When you know, you act?

Weather forecasts, defensive action, and heat-related mortality

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Climate change and defensive actions

- **How will individuals and society respond to climate change?**
- As climate changes, so will behavior
- Could be large public good projects provided by governments or smaller scale private actions

Figure 1: Maeslantkering outside of Rotterdam

Climate change and defensive actions

Figure 2: Wine grapes in Champagne

Climate change and defensive actions

"This heat is a killer. It's going to be like a blast furnace tomorrow and you need to adjust what you do. You need to take care. So put off the sporting events, put off the outside events, stay inside."

Paul Holman, state ambulance commander
Victoria, Australia (January 5, 2018)

Small private defensive actions

- Could include dietary choices (Beatty et al 2017), clothing choice (Zhang et al 2017), activity choices (Zivin & Neidall 2014), medications (Deschenes et al 2017), etc.
- May or may not be linked to markets
- Even if the effect of an individual choice is small, the cumulative effect of many small actions could be large

Using expectations to measure adaptation

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- Variation in expectations can be used to estimate adaptation
- Recent applications to fishing revenue (Shrader 2017) and land markets (Severen et al 2017)

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- Variation in expectations can be used to estimate adaptation
- Recent applications to fishing revenue (Shrader 2017) and land markets (Severen et al 2017)
- Central idea: expectations affect outcomes solely through agent actions

Model of Forecasts (1/3)

- Every temperature observation (t_d) consists of its forecast (f_d) and an unforecasted shock (s_d):

$$t_d = f_d + s_d \tag{1}$$

- $T \sim N(\mu, \sigma_T^2)$
- $S \sim N(0, \sigma_S^2)$
- $F \sim N(\mu, \sigma_F^2)$
- Thus, temperature is distributed:

$$T \sim N(\mu, \sigma_F^2) + N(0, \sigma_S^2) \tag{2}$$

Model of Forecasts

- Two key insights:

$$\textbf{Implication 1:} \qquad E[s_t|t_d = \mu] = 0 \tag{3}$$

$$\textbf{Implication 2:} \qquad \frac{\partial E[s_d|t_d]}{\partial t_d} > 0 \tag{4}$$

- Hot temperatures are likely to be underforecasted, cold temperatures overforecasted
- Are extreme temperatures intrinsically damaging or are we just poorly prepared for them?

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- Do individuals take defensive action in response to forecasts of temperature?
- Do these actions affect mortality?
- I will use variation in the foreknowledge of temperature events caused by errors in publicly available weather forecasts to estimate the magnitude of these defensive actions

Data

- Mortality data comes from the CDC and is available at the county-month level
- Daily maximum temperature is provided by the CDC and originally comes from the North America Land Data Assimilation System (NLDAS)
- Forecast data comes from NOAA and comes from a gridded product that is fit to actual NWS station forecasts
- Since forecasts of a given observation are highly collinear across time, I take the average of the one through five-day forecasts as a single metric of the forecast
- I use 43,129 observations from June-September from years 2005 to 2011

Relationship between temperature and unforecasted shocks

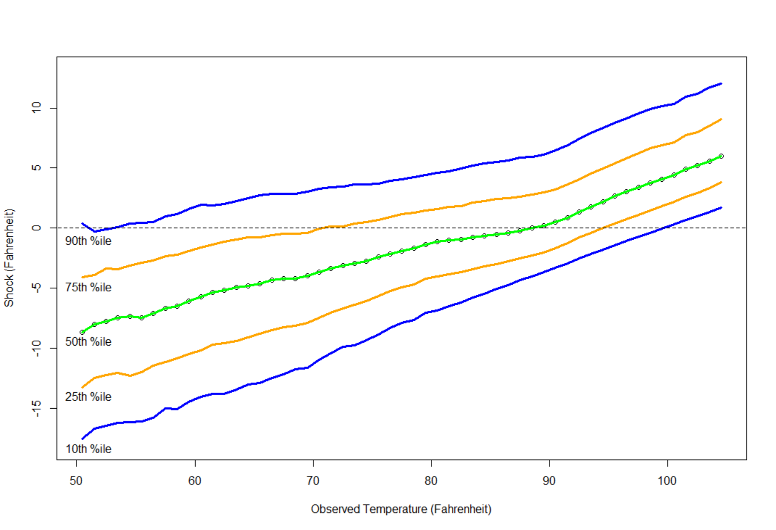

Figure 3: Forecast shock and observed temperature

Constructing temperature variables

- Need to aggregate daily observations to monthly level
- I use counts of days where maximum temperature falls within a given interval: below 75, 75-85, 85-95, and above 95
- Thus, each temperature variable takes a value between 0 and 31 for each county-month

Constructing forecast variables

- Again need to aggregate daily observations to monthly level
- I classify days with observed temperature above 95F as *warm* days
- I interact the monthly mean forecast shock on warm days with the count of warm days
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- If negative, we'd expect individuals to have taken excessive defensive actions and experience less mortality

Empirical Specification

The model is:

$$y_{it} = \sum_j \beta^j C_{it}^j + \theta C_{it}^{>95} * \overline{s_{it}^{>95}} + \phi_{stateMOY} + \alpha_i + \epsilon_{it} \qquad (5)$$

- y_{it} is the logarithm of county-month mortality
- C_{it}^j is the count of days in temperature interval j
- $\overline{s_{it}^{>95}}$ is the average shock on warm days

Results

100*$\beta^{<75^\circ}$	-0.046
	(0.040)
100*β^{85-95°	0.024
	(0.025)
100*$\beta^{>95^\circ}$	0.063
	(0.041)
100*θ	**0.009***
	(0.005)

Table 1: Full-sample Results

- Since above average temperature days have higher shocks, the average value of $s_{id}^{>95}$ is 5.2
- The total effect of an average warm day is $\beta^{>95}+5.2*\theta$
- Therefore, a warm day that is forecasted with average error increases monthly mortality by 0.1%, with underinvestment in defensive action due to forecast error representing 43% of the overall effect

Results for individuals >65 years old

100*$\beta^{<75^\circ}$	-0.084*
	(0.041)
100*β^{85-95°	0.026
	(0.024)
100*$\beta^{>95^\circ}$	0.140*
	(0.050)
100*θ	**0.018***
	(0.004)

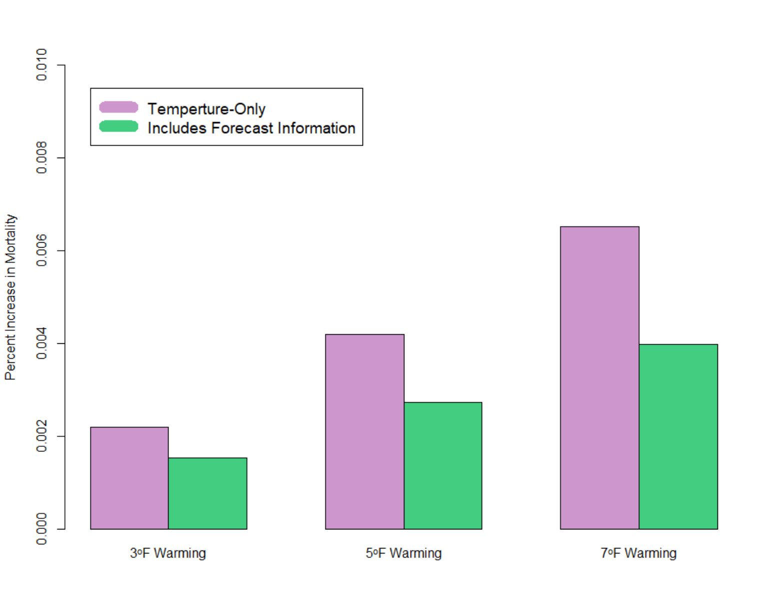
Table 2: >65 Results

- More sensitive to temperature **and** larger information effects
- Information effect represents 42% of the total effect of a hot day

Implications for Climate Change Impacts

- Warm days will occur more frequently under climate change
- However, warm days will also be forecasted more accurately
- For example, suppose climate change is a uniform 3 degree shift
  - This will result in an average of 2.6 more 95+ days per month
  - But forecasts of these days will underestimate the temperature by an average of 3.9 degrees, rather than the current 5.2 degrees
- If estimates don't account for this, impact estimates could be meaningfully different.

How different? Comparison of forecast model to 'naive' model



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- Preliminary evidence that even small adaptations may play a big role in reducing heat-related mortality
- Thank you!

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