Online Appendix

Robustness Checks

In this section, I provide several robustness checks to ensure that the estimates are not sensitive to model specification or other factors. Two of the two most important checks are discussed in the paper: the estimates that use leads in temperature in place of lags and the model estimated at the monthly level. Several other robustness checks are discussed here and are presented in Tables OA1 to OA4. Before discussing these, however, it should be mentioned that another sort of robustness check comes in the form of a previous version of this paper, wherein all estimates were conducted at the county-level (rather than zip-code). The estimates produced in this previous version were quite similar to the results discussed here.

These main estimates were estimated in levels rather than logs due to the fact that there are a significant number of zip-days with zero ED visits, especially when the analysis is broken down into smaller categories (e.g., ED visits for infectious / parasitic diseases). Table OA1 presents estimates of the baseline model carried out in logs and reports estimates that are nearly identical to those carried out in levels; because these were estimated in logs, the coefficients are not divided by the mean of the dependent variable. This table also presents separate estimates that exclude controls for holidays, estimates that exclude controls for the day-of-week, and estimates that exclude controls for precipitation. All of these estimates yield similar results to the baseline model. Finally, this table presents a model estimated as using a fixed-effects Poisson specification, where the outcomes are measured in counts rather than rates (zip-code population is used as an exposure variable). The disadvantage of the Poisson specification is that only one set of high-dimensional fixed effects can be included due to the potential for an incidental parameters problem; further, standard errors must be clustered at the level of the included fixed effect. This model includes zip-by-week and year fixed effects, and standard errors are accordingly clustered at the zip-by-week level. The standard errors are much smaller, which is unsurprising given the fine scale at which the standard errors are clustered, but the point estimates are very similar to those estimated in the primary analysis, providing further reassurance that the main estimates are not driven by model specification.

Because identification of the causal effects of weather in this study relies on a suitable set of fixed effects, it is important to probe the robustness of the main results to the specification of fixed effects. While I believe that the set of fixed included in the baseline model strikes an optimal balance between providing a suitable set of controls and not asking too much of the data, there do exist other options. Table OA2 displays the main results for five sets of fixed effects distinct from the baseline model. For the most part, these models produce estimates that are quite similar to the primary estimates. One exception lies in models that include exact-date fixed effects, in which the estimates for hot temperatures are somewhat attenuated and the standard errors nearly double in size. Because of the high degree of correlation in weather across counties within California, the difficulty in estimating models with exact-date fixed effects is unsurprising, though the inability to estimate such models precisely is an important caveat that should be noted.

I test the robustness of the main results to an alternative set of weather stations that additionally measure humidity and wind speed. These data are from the NCDC's Quality Controlled Local Climatological Data (QCLCD) system. This smaller set of stations are typically located in airports and provide highly reliable measurements of various weather variables, though the spatial coverage of these stations is somewhat more limited relative to the GHCN. Using this data, I first confirm the results of the main analysis using only temperature and precipitation. In another regression, I add quartiles for absolute humidity, and finally I add both humidity quartiles as well as quartiles in average wind speed. In all regressions, the estimates are essentially identical to those estimated using the GHCN. These estimates are presented in Table OA3 and the process by which the QCLCD data is constructed is described below

Finally, I make use of an alternate strategy to classify admissions into more or less deferrable categories. This strategy follows number of papers that argue that diagnosis codes with weekend-weekday admission ratio near 2/7 are less likely to be deferrable in nature (Dobkin, 2003; Card *et al.* , 2009; Doyle *et al.* , 2015). The intuition behind this approach is that if a medical emergency cannot be deferred to a later date, then the admission rate should be roughly equal across days of the week. To employ this approach, I test the hypothesis that the weekend-weekday admission ratio for each ICD code is equal to 2/7, and define diseases codes as "more deferrable" or " less deferrable" if the absolute value of the t-statistic of this test lies in the first or fourth quartile of the distribution of t-statistics, respectively. These results are presented in Table OA4, and are similar to the preferred strategy described earlier.

Additional Results

The goal of this paper has been to make headway in understanding the general relationship between weather and hospital usage. While not necessarily of first-order importance in understanding this general relationship, there are many additional features of this relationship and dimensions of heterogeneity that can be explored. In this section, I present a number of these additional results.

The first of these additional results uses the humidity data in the QCLCD to test whether absolute humidity has an independent effect on hospital usage. The models tested here incorporate quartiles in absolute humidity into the baseline specification.[1] Similar to the temperature variables, 30 lags in all humidity variables are included and I report results for both the contemporaneous and cumulative effects of humidity. The first quartile is omitted and as such coefficients should be interpreted as relative to the low humidity levels represented by the first quartile. These results are reported in Table OA5. The first set of results represent all visits. These estimates indicate that levels of humidity above the first quartile are responsible for a small contemporaneous increase in ED visits, and a sizeable cumulative decrease. The estimates in general imply that low levels of humidity can be dangerous and are consistent with a literature relating influenza transmission and mortality to low humidity levels (Shaman & Kohn, 2009; Barreca & Shimshack, 2012). Exploring this further, I estimate similar models that restrict the sample to visits with either respiratory or non-respiratory principal diagnoses. These additional estimates, which show a strong effect of low humidity levels on respiratory-related visits and little impact for non-respiratory visits, further support the literature on disease transmission and humidity.

A natural question to ask is whether individuals can adapt to temperature either through physiological or behavioral means. Focusing on behavioral adaptation, it is possible that people who are frequently exposed to temperature extremes learn to adapt to these temperatures and behave differently than people who are not conditioned to these extremes. For example, individuals who frequently experience hot (cold) temperatures may be induced to purchase air conditioning (heating), or take other measures to avoid exposure to such extremes. I follow the strategy of Graff-Zivin & Neidell (2014) to test for such adaptation. This strategy relies on separately estimating the effects of temperature by climate region, where climate is measured as the total number of days that fall into either the coldest or hottest temperature bin in a given zip-code. I categorize zip-codes into above- and below-median climate groups, and I do this separately for hot and cold temperatures. The results of this exercise are presented in Tables OA6 and OA7. The estimates do suggest some level of adaptation, as there tend to be stronger negative impacts of both cold

[1]The cutoffs for the absolute humidity quartiles are 5.49, 7.14 and 8.77.

and hot temperatures when such temperatures are experienced less frequently. Note that the estimates for cold temperatures are somewhat more difficult to interpret as there are almost no days that fall into the lowest temperature bin for the zip-codes with a below-median number of cold days per year (and the standard errors are very large); the less extreme cold weather bins, however (i.e., 40-45 and 45-50 degrees) suggest a significantly stronger effect of cold weather relative to zip-codes with an above-median number of cold days.

In Table OA8, I explore two additional dimensions of heterogeneity: gender and income. First, these estimates indicate essentially no differential impact of temperature by gender. Income heterogeneity is another dimension of interest as lower income individuals may be less able to protect themselves from exposure to temperature extremes through adaptation mechanisms such as the purchase of air conditioning or heating. To explore income heterogeneity, I make use of the fact that each patient reports their expected source of payment to get at whether this relationship varies by income; I consider individuals that expect to pay with Medicaid as relatively low income and individuals expecting to pay with private insurance as relatively high income. Since patients in these groups differ on dimensions other than income, this interpretation should be taken with some caution. The estimates indicate that the Medicaid population is more strongly affected by cold temperatures (27.4% cumulative effect) relative to the private insurance population (10.1% cumulative effect). Somewhat surprisingly, the estimates for the effects of high temperatures are quite similar between these two groups, though large standard errors mean that sizeable differences cannot be rejected.

Finally, in Table OA9, I ask whether heat waves or cold waves confer any additional impact relative to a temperature shock experienced in isolation. I use two strategies to estimate these impacts. In the first strategy, I use a model estimated at the daily level (similar to the baseline specification), and create two new variables indicating that each of the last two days and the present day had temperatures falling into the under 40°F bin (cold waves) or the over 80°F bin (heat waves). The model I estimate includes all of the same variables as the baseline specification, as well as the cold and heat wave variables along with 30 lags in each. These variables are intended to indicate whether the third day (or beyond) of a cold or heat wave has any additional impact beyond the effect of a temperature shock experienced in isolation. The results indicate that there is no additional contemporaneous effect for either heat or cold waves; the cumulative effect for cold temperatures, however, appears to be driven by cold waves. Because this strategy is somewhat cumbersome, I estimate a second model using monthly data that is intended to capture the same effect. The monthly model is the same as that reported in final column of Table 3 in the paper, except that I add two additional variables that measure the number of days in either the lowest or highest temperature bin that are part of an event lasting at least three days. These variables are again intended to measure whether an additional day in each bin that is part of a heat wave or cold wave has any additional effect beyond the impact of a day that is not part of such an event. The estimates from this strategy are very similar to the daily model, indicating that the negative effects of cold weather are driven by cold waves rather than cold days in isolation, and there is no statistically significant differential effect for heat waves.

QCLCD Weather Data Construction

This section describes the process by which weather data was constructed for testing the robustness of the main results to an alternative weather database, the Quality Controlled Local Climatological Data (QCLCD). This data is only available beginning in 2005, and consists of a smaller set of stations than the GHCN (the dataset used in the main analysis) that are generally located in airports. That being said, the quality of data from these stations is high, with a relatively small number of missing values, information on more weather variables, and quality control procedures that the GHCN lacks. Further, these data allow for the use of a consistent set of stations that operate consistently between 2005 and 2013 (where the set of stations can be different in each year using the GHCN).

To be included in the analysis, each station must have at least 95% valid daily observations for the entire period 2005-2013. This process ensures that stations must have observations in all years, and results in a total of 66 stations throughout California. To fill in the the missing values, I use a procedure to that used in (Auffhammer & Kellogg, 2011). For each station and weather variable (i.e., temperature, precipitation, dew point temperature, etc.), I regress that variable on the value of the same variable in each the 10 closest stations, as well as month fixed effects. The predicted values from these regressions are used to interpolate any missing values. If a value is missing from one of the 10 closest stations, then I repeat this process using the 9 closest stations. This process is repeated until only the closest station is used. Unsurprisingly, the predicted value from the 10 nearest stations is used the vast majority of the time, given that only stations with 95% non-missing observations are included. This process fills in the remainder of the data, and yields a station-by-day file. From there, the same inverse-distance weighting procedure is used to map station-level data into county-level data (also with a 100km radius).

Climate Forecasts

In order to estimate the impacts of climate change, I require predictions on the change in the number of days (between now and some point in the future – I choose to focus on end-of-century) that fall into each temperature bin, for each county in my sample. I use predictions based on the Hadley Centre's Global Environment Model version 2 (GEM2-ES). This is one of the major climate models used in the IPCC's Fifth Assessment Report. This model is available for four "Representative Concentration Pathways" (RCP's), which represent different pathways for emissions (driven by population changes, policy decisions, etc.) and thus greenhouse gas concentrations. I focus on RCP8.5, which simulates a continuation of current emission growth rates (i.e., "business-as-usual"). This model produces daily predictions of temperature (and other climate variables) between 1860 and 2099 for grid-points across the globe.

I restrict the sample to grid-points near California and focus on changes in climate between now and the end of century. First, for each grid-point, I calculate the average number of days per year in each temperature bin for the period 1980-2009. I then repeat this process for the period 2070-2099. Then, for each grid-point and temperature bin, I take the difference between these averages. The result is, for each grid-point, the predicted change in the average number of days per year that falls into each temperature bin. To aggregate grid-points to counties, I use the same inverse-distance weighting procedure used in **??**, but with grid-points in place of weather stations. The result is a dataset that indicates, for each county, the predicted changes in the number of days that fall into each temperature bin between the "current" climate (1980-2009) and the end-of-century climate (2070-2099).

Table OA1: Robustness Checks – Specification Checks

	(1)		(2)		(3)		(4)		(5)	
	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.
<40	-0.059**	0.098**	-0.062**	0.115**	-0.061**	0.110**	-0.070**	0.100	-0.055**	0.132**
	(0.006)	(0.036)	(0.008)	(0.037)	(0.007)	(0.036)	(0.008)	(0.041)	(0.002)	(0.008)
40-45	-0.046**	0.079	-0.047**	0.065	-0.046**	0.065	-0.052**	0.046	-0.046**	0.038**
	(0.004)	(0.041)	(0.005)	(0.053)	(0.005)	(0.054)	(0.005)	(0.055)	(0.001)	(0.005)
75-80	0.028**	0.030	0.031**	0.041*	0.028**	0.041*	0.029**	0.040*	0.031**	0.066**
	(0.002)	(0.020)	(0.003)	(0.019)	(0.002)	(0.019)	(0.002)	(0.019)	(0.001)	(0.004)
>80	0.034**	0.039	0.035**	0.050*	0.034**	0.051*	0.035**	0.050*	0.036**	0.056**
	(0.003)	(0.021)	(0.004)	(0.021)	(0.003)	(0.021)	(0.003)	(0.021)	(0.001)	(0.004)
Mean Dep. Var.	77.1		77.1		77.1		77.1		77.1	
# Admissions	94,225,592		94,225,592		94,225,592		94,225,592		94,225,592	
N	3,905,239		3,905,239		3,905,239		3,905,239		3,905,239	
Logs	X		-		-		-		-	
Exclude Day-of-Week	-		X		-		-		-	
Exclude Holidays	-		-		X		-		-	
No Precip.	-		-		-		X		-	
Poisson	-		-		-		-		X	

Note – Standard errors are two-way clustered at the county and year-month levels. All regressions are weighted by total zip-code population. Regressions are estimated in levels, but reported in percent changes (the level effect divided by the reported mean dependent variable). ** significant at the 1% level. * significant at the 5% level.

Table OA2: Robustness Checks – Fixed Effects

	(1)		(2)		(3)		(4)		(5)	
	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.
<40	-0.072**	0.078*	-0.064**	0.147**	-0.039**	0.131*	-0.065**	0.105**	-0.041**	0.132*
	(0.008)	(0.031)	(0.008)	(0.045)	(0.008)	(0.058)	(0.009)	(0.038)	(0.009)	(0.059)
40-45	-0.055**	-0.025	-0.051**	-0.004	-0.038**	-0.032	-0.048**	0.058	-0.039**	-0.033
	(0.004)	(0.040)	(0.005)	(0.055)	(0.005)	(0.060)	(0.006)	(0.056)	(0.005)	(0.061)
75-80	0.029**	0.063**	0.030**	0.060**	0.025**	0.060	0.031**	0.041*	0.025**	0.060
	(0.003)	(0.019)	(0.003)	(0.023)	(0.003)	(0.034)	(0.003)	(0.019)	(0.003)	(0.034)
>80	0.030**	0.016	0.035**	0.040	0.027**	0.023	0.036**	0.051*	0.026**	0.023
	(0.004)	(0.022)	(0.003)	(0.024)	(0.004)	(0.042)	(0.004)	(0.021)	(0.004)	(0.042)
Mean Dep. Var.	77.1		77.1		77.1		77.1		77.1	
# Admissions	94,225,592		94,225,592		94,225,592		94,225,592		94,225,592	
N	3,905,239		3,905,239		3,905,239		3,905,239		3,905,239	
Zip	X		-		-		-		-	
Year	X		X		-		-		-	
Month	X		-		-		-		-	
Zip-Month	-		X		-		-		-	
Zip-Week	-		-		X		-		-	
Exact Date	-		-		X		-		X	
County-Year	-		-		-		X		-	
Zip-Day of Year	-		-		-		X		X	

Note – Standard errors are two-way clustered at the county and year-month levels. All regressions are weighted by total zip-code population. Regressions are estimated in levels, but reported in percent changes (the level effect divided by the reported mean dependent variable). ** significant at the 1% level. * significant at the 5% level.

Table OA3: Robustness Checks – Alternate Weather Data (QCLCD)

	(1)		(2)		(3)	
	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.
<40	-0.049**	0.118*	-0.046**	0.091	-0.045**	0.087
	(0.006)	(0.059)	(0.007)	(0.063)	(0.007)	(0.064)
40-45	-0.044**	0.093	-0.040**	0.063	-0.040**	0.058
	(0.004)	(0.055)	(0.005)	(0.057)	(0.005)	(0.057)
75-80	0.032**	0.054**	0.034**	0.053**	0.031**	0.053**
	(0.003)	(0.015)	(0.003)	(0.013)	(0.003)	(0.013)
>80	0.042**	0.077**	0.044**	0.077**	0.040**	0.077**
	(0.003)	(0.018)	(0.003)	(0.017)	(0.004)	(0.017)
Mean Dep. Var.	76.4		76.4		76.4	
# Admissions	80,459,816		80,459,816		80,459,816	
N	3,142,125		3,142,125		3,142,125	
Precip. Only	X		X		X	
Add Humidity	-		X		X	
Add Windspeed	-		-		X	

Note – This table probes the robustness of the main results to the use of another weather dataset. The first column reports estimates that duplicate the main result, but using weather data from the QCLCD rather than GHCN. The second column adds humidity quartiles. The third column adds humidity quartiles and windspeed quartiles. Standard errors are two-way clustered at the county and year-month levels. All regressions are weighted by total zip-code population. Regressions are estimated in levels, but reported in percent changes (the level effect divided by the reported mean dependent variable). ** significant at the 1% level. * significant at the 5% level.

Table OA4: Deferrability – Alternate Classification

	More Deferrable		Less Deferrable	
	Contemp.	Cumul.	Contemp.	Cumul.
<40	-0.065**	0.170**	-0.058**	0.098**
	(0.011)	(0.041)	(0.006)	(0.021)
40-45	-0.044**	0.115	-0.042**	0.050
	(0.007)	(0.073)	(0.004)	(0.037)
75-80	0.026**	0.064*	0.030**	0.031*
	(0.003)	(0.026)	(0.003)	(0.015)
>80	0.030**	0.065*	0.036**	0.039*
	(0.003)	(0.027)	(0.003)	(0.018)
Mean Dep. Var.	13.9		10.6	
# Admissions	16939112		12926923	
N	3905239		3905239	

Note – Standard errors are two-way clustered at the county and year-month levels. All regressions are weighted by total zip-code population. Regressions are estimated in levels, but reported in percent changes (the level effect divided by the reported mean dependent variable). ** significant at the 1% level. * significant at the 5% level.

Table OA5: Impacts of Humidity

	All Visits		Respiratory		Non-Respiratory	
	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.
Quartile 2	0.006**	-0.034*	0.001	-0.208*	0.007**	-0.009
	(0.001)	(0.015)	(0.006)	(0.083)	(0.001)	(0.010)
Quartile 3	0.010**	-0.029	0.005	-0.159	0.011**	-0.010
	(0.001)	(0.018)	(0.005)	(0.088)	(0.001)	(0.012)
Quartile 4	0.012**	-0.024	0.003	-0.117	0.014**	-0.011
	(0.002)	(0.023)	(0.007)	(0.092)	(0.002)	(0.018)
Mean Dep. Var.	76.0		9.7		66.3	
# Admissions	80,718,016		10,272,140		70,445,880	
N	3,142,125		3,142,125		3,142,125	

Note – This table reports results from the same model including all temperature variables as well as quartiles in absolute humidity. The first quartile is omitted and thus all estimate should be interpreted relative to that. The cutoffs in absolute humidity corresponding for the quartiles are 5.49, 7.14 and 8.77. Standard errors are two-way clustered at the county and year-month levels. All regressions are weighted by total zip-code population. Regressions are estimated in levels, but reported in percent changes (the level effect divided by the reported mean dependent variable). ** significant at the 1% level. * significant at the 5% level.

Table OA6: Adaptation (Cold Regions)

	Below Median (Less Cold)		Above Median (More Cold)	
	Contemp.	Cumul.	Contemp.	Cumul.
<40	-0.070**	-0.106	-0.058**	0.078*
	(0.013)	(0.179)	(0.007)	(0.036)
40-45	-0.042**	0.165*	-0.044**	0.026
	(0.005)	(0.076)	(0.005)	(0.047)
Mean Dep. Var.	72.2		85.0	
# Visits	54,827,928		39,397,664	
N	2,162,884		1,742,355	

The categories are zip-codes that are above or below the median number of cold days (<40) per year. Standard errors are two-way clustered at the county and year-month levels. All regressions are weighted by total zip-code population. Regressions are estimated in levels, but reported in percent changes (the level effect divided by the reported mean dependent variable). ** significant at the 1% level. * significant at the 5% level.

Table OA7: Adaptation (Hot Regions)

	Below Median (Less Hot)		Above Median (More Hot)	
	Contemp.	Cumul.	Contemp.	Cumul.
75-80	0.027**	0.050*	0.029**	0.033
	(0.003)	(0.020)	(0.003)	(0.020)
>80	0.038**	0.067**	0.034**	0.045*
	(0.004)	(0.026)	(0.003)	(0.021)
Mean Dep. Var.	73.7		80.4	
# Visits	44,117,396		50,108,192	
N	1,920,031		19,852,081	

The categories are zip-codes that are above or below the median number of hot days (>80) per year. Standard errors are two-way clustered at the county and year-month levels. All regressions are weighted by total zip-code population. Regressions are estimated in levels, but reported in percent changes (the level effect divided by the reported mean dependent variable). ** significant at the 1% level. * significant at the 5% level.

Table OA8: Insurance Status and Gender

	Medicaid		Private Ins.		Male		Female	
	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.
<40	-0.054**	0.274**	-0.059**	0.101	-0.064**	0.111**	-0.058**	0.110**
	(0.008)	(0.076)	(0.010)	(0.059)	(0.008)	(0.036)	(0.007)	(0.038)
40-45	-0.035**	0.225*	-0.051**	0.039	-0.051**	0.055	-0.040**	0.076
	(0.007)	(0.096)	(0.005)	(0.046)	(0.005)	(0.053)	(0.005)	(0.055)
75-80	0.028**	0.083	0.028**	0.068**	0.032**	0.040*	0.025**	0.040*
	(0.005)	(0.045)	(0.003)	(0.025)	(0.003)	(0.019)	(0.003)	(0.019)
>80	0.035**	0.070	0.032**	0.077**	0.040**	0.055**	0.030**	0.045*
	(0.008)	(0.073)	(0.003)	(0.027)	(0.004)	(0.020)	(0.003)	(0.022)
Mean Dep. Var.	21.0		24.9		35.1		42.0	
# Admissions	25,650,384		30,445,238		42,867,528		51,322,740	
N	3,905,239		3,905,239		3,905,239		3,905,239	

Note – Standard errors are two-way clustered at the county and year-month levels. All regressions are weighted by total zip-code population. Regressions are estimated in levels, but reported in percent changes (the level effect divided by the reported mean dependent variable). ** significant at the 1% level. * significant at the 5% level.

Table OA9: Cold Waves and Heat Waves

	Daily Model		Monthly Model
	Contemp.	Cumul.	Cumul.
<40	-0.055**	0.051	0.003
	(0.006)	(0.052)	(0.074)
Cold Wave (3+ Days)	-0.004	0.136*	0.197**
	(0.002)	(0.067)	(0.075)
>80	0.034**	0.090**	0.106*
	(0.003)	(0.024)	(0.044)
Heat Wave (3+ Days)	-0.002	-0.049	-0.054
	(0.002)	(0.036)	(0.033)
Mean Dep. Var.	77.1		2345.6
# Admissions	94,225,592		94,330,160
N	3,905,239		128,575

Note – The "<40" and ">80" are intended to measure the effect of an additional day in each bin, when the day is not part of a heat or cold wave event lasting at least three days. The "Cold Wave (3+ Days)" and "Heat Wave (3+ Days)" variables are intended to measure the differential effect of an additional day in each bin when the day is part of such an event. Standard errors are two-way clustered at the county and year-month levels. All regressions are weighted by total zip-code population. Regressions are estimated in levels, but reported in percent changes (the level effect divided by the reported mean dependent variable). ** significant at the 1% level. * significant at the 5% level.

Full Results (All Temperature Bins)

Table OA10: Baseline Results

	(1)		(2)		(3)		(4)	
	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.
<40	-0.061	0.110	-0.064	0.121	-0.040	0.053	-0.001	-0.008
	(0.007)	(0.036)	(0.008)	(0.042)	(0.005)	(0.025)	(0.010)	(0.036)
40-45	-0.045	0.064	-0.048	0.070	-0.029	0.036	-0.002	0.009
	(0.005)	(0.054)	(0.005)	(0.059)	(0.004)	(0.032)	(0.006)	(0.017)
45-50	-0.036	0.035	-0.039	0.036	-0.023	0.033	0.006	-0.007
	(0.004)	(0.020)	(0.004)	(0.023)	(0.003)	(0.015)	(0.005)	(0.016)
50-55	-0.024	0.016	-0.025	0.018	-0.017	0.002	-0.000	-0.016
	(0.002)	(0.014)	(0.002)	(0.016)	(0.002)	(0.008)	(0.004)	(0.012)
55-60	-0.012	0.003	-0.013	0.007	-0.012	-0.019	-0.000	-0.007
	(0.001)	(0.012)	(0.001)	(0.013)	(0.002)	(0.010)	(0.002)	(0.011)
65-70	0.009	-0.009	0.010	-0.005	0.008	-0.030	0.000	-0.009
	(0.001)	(0.010)	(0.001)	(0.010)	(0.001)	(0.012)	(0.002)	(0.009)
70-75	0.021	0.013	0.021	0.018	0.017	-0.018	0.005	0.004
	(0.002)	(0.011)	(0.002)	(0.012)	(0.002)	(0.010)	(0.002)	(0.012)
75-80	0.028	0.041	0.029	0.047	0.026	0.004	0.004	0.001
	(0.002)	(0.019)	(0.003)	(0.020)	(0.002)	(0.014)	(0.003)	(0.011)
>80	0.035	0.051	0.035	0.054	0.034	0.033	0.007	0.015
	(0.003)	(0.021)	(0.003)	(0.022)	(0.004)	(0.017)	(0.005)	(0.015)
Mean Dep. Var.	77.1		65.0		12.1		14.7	
# Admissions	94,225,592		79,491,760		14,733,830		18,020,504	
N	3,905,239		3,905,239		3,905,239		3,905,239	
Outpatient Emerg.	X		X		-		-	
Inpatient Emerg.	X		-		X		-	
Inpatient Non-Emerg.	-		-		-		X	

Table OA11: Cumulative Effects

	30 Days (Baseline)	40 Days	50 Days	60 Days	Monthly Model
<40	0.110	0.150	0.167	0.170	0.153
	(0.036)	(0.042)	(0.049)	(0.056)	(0.058)
40-45	0.064	0.083	0.100	0.089	0.088
	(0.054)	(0.058)	(0.057)	(0.056)	(0.065)
45-50	0.035	0.038	0.037	0.029	0.048
	(0.020)	(0.023)	(0.024)	(0.026)	(0.029)
50-55	0.016	0.015	0.014	0.010	0.020
	(0.014)	(0.015)	(0.017)	(0.019)	(0.020)
55-60	0.003	0.005	0.013	0.011	0.008
	(0.012)	(0.013)	(0.016)	(0.018)	(0.017)
65-70	-0.009	-0.014	-0.017	-0.023	-0.015
	(0.010)	(0.011)	(0.013)	(0.015)	(0.016)
70-75	0.013	0.008	0.004	-0.005	0.010
	(0.011)	(0.013)	(0.014)	(0.017)	(0.018)
75-80	0.041	0.045	0.044	0.041	0.047
	(0.019)	(0.022)	(0.023)	(0.026)	(0.028)
>80	0.051	0.049	0.048	0.042	0.046
	(0.021)	(0.023)	(0.026)	(0.029)	(0.033)
Mean Dep. Var.	77.1	77.1	77.1	77.1	2,345.6
# Admissions	94,009,920	94,009,920	94,009,920	94,009,920	94,330,160
N	3,891,199	3,891,199	3,891,199	3,891,199	128,575

Table OA12: Age Heterogeneity

	Under 5		5-14		15-24		25-64		Over 64	
	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.
<40	-0.070	0.277	-0.117	0.222	-0.061	0.102	-0.049	0.069	-0.056	0.115
	(0.014)	(0.109)	(0.017)	(0.108)	(0.009)	(0.049)	(0.007)	(0.036)	(0.007)	(0.043)
40-45	-0.064	0.137	-0.083	0.128	-0.037	0.043	-0.037	0.034	-0.049	0.100
	(0.010)	(0.108)	(0.011)	(0.121)	(0.005)	(0.060)	(0.005)	(0.043)	(0.006)	(0.036)
45-50	-0.055	0.078	-0.061	0.113	-0.031	-0.003	-0.029	0.005	-0.038	0.083
	(0.007)	(0.058)	(0.008)	(0.066)	(0.004)	(0.022)	(0.004)	(0.018)	(0.004)	(0.016)
50-55	-0.042	0.047	-0.042	0.014	-0.017	-0.016	-0.019	0.006	-0.024	0.052
	(0.006)	(0.039)	(0.005)	(0.043)	(0.003)	(0.018)	(0.002)	(0.014)	(0.002)	(0.010)
55-60	-0.019	0.050	-0.022	-0.013	-0.011	-0.018	-0.010	-0.004	-0.014	0.015
	(0.003)	(0.034)	(0.003)	(0.025)	(0.003)	(0.014)	(0.001)	(0.012)	(0.002)	(0.008)
65-70	0.016	0.002	0.010	-0.044	0.008	-0.010	0.006	-0.005	0.012	-0.017
	(0.003)	(0.023)	(0.003)	(0.031)	(0.002)	(0.012)	(0.001)	(0.010)	(0.001)	(0.010)
70-75	0.032	0.029	0.021	-0.005	0.020	0.016	0.015	0.009	0.027	0.013
	(0.005)	(0.029)	(0.005)	(0.035)	(0.003)	(0.015)	(0.002)	(0.012)	(0.002)	(0.010)
75-80	0.048	0.074	0.024	0.098	0.029	0.037	0.022	0.035	0.034	0.007
	(0.008)	(0.051)	(0.007)	(0.042)	(0.003)	(0.019)	(0.003)	(0.020)	(0.003)	(0.012)
>80	0.064	0.086	0.021	0.095	0.039	0.034	0.027	0.040	0.037	0.027
	(0.012)	(0.053)	(0.008)	(0.047)	(0.004)	(0.024)	(0.005)	(0.024)	(0.004)	(0.018)
Mean Dep. Var.	118.4		48.1		71.3		71.3		126.4	
# Admissions	10,322,464		8,105,756		12,911,893		45,855,312		17,030,166	
N	3,905,239		3,905,239		3,905,239		3,905,239		3,905,239	

Table OA13: Deferrability

	More Deferrable		Less Deferrable	
	Contemp.	Cumul.	Contemp.	Cumul.
<40	-0.065	0.170	-0.058	0.098
	(0.011)	(0.041)	(0.006)	(0.021)
40-45	-0.044	0.115	-0.042	0.050
	(0.007)	(0.073)	(0.004)	(0.037)
45-50	-0.036	0.069	-0.029	0.044
	(0.006)	(0.030)	(0.003)	(0.019)
50-55	-0.025	0.031	-0.019	0.021
	(0.003)	(0.019)	(0.002)	(0.010)
55-60	-0.012	0.011	-0.011	0.007
	(0.002)	(0.017)	(0.002)	(0.007)
65-70	0.007	-0.014	0.011	-0.006
	(0.002)	(0.014)	(0.002)	(0.007)
70-75	0.018	0.020	0.020	0.004
	(0.003)	(0.017)	(0.002)	(0.010)
75-80	0.026	0.064	0.030	0.031
	(0.003)	(0.026)	(0.003)	(0.015)
>80	0.030	0.065	0.036	0.039
	(0.003)	(0.027)	(0.003)	(0.018)
Mean Dep. Var.	13.9		10.6	
# Admissions	16,939,112		12,926,923	
N	3,905,239		3,905,239	

Table OA14: Costs

	All Emergency-Related	Emergency Inpatient	Emergency Outpatient
<40	12176	8542	3406
	(10877)	(10202)	(1422)
40-45	11364	8543	2573
	(9998)	(8705)	(1884)
45-50	14676	13620	842
	(4094)	(3749)	(830)
50-55	1728	1009	558
	(2587)	(2456)	(613)
55-60	-2347	-2711	285
	(2240)	(1988)	(439)
65-70	-7334	-7418	133
	(2537)	(2405)	(344)
70-75	-2712	-3775	994
	(2696)	(2516)	(479)
75-80	1639	-499	2086
	(3732)	(3270)	(803)
>80	7994	5498	2301
	(3773)	(3310)	(882)
Mean Dep. Var.	$230,846	$184916	$45583
# Visits	94,225,592	14,733,830	78,745,280
N	3,905,239	3,905,239	3,905,239

Table OA15: Robustness Checks – Specification Checks

	(1)		(2)		(3)		(4)		(5)	
	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.
<40	-0.059	0.098	-0.062	0.115	-0.061	0.110	-0.070	0.100	-0.055	0.132
	(0.006)	(0.036)	(0.008)	(0.037)	(0.007)	(0.036)	(0.008)	(0.041)	(0.002)	(0.008)
40-45	-0.046	0.079	-0.047	0.065	-0.046	0.065	-0.052	0.046	-0.046	0.038
	(0.004)	(0.041)	(0.005)	(0.053)	(0.005)	(0.054)	(0.005)	(0.055)	(0.001)	(0.005)
45-50	-0.038	0.033	-0.036	0.036	-0.036	0.036	-0.042	0.024	-0.036	0.068
	(0.003)	(0.023)	(0.004)	(0.021)	(0.004)	(0.020)	(0.004)	(0.020)	(0.001)	(0.004)
50-55	-0.025	0.027	-0.023	0.016	-0.024	0.015	-0.028	0.002	-0.024	0.023
	(0.002)	(0.013)	(0.002)	(0.014)	(0.002)	(0.014)	(0.003)	(0.014)	(0.001)	(0.003)
55-60	-0.013	0.006	-0.013	0.003	-0.013	0.003	-0.014	-0.001	-0.012	0.017
	(0.001)	(0.013)	(0.001)	(0.012)	(0.001)	(0.012)	(0.001)	(0.012)	(0.001)	(0.004)
65-70	0.009	-0.018	0.010	-0.008	0.009	-0.008	0.010	-0.007	0.009	-0.014
	(0.001)	(0.013)	(0.001)	(0.010)	(0.001)	(0.010)	(0.001)	(0.010)	(0.001)	(0.003)
70-75	0.022	0.023	0.022	0.013	0.020	0.013	0.021	0.012	0.022	0.031
	(0.001)	(0.013)	(0.002)	(0.011)	(0.002)	(0.011)	(0.002)	(0.011)	(0.001)	(0.004)
75-80	0.028	0.030	0.031	0.041	0.028	0.041	0.029	0.040	0.031	0.066
	(0.002)	(0.020)	(0.003)	(0.019)	(0.002)	(0.019)	(0.002)	(0.019)	(0.001)	(0.004)
>80	0.034	0.039	0.035	0.050	0.034	0.051	0.035	0.050	0.036	0.056
	(0.003)	(0.021)	(0.004)	(0.021)	(0.003)	(0.021)	(0.003)	(0.021)	(0.001)	(0.004)
Mean Dep. Var.	77.1		77.1		77.1		77.1		77.1	
# Admissions	94,225,592		94,225,592		94,225,592		94,225,592		94,225,592	
N	3,905,239		3,905,239		3,905,239		3,905,239		3,905,239	
Logs	X		-		-		-		-	
Exclude Day-of-Week	-		X		-		-		-	
Exclude Holidays	-		-		X		-		-	
No Precip.	-		-		-		X		-	
Poisson	-		-		-		-		X	

Table OA16: Robustness Checks – Fixed Effects

	(1)		(2)		(3)		(4)		(5)	
	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.
<40	-0.072	0.078	-0.064	0.147	-0.039	0.131	-0.065	0.105	-0.041	0.132
	(0.008)	(0.031)	(0.008)	(0.045)	(0.008)	(0.058)	(0.009)	(0.038)	(0.009)	(0.059)
40-45	-0.055	-0.025	-0.051	-0.004	-0.038	-0.032	-0.048	0.058	-0.039	-0.033
	(0.004)	(0.040)	(0.005)	(0.055)	(0.005)	(0.060)	(0.006)	(0.056)	(0.005)	(0.061)
45-50	-0.038	0.061	-0.036	0.065	-0.027	0.047	-0.037	0.028	-0.027	0.046
	(0.004)	(0.022)	(0.004)	(0.018)	(0.004)	(0.034)	(0.005)	(0.022)	(0.004)	(0.035)
50-55	-0.024	0.021	-0.024	0.012	-0.019	0.005	-0.025	0.012	-0.019	0.005
	(0.002)	(0.009)	(0.002)	(0.011)	(0.003)	(0.024)	(0.003)	(0.014)	(0.003)	(0.024)
55-60	-0.012	0.010	-0.012	0.007	-0.011	0.005	-0.013	-0.001	-0.011	0.005
	(0.001)	(0.011)	(0.001)	(0.013)	(0.001)	(0.018)	(0.001)	(0.012)	(0.001)	(0.018)
65-70	0.010	-0.003	0.009	-0.015	0.008	-0.008	0.010	-0.008	0.007	-0.008
	(0.001)	(0.009)	(0.001)	(0.011)	(0.001)	(0.017)	(0.001)	(0.010)	(0.001)	(0.017)
70-75	0.021	0.018	0.021	0.017	0.018	0.041	0.023	0.012	0.017	0.041
	(0.002)	(0.013)	(0.002)	(0.014)	(0.002)	(0.020)	(0.002)	(0.012)	(0.002)	(0.020)
75-80	0.029	0.063	0.030	0.060	0.025	0.060	0.031	0.041	0.025	0.060
	(0.003)	(0.019)	(0.003)	(0.023)	(0.003)	(0.034)	(0.003)	(0.019)	(0.003)	(0.034)
>80	0.030	0.016	0.035	0.040	0.027	0.023	0.036	0.051	0.026	0.023
	(0.004)	(0.022)	(0.003)	(0.024)	(0.004)	(0.042)	(0.004)	(0.021)	(0.004)	(0.042)
Mean Dep. Var.	77.1		77.1		77.1		77.1		77.1	
# Admissions	94,225,592		94,225,592		94,225,592		94,225,592		94,225,592	
N	3,905,239		3,905,239		3,905,239		3,905,239		3,905,239	
Zip	X		-		-		-		-	
Year	X		X		-		-		-	
Month	X		-		-		-		-	
Zip-Month	-		X		-		-		-	
Zip-Week	-		-		X		-		-	
Exact Date	-		-		X		-		X	
County-Year	-		-		-		X		-	
Zip-Day of Year	-		-		-		X		X	

Table OA17: Robustness Checks – Alternate Weather Data (QCLCD)

	(1)		(2)		(3)	
	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.
<40	-0.049	0.118	-0.046	0.091	-0.045	0.087
	(0.006)	(0.059)	(0.007)	(0.063)	(0.007)	(0.064)
40-45	-0.044	0.093	-0.040	0.063	-0.040	0.058
	(0.004)	(0.055)	(0.005)	(0.057)	(0.005)	(0.057)
45-50	-0.035	0.040	-0.033	0.019	-0.032	0.020
	(0.004)	(0.015)	(0.004)	(0.021)	(0.004)	(0.021)
50-55	-0.024	0.025	-0.024	0.015	-0.023	0.015
	(0.002)	(0.013)	(0.003)	(0.017)	(0.003)	(0.017)
55-60	-0.012	0.010	-0.012	0.009	-0.011	0.009
	(0.001)	(0.010)	(0.001)	(0.010)	(0.001)	(0.010)
65-70	0.011	0.004	0.012	0.002	0.011	0.002
	(0.001)	(0.012)	(0.001)	(0.010)	(0.001)	(0.010)
70-75	0.022	0.015	0.024	0.014	0.022	0.013
	(0.002)	(0.011)	(0.002)	(0.011)	(0.002)	(0.011)
75-80	0.032	0.054	0.034	0.053	0.031	0.053
	(0.003)	(0.015)	(0.003)	(0.013)	(0.003)	(0.013)
>80	0.042	0.077	0.044	0.077	0.040	0.077
	(0.003)	(0.018)	(0.003)	(0.017)	(0.004)	(0.017)
Mean Dep. Var.	76.4		76.4		76.4	
# Admissions	80,459,816		80,459,816		80,459,816	
N	3,142,125		3,142,125		3,142,125	
Precip. Only	X		X		X	
Add Humidity	-		X		X	
Add Windspeed	-		-		X	

Table OA18: Deferrability – Alternate Classification

	More Deferrable		Less Deferrable	
	Contemp.	Cumul.	Contemp.	Cumul.
$<$40	-0.065	0.170	-0.058	0.098
	(0.011)	(0.041)	(0.006)	(0.021)
40-45	-0.044	0.115	-0.042	0.050
	(0.007)	(0.073)	(0.004)	(0.037)
45-50	-0.036	0.069	-0.029	0.044
	(0.006)	(0.030)	(0.003)	(0.019)
50-55	-0.025	0.031	-0.019	0.021
	(0.003)	(0.019)	(0.002)	(0.010)
55-60	-0.012	0.011	-0.011	0.007
	(0.002)	(0.017)	(0.002)	(0.007)
65-70	0.007	-0.014	0.011	-0.006
	(0.002)	(0.014)	(0.002)	(0.007)
70-75	0.018	0.020	0.020	0.004
	(0.003)	(0.017)	(0.002)	(0.010)
75-80	0.026	0.064	0.030	0.031
	(0.003)	(0.026)	(0.003)	(0.015)
$>$80	0.030	0.065	0.036	0.039
	(0.003)	(0.027)	(0.003)	(0.018)
Mean Dep. Var.	13.9		10.6	
# Admissions	16939112		12926923	
N	3905239		3905239	

Table OA19: Adaptation (Cold Regions)

	Below Median (Less Cold)		Above Median (More Cold)	
	Contemp.	Cumul.	Contemp.	Cumul.
<40	-0.070	-0.106	-0.058	0.078
	(0.013)	(0.179)	(0.007)	(0.036)
40-45	-0.042	0.165	-0.044	0.026
	(0.005)	(0.076)	(0.005)	(0.047)
45-50	-0.037	0.057	-0.034	0.004
	(0.004)	(0.029)	(0.004)	(0.030)
Mean Dep. Var.	72.2		85.0	
# Visits	54,827,928		39,397,664	
N	2,162,884		1,742,355	

Table OA20: Adaptation (Hot Regions)

	Below Median (Less Hot)		Above Median (More Hot)	
	Contemp.	Cumul.	Contemp.	Cumul.
70-75	0.019	0.004	0.021	0.013
	(0.002)	(0.012)	(0.002)	(0.014)
75-80	0.027	0.050	0.029	0.033
	(0.003)	(0.020)	(0.003)	(0.020)
>80	0.038	0.067	0.034	0.045
	(0.004)	(0.026)	(0.003)	(0.021)
Mean Dep. Var.	73.7		80.4	
# Visits	44,117,396		50,108,192	
N	1,920,031		19,852,081	

Table OA21: Insurance Status and Gender

	Medicaid		Private Ins.		Male		Female	
	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.	Contemp.	Cumul.
<40	-0.054	0.274	-0.059	0.101	-0.064	0.111	-0.058	0.110
	(0.008)	(0.076)	(0.010)	(0.059)	(0.008)	(0.036)	(0.007)	(0.038)
40-45	-0.035	0.225	-0.051	0.039	-0.051	0.055	-0.040	0.076
	(0.007)	(0.096)	(0.005)	(0.046)	(0.005)	(0.053)	(0.005)	(0.055)
45-50	-0.027	0.127	-0.042	0.023	-0.043	0.035	-0.031	0.036
	(0.006)	(0.048)	(0.004)	(0.025)	(0.004)	(0.022)	(0.004)	(0.020)
50-55	-0.020	0.068	-0.026	0.025	-0.027	0.012	-0.020	0.024
	(0.004)	(0.040)	(0.002)	(0.018)	(0.002)	(0.014)	(0.002)	(0.014)
55-60	-0.013	0.015	-0.012	0.011	-0.014	0.004	-0.011	0.002
	(0.002)	(0.025)	(0.002)	(0.015)	(0.001)	(0.011)	(0.001)	(0.012)
65-70	0.007	-0.008	0.011	0.009	0.012	-0.003	0.007	-0.012
	(0.002)	(0.028)	(0.002)	(0.015)	(0.001)	(0.009)	(0.001)	(0.010)
70-75	0.019	0.014	0.021	0.040	0.024	0.012	0.018	0.011
	(0.004)	(0.036)	(0.002)	(0.016)	(0.002)	(0.011)	(0.002)	(0.012)
75-80	0.028	0.083	0.028	0.068	0.032	0.040	0.025	0.040
	(0.005)	(0.045)	(0.003)	(0.025)	(0.003)	(0.019)	(0.003)	(0.019)
>80	0.035	0.070	0.032	0.077	0.040	0.055	0.030	0.045
	(0.008)	(0.073)	(0.003)	(0.027)	(0.004)	(0.020)	(0.003)	(0.022)
Mean Dep. Var.	21.0		24.9		35.1		42.0	
# Admissions	25,650,384		30,445,238		42,867,528		51,322,740	
N	3,905,239		3,905,239		3,905,239		3,905,239	

References

Auffhammer, Maximilian, & Kellogg, Ryan. 2011. Clearing the air? the effects of gasoline content regulation on air quality. *The American Economic Review*, 2687–2722.

Barreca, Alan I, & Shimshack, Jay P. 2012. Absolute humidity, temperature, and influenza mortality: 30 years of county-level evidence from the united states. *American Journal of Epidemiology*, 176(7), S114–S122.

Card, David, Dobkin, Carlos, & Maestas, Nicole. 2009. Does medicare save lives? *The Quarterly Journal of Economics*, 124(2), 597–636.

Dobkin, Carlos. 2003. Hospital staffing and inpatient mortality. *Unpublished Manuscript*.

Doyle, Joseph, Graves, John, Gruber, Jonathan, & Kleiner, Samuel. 2015. Measuring returns to hospital care: Evidence from ambulance referral patterns. *The Journal of Political Economy*, 123(1), 170.

Graff-Zivin, Joshua, & Neidell, Matthew J. 2014. Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, 31(1).

Shaman, Jeffrey, & Kohn, Melvin. 2009. Absolute humidity modulates influenza survival, transmission, and seasonality. *Proceedings of the National Academy of Sciences*, 106(9), 3243–3248.