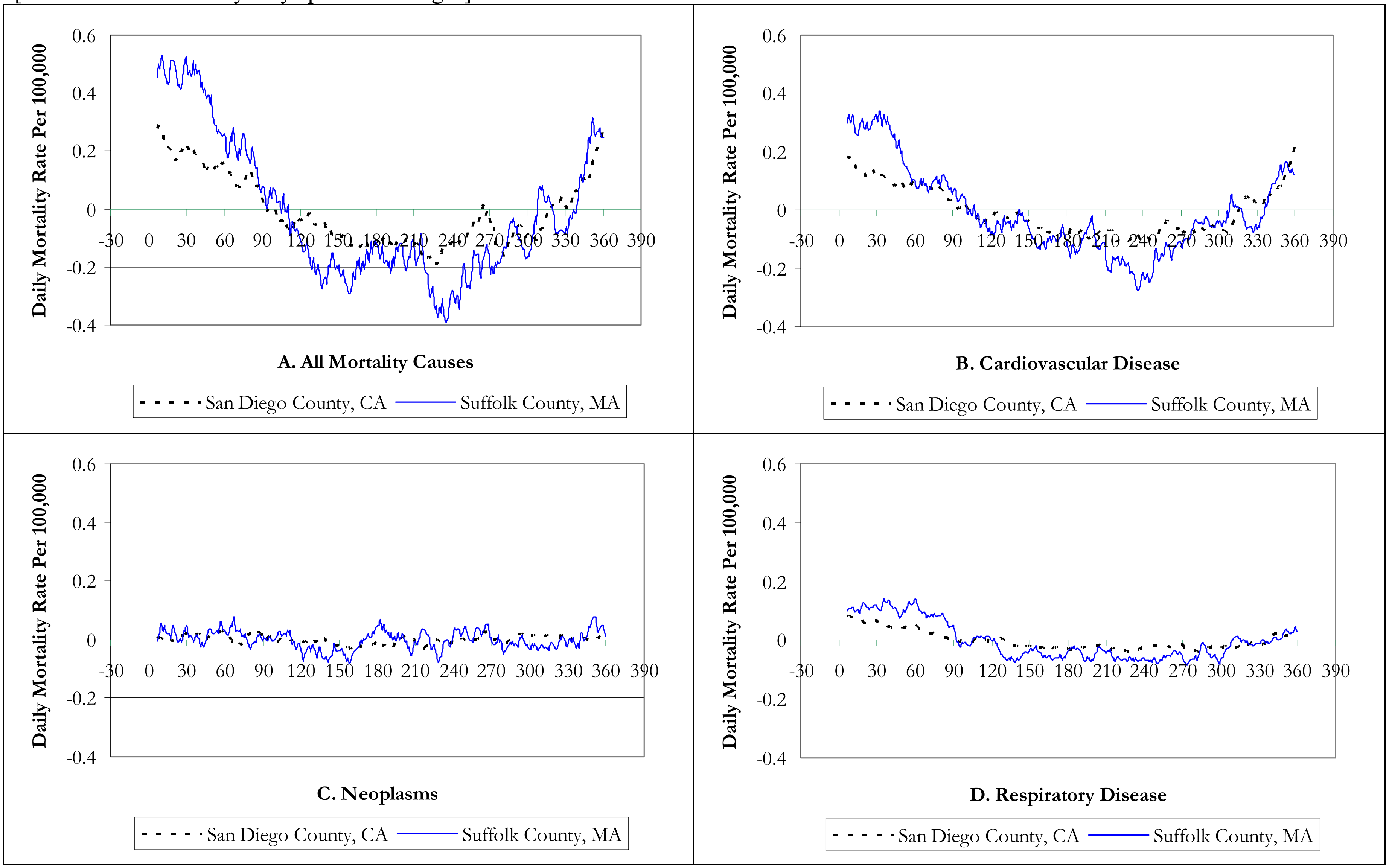

Table 1. Average Daily Mortality Rates, by County

Age group:	All	0	1-9	10-19	20-34	35-44	45-54	55-64	65-74	75-84	85+
All Cause Mortality:	**2.5445**	**3.1586**	**0.1138**	**0.1721**	**0.3140**	**0.5588**	**1.4835**	**3.6146**	**8.1233**	**18.5445**	**44.3405**
[A] Cause-Specific:											
1. Infectious Diseases	0.0249	0.0820	0.0042	0.0020	0.0069	0.0136	0.0165	0.0315	0.0664	0.1554	0.3817
2. Neoplasms	0.5462	0.0147	0.0148	0.0144	0.0323	0.1320	0.4736	1.1974	2.2613	3.4530	4.4309
3. Cardiovascular Diseases	1.3011	0.0680	0.0049	0.0059	0.0220	0.1358	0.5520	1.5797	4.1263	11.1386	30.2855
4. Respiratory Diseases	0.1758	0.1367	0.0069	0.0040	0.0068	0.0164	0.0564	0.2023	0.6056	1.4960	3.8013
5. Motor-Vehicle Accidents	0.0579	0.0161	0.0187	0.0696	0.0830	0.0471	0.0432	0.0440	0.0530	0.0793	0.0714
6. Suicide	0.0359	---	0.0000	0.0141	0.0435	0.0446	0.0499	0.0511	0.0536	0.0621	0.0548
7. Diabetes	0.0443	0.0005	0.0002	0.0005	0.0030	0.0088	0.0224	0.0658	0.1685	0.3669	0.6131
[B] All Cause Mortality, by Season:											
Winter	2.6519	3.2520	0.1147	0.1506	0.2913	0.5629	1.5483	3.8154	8.6729	20.3121	49.9197
Spring	2.4069	3.1221	0.1199	0.1808	0.3180	0.5533	1.4650	3.5673	7.9719	17.9481	42.0083
Summer	2.3229	3.0807	0.1159	0.1954	0.3373	0.5597	1.4390	3.4525	7.6372	17.1000	39.8926
Fall	2.4972	3.1809	0.1048	0.1615	0.3089	0.5595	1.4827	3.6260	8.2188	18.8412	45.6132

Table 2. Difference-in-Difference Estimates of Excess Winter Mortality: Suffolk County, MA and San Diego County, CA.

	(1)	(2)
Age group:	**All Ages**	**All Ages** (Adjusted to 1980 Population Standard)
<u>All Cause:</u>		
Suffolk County	2.7351	2.1002
	(0.0169)	(0.0162)
Winter	0.2178	0.2409
	(0.0124)	(0.0140)
Suffolk*Winter	0.2433	0.1419
	(0.0349)	(0.0333)
<u>Cause-Specific (Suffolk*Winter Interactions Only):</u>		
1. Infectious Diseases	-0.0010	-0.0014
	(0.0045)	(0.0042)
2. Neoplasms	0.0101	0.0094
	(0.0161)	(0.0156)
3. Cardiovascular Diseases	0.1319	0.0688
	(0.0227)	(0.0214)
4. Respiratory Diseases	0.0731	0.0465
	(0.0107)	(0.0097)
5. Motor-Vehicle Accidents	-0.0039	-0.0056
	(0.0035)	(0.0034)
6. Suicide	-0.0003	-0.0014
	(0.0031)	(0.0030)
7. Diabetes	0.0055	0.0043
	(0.0038)	(0.0035)

Notes: Standard errors in parenthesis. Entries in column 1 of the top panel are from a linear regression model of daily mortality rate on a dummy for Suffolk County, a dummy for winter months, and an interaction between Suffolk and winter months. Entries in column 2 of the top panel are from a similar model where the dependent variable is age-adjusted mortality rate, so that the estimates are not confounded by secular age differences. Entries in the bottom panel are estimates of the coefficient on the interaction between Suffolk and winter months in models where the dependent variable is cause-specific mortality. Each regression is based on 6,205 observations.

Table 3. Contemporaneous Estimates of the Effect of Cold and Hot Temperature on Daily All-Cause Mortality Rates

	A: Cold Temperature			B: Hot Temperature		
Mean Daily Temperature:	**<10**	**<20**	**<30**	**>70**	**>80**	**>90**
Average	0.010	0.028	0.070	0.272	0.074	0.006
All Cause Mortality:	0.0252	0.0118	0.0142	0.0641	0.1011	0.0945
(std error)	(0.0104)	(0.0069)	(0.0057)	(0.0055)	(0.0122)	(0.0351)
Percent Effect	*1.0*	*0.5*	*0.6*	*2.5*	*4.0*	*3.7*
Cause-Specific:						
1. Infectious Diseases	-0.0004	-0.0005	-0.0005	0.0007	-0.0003	-0.0033
	(0.0009)	(0.0007)	(0.0007)	(0.0003)	(0.0006)	(0.0009)
2. Neoplasms	-0.0011	-0.0007	-0.0057	0.0134	0.0168	0.0159
	(0.0059)	(0.0037)	(0.0024)	(0.0018)	(0.0030)	(0.0037)
3. Cardiovascular Diseases	0.0320	0.0193	0.0237	0.0254	0.0516	0.0557
	(0.0094)	(0.0051)	(0.0046)	(0.0043)	(0.0094)	(0.0172)
4. Respiratory Diseases	0.0023	0.0013	-0.0004	0.0059	0.0073	0.0012
	(0.0034)	(0.0019)	(0.0019)	(0.0011)	(0.0016)	(0.0074)
5. Motor-Vehicle Accidents	-0.0080	-0.0059	-0.0044	0.0014	0.0004	0.0051
	(0.0017)	(0.0015)	(0.0010)	(0.0006)	(0.0009)	(0.0071)
6. Suicide	-0.0034	-0.0033	-0.0032	0.0025	0.0012	-0.0027
	(0.0011)	(0.0009)	(0.0005)	(0.0005)	(0.0007)	(0.0008)
7. Diabetes	-0.0009	-0.0003	0.0009	0.0007	0.0026	0.0030
	(0.0015)	(0.0010)	(0.0008)	(0.0004)	(0.0007)	(0.0015)

Notes: Standard errors clustered by county in parenthesis. The first row shows the fraction of days in our sample where the mean temperature falls below or above a given threshold. Entries in all the other rows are estimates of the coefficient on whether mean daily temperature is above or below a given threshold (the coefficient β in equation 1). Each entry is from a separate regression. The dependent variable is mortality rate. All models include a series of county-by-year-by-month effects (there are approximately 400,000 such effects). Percent effect is the ratio of the estimated effect and the mean daily mortality rate reported in Table 1.

Table 4. Cumulative Dynamic Estimates of the Effect of Cold and Hot Temperature on Daily All-Cause Mortality Rate

	A: Cold Temperature			B: Hot Temperature		
Mean Daily Temperature:	**<10**	**<20**	**<30**	**>70**	**>80**	**>90**
Fraction of Cold/Hot Days	0.010	0.028	0.070	0.272	0.074	0.006
Independent Effect of Lags:						
0	0.0003	-0.0068	-0.0118	0.0843	0.0904	0.0450
	(0.0066)	(0.0048)	(0.0031)	(0.0036)	(0.0068)	(0.0129)
	0.0	*-0.3*	*-0.5*	*3.3*	*3.6*	*1.8*
1-2	0.0687	0.0796	0.0732	-0.0339	0.0481	0.0599
	(0.0092)	(0.0054)	(0.0038)	(0.0046)	(0.0109)	(0.0211)
	2.7	*3.1*	*2.9*	*-1.3*	*1.9*	*2.4*
3-6	0.0979	0.0928	0.0844	-0.0456	-0.0123	0.0156
	(0.0124)	(0.0063)	(0.0055)	(0.0041)	(0.0071)	(0.0215)
	3.8	*3.6*	*3.3*	*-1.8*	*-0.5*	*0.6*
7-14	0.0348	0.0439	0.0546	-0.0796	-0.0463	-0.0217
	(0.0133)	(0.0089)	(0.0056)	(0.0056)	(0.0077)	(0.0206)
	1.4	*1.7*	*2.1*	*-3.1*	*-1.8*	*-0.9*
15-30	-0.0467	-0.0045	0.0268	-0.0812	-0.0987	-0.1172
	(0.0120)	(0.0107)	(0.0083)	(0.0069)	(0.0121)	(0.0309)
	-1.8	*-0.2*	*1.1*	*-3.2*	*-3.9*	*-4.6*
30-day Cumulative Effect	0.1550	0.2050	0.2273	-0.1560	-0.0187	-0.0185
	(0.0301)	(0.0164)	(0.0117)	(0.0115)	(0.0192)	(0.0468)
	6.1	*8.1*	*8.9*	*-6.1*	*-0.7*	*-0.7*

Notes: Standard errors clustered by county in parenthesis. Each column is a separate regression. The first row shows the fraction of days in our sample where the mean temperature falls below or above a given threshold. Entries in all the other rows are the effects of lagged temperature dummies, estimated in a model where 30 lags are included. For example, the coefficients in the second row (the "0" lag independent effect) measure the contemporaneous effect of today's temperature on today's mortality, conditional on the temperature for the last 30 days. The coefficients in the third row (the lag "1-2" independent effect) measure the combined effect of the temperature in the two preceding days on today's mortality, conditional on today's temperature and on the other lags (this is $\hat{\beta}_1+\hat{\beta}_2$ in equation 2). The 30-day dynamic causal effect in the last row is the sum of the coefficients on the contemporaneous temperature dummy variable and the coefficients on all lagged temperature dummy variables: $\sum_{j=0}^{30}\hat{\beta}_j$.

Table 5. Cumulative Dynamic Estimates of the Effect of Cold Temperature on Daily Mortality Rates: By Age and Cause of Death

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Age group:	**All**	**0**	**1-9**	**10-19**	**20-34**	**35-44**	**45-54**	**55-64**	**65-74**	**75-84**	**85+**
All Cause Mortality:											
Mean (daily)	2.5445	3.1586	0.1138	0.1721	0.3140	0.5588	1.4835	3.6146	8.1233	18.5445	44.3405
30-day Cumulative Effect:	0.2273	0.1194	0.0112	-0.0109	-0.0257	0.0025	0.0779	0.2447	0.4749	1.9899	8.8723
(std error)	(0.0117)	(0.0896)	(0.0064)	(0.0059)	(0.0060)	(0.0140)	(0.0253)	(0.0402)	(0.0703)	(0.1483)	(0.4172)
Percent Effect	*8.9*	*3.8*	*9.8*	*-6.3*	*-8.2*	*0.4*	*5.3*	*6.8*	*5.8*	*10.7*	*20.0*
Cause-Specific Mortality:											
1. Infectious	0.0046	0.0082	0.0013	0.0001	-0.0005	0.0006	-0.0045	0.0057	0.0178	0.0477	0.1151
	(0.0010)	(0.0135)	(0.0013)	(0.0006)	(0.0010)	(0.0021)	(0.0025)	(0.0034)	(0.0062)	(0.0129)	(0.0359)
2. Neoplasms	0.0006	0.0063	0.0006	-0.0017	0.0020	-0.0006	0.0189	0.0315	-0.0687	0.0378	0.1128
	(0.0051)	(0.0067)	(0.0020)	(0.0018)	(0.0022)	(0.0064)	(0.0129)	(0.0242)	(0.0363)	(0.0620)	(0.1198)
3. Cardiovascular	0.1517	0.0183	0.0021	0.0006	-0.0029	0.0141	0.0564	0.1179	0.3156	1.2226	6.1047
	(0.0080)	(0.0138)	(0.0013)	(0.0012)	(0.0018)	(0.0067)	(0.0149)	(0.0265)	(0.0533)	(0.1009)	(0.3340)
4. Respiratory	0.0476	0.0449	0.0018	0.0008	0.0021	0.0054	0.0139	0.0381	0.1129	0.3844	1.6866
	(0.0035)	(0.0214)	(0.0016)	(0.0012)	(0.0009)	(0.0021)	(0.0050)	(0.0096)	(0.0197)	(0.0482)	(0.1312)
5. Motor-Vehicle	-0.0072	0.0004	-0.0013	-0.0174	-0.0177	0.0014	-0.0009	0.0049	-0.0053	0.0067	-0.0386
Accidents	(0.0014)	(0.0055)	(0.0022)	(0.0036)	(0.0033)	(0.0034)	(0.0038)	(0.0037)	(0.0050)	(0.0081)	(0.0137)
6. Suicide	-0.0051	---	0.0001	0.0008	-0.0074	-0.0087	-0.0027	-0.0079	-0.0103	-0.0081	-0.0125
	(0.0010)		(0.0001)	(0.0018)	(0.0023)	(0.0039)	(0.0040)	(0.0040)	(0.0043)	(0.0066)	(0.0110)
7. Diabetes	0.0058	0.0003	0.0001	0.0002	0.0005	0.0036	0.0081	0.0052	0.0140	0.0577	0.1024
	(0.0013)	(0.0013)	(0.0003)	(0.0003)	(0.0007)	(0.0018)	(0.0032)	(0.0058)	(0.0102)	(0.0196)	(0.0481)

Notes: Standard errors clustered by county in parenthesis. Entries are estimates of the cumulative effect of cold temperature on mortality over 30 days. Each column corresponds to an age group (adjusted to the 1980 population standard), and each row corresponds to a specific cause of death. We report the 30-day total effect corresponding to days with temperature below 30°F.

Table 6. Estimates by Income and Relative Exposure

	Point Estimate	Percent Effect	Observations
1. Baseline Estimate (All-cause, All-ages Table 5)	0.2273	*8.9*	11,565,622
(std error)	(0.0017)		
2. Models Estimated By Income Subgroups			
10% Poorest Counties	0.3696	*14.5*	1,114,403
(std error)	(0.1373)		
10% Richest Counties	0.2174	*8.5*	1,171,475
(std error)	(0.0180)		
Remaining 80% of Counties	0.2320	*9.1*	9,344,941
(std error)	(0.0167)		
3. Models Estimated by Normal Exposure to Cold Days			
Counties with 10 Days of Cold Temperature Per Year	0.6238	*24.5*	2,541,386
(std error)	(0.1248)		
Counties with 90 Days of Cold Temperature Per Year	0.1569	*6.2*	1,384,987
(std error)	(0.0331)		
Counties with 11-89 Days of Cold Temperature Per Year	0.2290	*9.0*	7,639,248
(std error)	(0.0123)		
4. Relative Temperature Models:			
Impact of 1 Day with Mean Temperature 10 Degrees Below County Monthly Mean	0.2238	*8.8*	12,442,512
	(0.0081)		
Impact of 1 Day with Mean Temperature 20 Degrees Below County Monthly Mean	0.4678	*18.4*	12,442,512
	(0.0317)		

Notes: Standard errors clustered by county in parenthesis. Entries are estimates of the cumulative effect of cold temperature on mortality over 30 days. Each row corresponds to a different regression. We report the 30-day total effect corresponding to days with temperature below 30°F

Table 7. Number of Deaths caused by Cold Temperature and Years of Life Lost

Age Group	(1) White Population in 2000 [in 100,000]	(2) Cumulative Effect of 1 Cold Day on Mortality Per 100,000	(3) Implied Annual Deaths	(4) Years of Life Lost (YLL, 2000)	(5) Total YLL
0	31.6	0.1194	150.8	77.4	11,670.2
1-9	276.3	0.0112	123.8	73.9	9,146.9
10-19	316.5	-0.0109	-138.0	64.1	-8,845.4
20-34	461.3	-0.0257	-474.3	51.6	-24,471.7
35-44	365.0	0.0025	36.5	39.3	1,434.4
45-54	312.0	0.0779	972.3	30.2	29,362.1
55-64	205.7	0.2447	2,013.0	21.8	43,883.4
65-74	159.3	0.4749	3,025.9	14.4	43,572.6
75-84	110.1	1.9899	8,761.9	8.5	74,476.4
85+	38.0	8.8723	13,468.2	5.5	74,074.8
Annual deaths attributable to cold temperature (all ages):			**27,940**	**YLL per death:**	**9.1**

Notes: We begin by multiplying the white population in that age group is 2000 (column 1) by the age-specific estimate of the effect of 1 cold day on mortality (column 2). The product of column 1 and 2 times 40 (the annual number of cold days for the typical county) provides an estimate of annual deaths associated with cold shocks (column 3). The product of column 3 by the years of life lost per death in each age group in column 4 represents the number of years of life lost per death caused by cold temperature (column 5). Finally, we divide column 5 by the total number of deaths attributable to cold temperature to obtain the number of years of life lost per death caused by cold temperature (YYL per death).

Table 8. Deaths caused by Cold Temperature as a Fraction of Total Deaths, by MSA

MSA:	Population 65+ (2000 Census)	Annual Deaths (2000 MCOD)	Annual Cold Days	Implied Deaths	% of Actual Deaths
Chicago	562,627	37,953	57	557	0.015
Philadelphia	486,631	31,720	31	263	0.008
New York	470,886	39,414	36	295	0.007
Los Angeles	445,930	34,202	0	0	0.000
Tampa Bay	368,846	21,454	0	0	0.000
Detroit	368,029	23,178	69	440	0.019
Boston	350,735	34,995	50	304	0.009
Pittsburgh	343,651	20,914	47	278	0.013
Phoenix	304,530	17,153	0	0	0.000
Nassau	276,207	16,579	36	171	0.010
San Jose	267,129	15,929	5	25	0.002
Riverside	258,082	15,722	0	0	0.000
Washington DC	250,538	15,462	28	123	0.008
Minneapolis	243,760	13,997	109	462	0.033
Cleveland	239,825	14,914	56	232	0.016
San Diego	224,365	13,905	0	0	0.000
Atlanta	217,045	12,977	9	33	0.003
Baltimore	215,204	13,237	28	106	0.008
West Palm Beach	211,025	10,267	0	0	0.000
Houston	205,557	12,369	1	4	0.000
Total	6,310,602	416,341	---	3,294	0.008

Notes: In this table we focus on the population of age 65+ and on the 20 metropolitan areas with the largest number of elderly white residents.

Table 9. Estimates from Mobility Models, Mobility Defined Based on State of Birth

Dependent variable is mobility indicator (=1 moved from state of birth)						
Difference in annual cold days	-0.0077	-0.0064	-0.0061	-0.0068	-0.0048	-0.0037
	(0.00002)	(0.00004)	(0.00003)	(0.00003)	(0.00003)	(0.0011)
Difference in annual cold days * Age						
35-44	---	---	---	---		
45-54	---	-0.0006	-0.0006	-0.0005	-0.0003	-0.0004
55-64	---	-0.0013	-0.0012	-0.0012	-0.0006	-0.0008
65-74	---	-0.0025	-0.0024	-0.0023	-0.0013	-0.0015
75-84	---	-0.0029	-0.0028	-0.0026	-0.0015	-0.0017
85+	---	-0.0029	-0.0028	-0.0026	-0.0015	-0.0018
F-statistics						
Interactions = 0	---	1,106.7	1,045.0	977.6	385.0	496.9
Interactions all equal	---	841.8	806.2	743.3	306.3	371.2
Age Dummies	No	Yes	Yes	Yes	Yes	Yes
Demographic Controls	No	No	Yes	Yes	Yes	Yes
State Birth Effects	No	No	No	Yes	No	Yes
State Residence Effects	No	No	No	No	Yes	Yes

Notes: Standard errors in parenthesis. Entries are estimates of the impact of differential exposure to cold weather on the probability of moving, by age. The dependent variable is a dummy equal one if the relevant individual resides in a state different than their state of birth in 2000. The level of analysis is the individual, and the data are from the 2000 Census of Population. The sample includes white males and females, born in the 48 continental states and the District of Columbia. The independent variable in column 1 is the difference in the number of cold days between the state of residence and the state of birth. In column 2, we interact the difference in the number of cold days with indicators for each age group. For example, for individuals 33-44, a one day decline in the number of annual cold exposure is associated with an increase in the probability of mobility by .0008. For individuals above 75, a one day decline in the number of annual cold exposure is associated with an increase in the probability of mobility by 0.32 percentage points. In column 3 we control for a full set of demographic variables, including sex, educational attainment, marital status, family size, work disability, weeks worked, and total income. In column 4 we include dummies for state of birth, and in column 5 we include dummies for state of residence. The model in column 5 is close to be fully saturated.