SANDEE

Working Paper No. 103–15

Evaluating the Role of Media in Averting Heat Stroke Mortality:

A Daily Panel Data Analysis

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ECONOMICS & THE ENVIRONMENT

Published by the South Asian Network for Development and Environmental Economics (SANDEE)
PO Box 8975, EPC 1056, Kathmandu, Nepal.
Tel: 977-1-5003222 Fax: 977-1-5003299

SANDEE research reports are the output of research projects supported by the South Asian Network for Development and Environmental Economics. The reports have been peer reviewed and edited. A summary of the findings of SANDEE reports are also available as SANDEE Policy Briefs.

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(SANDEE Working Papers, ISSN 1893-1891; WP 103–15)

ISBN: 978-9937-596-30-5

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Daily panel data
Heat waves
Media use
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December 2015

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The South Asian Network for Development and Environmental Economics

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SANDEE is financially supported by the International Development Research Center (IDRC), The Swedish International Development Cooperation Agency (SIDA), the World Bank and the Norwegian Agency for Development Cooperation (NORAD). The opinions expressed in this paper are the author's and do not necessarily represent those of SANDEE's donors.

The Working Paper series is based on research funded by SANDEE and supported with technical assistance from network members, SANDEE staff and advisors.

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Abstract

This paper investigates the relative effectiveness of the different media used by the state government of Odisha, India to disseminate Information, Education and Communication (IEC) material to avert heat stroke mortality in the state. The government adopted awareness campaigns as an adaptation strategy for heat waves in the year 2003 and intensified the use of public media from 2007, when multiple newspapers, radio and television channels were used for dissemination. I analyze the district-level daily death occurrences due to heat stroke using count models and examine the role of media use in averting such mortality. Media used on the same day or on previous days are represented in the models by grouping them as either print, audio or video media. The estimated models account for the gap in data and the multidimensional nature of the panel (days, months, years). Media use on any day was not found to be affecting same day mortality, but repeated advertisements were estimated to decrease deaths significantly over the long run, but not within week, one month, or even one year. Of the three categories of media, repeated use of TV had the most robust effect in reducing deaths followed by newspapers and radio.

Keywords

Climate change adaptation, Daily panel data, Heat waves,
Media use, Awareness campaign, Public health communication,
Odisha

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1. Introduction

Heat waves are defined as 'a periods of unusually hot dry or hot humid weather compared to a threshold value near the upper ends of the range of observed values of the variables in the region and lasts for, at least, 2 to 3 days' (IPCC, 2012; McGregor *et al*., 2010). It is being regarded as a persistent calamity taking many innocent lives in both developed and developing countries (IPCC, 2014). Regional and national governments have devised many responses to this crisis such as sponsorship of research (EuroHeat Project), heat warning, activation of social and health networks, public education, etc., to enable people to adapt to this warming scenario (Ebi *et al.*, 2008; Matthies, F. *et al.*, 2008).[1]

The State of Odisha in eastern India has been witnessing regular casualties from heat waves since 1998. This new climatic phenomena, probably an indicator of the ongoing climate change, cripples the state in summer months and has forced the government to enact various adaptation measures. Thus, today, heat wave management constitutes an important and regular disaster management activity in the state.[2] One of the core activities is health education and awareness generation through the dissemination of information, education and communication (IEC) material on heat waves to bring behavioral changes so that people expose less to heat. The paper evaluates the media used for dissemination of these IEC materials.

There is evidence that health education brings improved health outcomes through behavioral change (Glanz *et al.*, 2008; Hornik, 2002). Studies have shown a positive effect of such interventions on health behavior in cases like smoking habits, cholesterol consumption, condom use, immunization of children, etc. (McCombie *et al.*, 2002; Pierce *et al.*, 2002; Roccella, 2002; Balraj and John, 1986). Public health authorities also consider Public Health Communication (PHC) a powerful tool for bringing about behavioral changes in people (Hornik, 2002). Knowledge or information on threats to life (i.e., awareness of threat, benefit of avoidance, etc.) are also determinants of the health outcome as they motivate people to take precautions against health risks (Pattanayak and Pfaff, 2009; Jalan and Somanathan, 2008; Madajewicz *et al.*, 2007). Thus, awareness generation on heat waves should motivate people to take precautions in the form of defensive activities or changes in behavior that can result in positive health outcomes. People in underdeveloped countries are constrained from all directions; a position described as a typical 'starting-at-origin' position by Pattanayak and Pfaff (2009) and may not have the capacity to spend extra on averting activities. However, with repeated information from Public Health Communication (PHC) programs, they may be motivated to reallocate resources to weather-friendly consumption goods or reallocate time to activities that minimize exposure to extreme weather conditions.

Inducing such behavioral changes in people, however, is challenging as behavioral changes occur slowly, processing of information could vary from individual to individual, and media accessibility may vary from region to region. Thus, there is need to make PHC messages convincing, catchy, in local vernacular, and disseminate such information repeatedly through different media so that it reaches maximum people and people understand it. This explains why PHC program messages are disseminated repeatedly over years and why different types of media are involved in dissemination. Theories such as Max Weber's 'social action theory', and George Gerbner's 'cultivation theory',

[1] For details on the definition, occurrences, specific studies, governmental interventions, etc., on heat waves, see Das and Smith (2012).

[2] http://www.osdma.org/ViewDetails.aspx?vchglinkid=GL002&vchplinkid=PL008, accessed on31st December, 2013.

developed in the field of media studies confirm that media audiences do construct meanings from the content they perceive and, thus, persistent exposure to media does have a measurable effect on the perception of the audience (Anderson and Meyer, 1988; Gerbner, 1998).

In the state of Odisha, heat–wave-related mortality has come down in spite of severe heat wave conditions (Das and Smith, 2012; also see section 2) and awareness programs could be having some impact on mortality by bringing about changes in public behavior. The paper econometrically examines whether the decline in mortality is linked to media use and if so, use of which media depicts the most consistent and strongest effect. Moreover, this paper evaluates the efficacy of individual media, on which the literature is comparatively limited. Both traditional (newspaper, radio, television, poster, pamphlet, etc.) and social media (Facebook and Twitter) have been used to promote health education, but media evaluation studies have focused mostly on interventions based on traditional media and have evaluated the aggregate effect of different media used. Despite the limited research on efficacy of individual media, there is some evidence that television and radio are usually more effective in terms of reach and message recall than newspapers (Newbold and Campos, 2011). The present results will add to such knowledge.

The results show that the media use does not have any immediate effect as use of media on any day did not show any significant effect on the mortalities occurring that day. However cumulative use was found to be significantly decreasing deaths. Results on repeated use of television or visual media were the most consistent ones compared to results on other media. Such findings can help policy makers in developing countries to select the right media in public health communication to bring changes in public behavior.

2. Odisha Heat Waves Awareness Campaign

After the 1998 heat wave calamity in Odisha in which more than 2000 people died, 980 people have succumbed to heat stroke in the state as per government report. However, some success with regard to heat wave management is discernible. 1998 was an outlier year as heat waves were so strongly experienced in the state for the first time. Deaths per heat wave day went up from 1999 till 2005, whereas they are coming down systematically after 2005 though the number of heat wave days has remained at an all-time historical high (see Table 1 and Figure 1). The details of the deceased recorded since 2005 depict some clear features. In between 2005 and 2012, 644 people have died, of which 77 percent were male, with roughly 85 percent being 40 years of age or above and 52 percent, being 60 years of age or above. More than 80 percent of deaths occurred during the months of May and June, the timing attesting to the combined effect of temperature and humidity on health as the study area witnesses random pre-monsoon rainfall during this period. The empirical analysis takes account of these features.

Odisha government's interventions to control the health impacts of heat waves after the 1998 calamity can be categorized into the following: (i) Heat wave warnings, provision of extra beds at government hospitals for heat-wave related emergencies, and the rescheduling of work hours, school-timings, bus-timings, etc.,[3] (ii) Heat wave management through grass root workers; and (iii) Awareness campaigns on heat waves through various media. The last two interventions started with the implementation of the Disaster Risk Management (DRM) Program[4] in the state in 2003, but still continue even after the DRM program ended in 2008. The second intervention was confined to 16 of the 30 districts of the state where DRM was implemented and the third intervention targets the whole state, though people get the awareness depending on their media accessibility. There could also be other private adaptations like people getting used to high temperatures gradually as heat waves become a regular occurrence (Davis *et al.*, 2003) or income based adaptations like purchasing air conditioner units or replacing two-wheelers with motor-cars, etc., to better deal with heat waves.

Das and Smith (2012) evaluated heat wave management under DRM program and found that the DRM districts of the state witnessed less heat wave mortality compared to the non-DRM districts, which could be attributed

[3] These activities have been going on since 1999 without any change with time (see the following links: http://orissa.gov.in/revenue/Relief_Notifications/10137_4_3_11.pdf ;http://www.odisha.gov.in/revenue/8245_27_2_12.pdf; for earlier years, online notifications are not available).

[4] http://www.ndmindia.nic.in/eqprojects/goiundp2.0.pdf, accessed on 9 April 2013.

to activities by grass root workers or awareness generation by media, but such details were not examined. The present study evaluates the media effect on mortality after controlling for all other interventions. The interventions under (i) are regular since 1999, time invariant and their effect is separated out by fixed effect estimates. The second intervention is limited to only DRM districts and is controlled by a DRM dummy variable. I use time trend and district per capita income to control for the physiological adaptations and the income based adaptations respectively. As explained later, there has been both temporal and spatial variation in awareness campaign during the study period and these variations are exploited in the empirical analysis to capture the effect of media on heat wave related mortality.

2.1 Features of Awareness Campaign

This awareness campaign targets the entire state. The state uses both public and private channels of print, audio and video media to disseminate the Information, Education and Communication (IEC) material on heat waves, the materials encouraging people to follow some of the traditional lifestyles and food habits of the region (see Das 2012).[5] With regard to the types of media in use, the selection of and preference for media have been changing over time. Table 2 and Figure 2 show the aggregate annual frequencies of newspaper, radio and television media used by the state. It shows more involvement of electronic media after 2006 and intensive use of radio channels from 2009 onwards. Over the years, the state agencies responsible for these activities have used around 14-20 newspapers, four radio channels and six television channels to disseminate IEC material. Almost all daily newspapers having circulation in more than one district, all radio channels and television channels have been used to disseminate the IEC, so there seems to have been no bias in media selection. The distribution of posters, like other regular heat wave management activities, has been time invariant (Table 2). In the case of newspapers, though many newspapers have been associated with the campaign, they get only a few advertisements per year, which explains why the annual frequency of involvement with the campaign is low for print media (Table 2).

Since people receive information depending on their accessibility to media, there are also spatial differences with respect to media use and accessibility. While there is a higher newspaper readership in the urbanized districts (as evident from circulation figures), television viewership including private channels is available to everybody who owns a television set with satellite connection. Television ownership is going up in the state, from 21.7 percent in 2001 to 26.7 percent in 2011, but there is wide variation across the districts. It varied from 6.4 to 53.2 percent across districts as per 2001 census. Nearly 85 percent of television-owning households had either satellite or DTH (direct-to-home) connections to view private channels in 2009 which reached 100 percent by 2010–11[6] which means all households having TV can watch cable television also. In contrast, radio/transistor ownership is going down in the state (14 percent in 2001 to 11percent in 2011) and it varied between 3.12 to 29.3 percent across districts in 2001. Radio listening depends both on radio ownership and on the transmission signal of radio channels. Though AIR (All India Radio) is transmitted throughout the state because of its status as a government channel, the transmission signals of all FM (frequency modulation) channels are only accessible within a 50–60 km radius of two urban pockets of Odisha, namely Cuttack and Rourkela. Such temporal and spatial variability in media availability are exploited in the study to define the media variables (discussed later) and identify the media that is most effective in reducing heat wave mortality.

The state's decision to select one type of media over another has been governed by both cost (radio channels being cheaper than video and newspapers) and maximum reach[7] though with little knowledge of media effectiveness, i.e., which media has the most motivational impact on the public. Thus, the present study finding would contribute towards more informed policy-making decisions. The analysis is limited to the years 2005–12 as the details on daily mortality (date of death, age, gender, address, etc.) were not available for earlier years (i.e., prior to 2005)[8].

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[5] Such suggestions are given by the panel of doctors, who prepare the IEC materials as told byProf.BijayeenMohapatra, the Director of the State Institute of Health and Family Welfare, Bhubaneswar, on 16th January, 2013.

[6] Data made available by ETV Odisha (a private TV channel) through PowerPoint presentation slides.

[7] Personal communication with Prof.Bijayeen Mohapatra on 16th January, 2013.

[8] District level total annual mortality figures are available for the earlier years and have been analyzed in Das and Smith (2012).

Moreover, the data set includes, for purposes of comparison, information for at least two years, 2005 and 2006 that had little awareness-raising activity since awareness generation activities picked up from 2007.

3. Methodology

The human mortality (y) on a given day in a district due to heat stress or bad weather is assumed to depend on prevailing weather conditions (W), behavioral adaptations (K) by people due to knowledge gained from media exposure, and income and other variables (Z) that may trigger other adaptations such as use of air conditioner, water cooler, car in place of two wheeler, etc. Hence, I express the mortality due to heat stress as a function of W, K and Z (Eq. 1).[9] Next, I define the behavioral adaptation (K) to depend on the media used (M) and other factors (P) that determine access to media by the people of the district (Eq. 2).

$$Y = f(W, K, Z) \qquad (1)$$

$$K = k(M,P) \Rightarrow = f(W, k(M,P),Z) \qquad (2)$$

Media use affect health outcomes indirectly by inducing behavioral adaptations that are triggered by knowledge gained from exposure to the IEC materials. The marginal effect of media use on health outcomes is realized through the marginal effect of media on behavioral adaptations.

However, there being no secondary data to measure behavioral adaptations, I use the reduced form equation for mortality from heat waves (y) as a function of weather (W), media used (M), factors determining media accessibility (P), and income and other variables (Z) that can induce other adaptations to heat waves, for estimation.

All variables are explained in estimation section. A non-linear specification is assumed for the estimating equation as weather conditions, especially temperature, have non-linear effects on human mortality (Das and Smith, 2012; Guo *et al.*, 2011) and, more so, if the dependent variable is of a count nature like mortality as is the case here.

4. Data

The paper uses secondary data collected from the following sources:

(i) Office of Special Relief Commissioner, Government of Odisha–daily heat wave mortality details; (ii) Indian Meteorological Department, Bhubaneswar – daily maximum temperature and humidity; (iii) Orissa State Disaster Management Authority and State Institute of Health and Family Welfare, Government of Odisha– daily details of heat wave related advertisements in newspapers, radio or television channels; (iv) Census of India reports – information on district-level asset ownership, population, literacy and employment categories; and (v) Some offices of the media– district-level newspaper circulation figures and radio and TV transmission data.

As mentioned before daily data on death, advertisement and weather pertain to 98 summer days (15 March to 20 June) for the years 2005 to 2012 for each of the 30 districts of the state. Thus, in between the years, the data set has a gap of 268 days (21st June to 19th March of next year) for each district as there is neither a heat wave nor any awareness campaign during this period[10]. The weather and media related variables vary across days whereas the socio-economic variables, collected from the census, vary across years, not months or days. Since census variables were available only for the census years, I could linearly interpolate themonly for other years, not days.

[9] Though, mortality depends on health status, there was no information to control for health status at district level. The analysis being over a period of just eight years, average health status is assumed time invariant across districts during these years.

[10] However, one can ignore the missing dates and data when looked at from the parameters of interest, which deal with the drop in mortality from heat waves due to the media campaign. Since there were neither campaigns nor heat waves, nor any likelihood in the occurrence of heat waves during the missing dates, one can use the standard panel data methods for consistent estimation (Verbeek and Nijman, 1996).

I ignored both posters and pamphlets as there was no variation in the use of these modes of communication over the years and fixed effect estimates or the set of district dummies, when random effect estimates are used, control for these. I clubbed the media used into three categories – print (all newspapers), audio (all radio channels) and video (all television channels including Gramsat (the village level special satellite televisions).

4.1 Defining Weather and Media Variables

Though the state has 30 districts, it has only 19 weather stations to record daily weather data. I therefore used the weather data (temperature and humidity) of the stations lying within a district for those particular districts while I calculated the weather data for the districts without a weather station as a weighted average of the weather data of the nearest three stations using the inverse of the distance ($1/d_i$) as weights (see Eq. 3):

$$\sum_{i=1}^{3}\left(\frac{w_i}{d_i}\right) \Big/ \sum_{i}\frac{1}{d_i} \tag{3}$$

where d_i is the minimum distance between the i^{th} weather station and the centre of the district and w_i is the i^{th} station's weather data.

To capture the media effect on mortality occurrences, I developed three variables for each media type – audio, video and print. In the case of video and audio media, I assumed that the heat wave advertisement would be available to all in the district who own a television or radio if transmission is available whereas, in the case of print media, that it would depend on the availability of newspapers (i.e., how many newspapers reach the districts) and how many can read and understand the newspapers. Hence, I constructed the variables keeping these differences in mind as described below.

1. Audio

(i) Total use of audio media today: Number of times AIR advertised the campaign on a particular day + the number of times FM channels advertised the campaign on the day x the FM transmission dummy. FM transmission dummy equals 1 for the district if the whole or more than half of the district falls within a 60 km radius of a FM transmission centre.

(ii) Cumulative use of audio media till today: cumulative sum of 'total use of audio media today' till the current day. The cumulative sum is measured since the beginning i.e. 15th March 2005, the start date of data set, till the current day. However, to cross check the results, the cumulative sum was also measured for the (1) last one year, (2) last one month, and (3) last one week.

(iii) Exposure to audio media today: 'total use of audio media today' × (percentage of district population having access to radio)

2. Video

(i) Total use of video media today: total number of television channels used today for advertisement;[11]

(ii) Cumulative number of use of video media till today: cumulative sum of 'total use of video media today' till today. The period over which the variable is summed is same as explained above for audio media

(iii) Exposure to video media today: 'total use of video media today' × (percentage of district population having access to television)

[11] Neither state-owned nor any private television channels have brought out the advertisement more than once on any given day.

3. Print

(i) Total use of print media today: total number of newspapers that published the advertisement today × average penetration rate of newspapers in the district.[12]

(ii) Cumulative number of use of print media till today: cumulative sum of 'total use of print media today' till today. The period over which the variable is summed is same as explained above for audio media.

(iii) Exposure to print media today: 'total use of print media today' X percentage of population having at least secondary education.[13]

5. Estimation

The study analyzes the daily heat wave caused mortalities in various districts of the state of Odisha which are non-negative count numbers, so a Poisson specification is used for estimation. The data used is a daily panel consisting of 98 summer days (15th March to 20th June, the usual summer period in Odisha) of the years 2005 to 2012 for each of the 30 districts of the state. Thus, there are 784 days (98 days × 8 years) of information for each of the 30 districts and the data resembles a macro panel where the time dimension is much larger than the panel size, though the period covered is only eight years. Of the 23,520 data points (784 days × 30 districts), only 522 reported heat wave mortality, of which 455 days had just one death each while 41 days had 2 deaths each. In addition, 12 days reported three deaths each while only two days reported 7 and 8 deaths each. Of the 30 districts, eight had only one or two deaths during these eight years. These features indicate strong temporal as well as spatial differences in heat wave impact as well as the suitability of the count models for estimation. The study uses a panel Poisson model for analysis which has the attractive property of modeling explicitly the unobserved heterogeneity or group effect to generate unbiased and consistent estimates (Trivedi, 2010), even though it has limitations that the marginal effects cannot be measured.[14] Following Trivedi (2010), I model the expected mortality as shown in Eq. 4 and 5, given the group (district) heterogeneity μd and the set of observables, X = (W, M, P, Z). In addition, the study includes month and year dummies to control for these different dimensions of the data.

$$E(Y_{dijt} \backslash \mu_{d,} X_{dijt}) = \mu_d exp(\alpha, + \varpi_t + \beta W_{dijt} + \varphi M_{dijt} + \gamma P_{dt} + \eta Z_{dt} + \varepsilon_{dijt}) \quad (4)$$

$$E(Y_{dijt}^{k} \backslash \mu_{d,} X_{dijt}) = \mu_d exp(\alpha, + \varpi_t + \beta W_{dijt} + \varphi M_{dijt} + \gamma P_{dt} + \eta Z_{dt} + \varepsilon_{dijt}) \quad (5)$$

where Y_{dijt} is number of deaths on i^{th} day of jth month of t^{th} year in the dthdistrict;

k is a specific category of death (male, female or a specific age group) and ε, the error term; α_j, and ω_t are month and year dummies; μ_d are unobserved district effects; W_{dijt} is the vector of weather variables on j^{th} day of the j^{th} month of j^{th} year over the d^{th} district; M_{dijt} is the vector of media used (print, electronic and audio) on the i^{th} day of the j^{th} month of tth year for the d^{th} district;[15] P_{dt} is the vector of variables determining media accessibility (tv, radio ownership, newspaper circulation, etc) of the d^{th} district on the t^{th} year; and Z_{dt} is the vector of socio-economic variables of the d^{th} district on the t^{th} year.

It is possible that the unobserved district effects could be correlated with explanatory variables such as agro-climatic zones of districts that can influence the local climate or economic well-being which could, in turn, influence

[12] As each newspaper can bring out only one advertisement per day and each district gets different types of newspapers, rather than adding up the newspapers, I thought it preferable to add the penetration rate of each newspaper(the share of the district in total circulation of a newspaper) for each district. But the district-wise penetration rates of different newspaperswas difficult to obtain and it was possible to obtain such information for only one leading newspaper Samay, the 4th largest daily of the state. Therefore, I used a simpler definition of the variable and used Samay's district-wise circulation rates as the average penetration rate of newspapers for each district.

[13] I assume that matriculates and above would read and process the information of advertisements more carefully than others.

[14] For a detailed discussion, see Das and Smith (2012).

[15] Some of the media variables differ across districts as FM radio is not available everywhere; similarly, not all newspapers are circulated in each district.

the behavioral responses of people to media or the effect of media on mortality. In the present case, this influence is likely to be magnified as the time period under consideration is much larger in the data. Thus, I consider random effect estimates to be inappropriate. Instead, I have used fixed effect Poisson estimates with robust standard errors to analyze the data. Usually, negative binomial regression is suggested to cross-check Poisson results that can seriously underestimate the standard error estimates in the presence of over dispersion. However, because of the concern that fixed effect NB allows for individual-specific variation in the dispersion parameter rather than in the conditional mean, as a result of which time-invariant variables are reported with non-zero coefficient estimates (Guimarães, 2008), I have reported robust standard errors for each of the Poisson estimates rather than estimating NB models. Tocrosscheck robustness of results, I have calculated other estimates like pooled Poisson estimates with district dummies and clustered robust standard errors, and linear estimates like ordinary least squares (OLS) estimates, panel corrected standard errors (PCSE) estimates and augmented mean group (AMG) estimates and compared the results. Both PCSE and AMG estimates are improved versions of panel OLS estimates and are used for linear panels (Beck and Katz, 1995; Eberhardtand Bond, 2009), especially for ones where time dimension is much larger than the panel units. To the extent of my knowledge, such estimates for non-linear count models are not so well developed. I use per capita deaths as dependent variables to estimate these linear models with the help of STATA software. The linear models used for generating PCSE and AMG estimates are given by Eq. 6 and 7 respectively.

$$Y_{dijt} = \alpha_j + \varpi_t + \beta W_{dijt} + \theta M_{dijt} + \gamma P_{dt} + \eta Z_{dt} + \varepsilon_{dijt}\,) \qquad (6)$$

$$Y_{dijt} = \alpha_j + \varpi_t + \beta_d W_{dijt} + \theta M_{dijt} + \gamma_d P_{dt} + \eta_d Z_{dt} + \varepsilon_{dijt}\,) \qquad (7)$$

The variables are the same as explained under Eq. 4 and 5. PCSE estimates for panel data are better alternatives to FGLS estimates as they do not assume the error to be independent across panels and time (iid), rather, the errors are assumed to be either heteroskedastic across panels or heteroskedastic and contemporaneously correlated across panels or autocorrelated within panel, with the further assumption of the autocorrelation parameter being either constant across panels or different for each panel. For long linear panels, PCSE estimates have advantage over fixed and random effect estimates as they achieve their asymptotic behavior when time unit for each panel tend to infinity whereas, the other two are asymptotic in the number of panel, N.[16]

The AMG estimates, takes care of slope heterogeneity, non-stationary variables and cross-section dependence of the error term (Eberhardtand Bond, 2009). As these estimates generate different slope coefficients (β_d or ϕ_d etc. rather than β or φ as shownin Eq. 7) for different panel units they were also suitable for present data. Of the 30 districts studied, some report either zero deaths or one death during the 786 days under consideration and thus, a random coefficient model may provide more appropriate results than the one that assumes the impact of messages on death outcomes to be same for districts after all the controls are taken into consideration. A random coefficient model assumes that there are still inherent and substantial heterogeneity in the districts in spite of the controls.

There were also reasons to assume dynamic specification of the models, especially to control for endogeneity between media exposure and death occurrences and lagged heat wave effect. Heat waves continue for more than one day and death today can be correlated with death the previous day or days (positive association between y_t and its lagged values). Heat wave deaths on consecutive days may also be linked through media reporting. If the occurrences of death due to high temperature are reported as media headlines on a particular day, it can affect behavior by making people take precautions or inducing them to stay indoors the next day, which may result in a lower number of deaths in spite of high temperature that day (negative association between y_t and y_{t-1}). However, it was difficult to check the days when heat wave deaths were reported as headlines or to gauge the sensitivity of people to news reporting. Thus, the nature of the association among y_t and its lagged values is uncertain. Following Wooldridge (2005), I modify equations 4 by including lag and initial values of y (heat wave deaths in the year 1998 is taken as initial values) as additional explanatory variables and obtain random effect estimates (as suggested in Wooldrige (2005), pp 51) for the dynamic models. Eq.8 below shows the dynamic specification related to Eq.4. The

[16] http://www.stata.com/manuals13/xtxtpcse.pdf, accessed on 6thJanuary, 2014.

extra terms added are Y_{d1998}, the initial condition and $Y_{d(ijt-l)}$, the lag values of dependent variable. The lag period 'l' is determined statistically with help of STATA software. As random effect estimates are used, district dummies, θ, are included in Eq.8 to control for omitted variable biases at district level.

$$E(Y_{dijt} \backslash \mu_{d,} X_{dijt}) = \mu_d exp(\alpha_j + \varpi_t + \delta Y_{d1998} + \nu Y_{d(ijt-1)} + \beta W_{dijt} + \varphi M_{dijt} + \gamma P_{dt} + \eta Z_{dt} + \varepsilon_{dijt}) \quad (8)$$

Thus, even though fixed effect Poisson estimates remain the preferred estimates keeping the nature of data in mind, linear estimates like OLS, PCSE, AMG and non-linear estimates like pooled Poisson, random effect Poisson with dynamic specification of the model have been generated to reinforce the identification of media effect on heat wave mortalities.I could not estimate panel zero-inflated count models even though maximum days witnessed zero deaths but I did estimate ZIP models using the pooled data and the full set of district, year and month dummies and compared the results.

6. Results

As mentioned, the study uses information related to only 98 summer days (15th March to 20th June) of years 2005 to 2012 and thus between each year there is a gap of 267 days. So I define a variable 'days' using the 'date' function in STATA that recognized the gap in data in between the consecutive years and collapsed the three time dimensions of data, day, month and year into a single date variable. Thus, 'days' is used as the time variable. Because of the gap in data, I could not carry out the panel time series tests for variables over the entire data set, but as an alternative, estimated the models for each of the 8 years separately using a panel of 30x98 observations and checked time series properties like the stationarity and co-integration of variables. I used the Leviv-Liv-Chu (2002) test which is appropriate when T is much larger than N and Westerlund error correction based panel co-integration test and other standard unit root tests in STATA. I found most of the variables were I(0) for different years except the cumulative variables which were trend stationary as expectedand temperature variables were I(1). The WEST test allows for the co-integration test of only 6 variables at a time and I found every set of 6 variables to be co-integrated. However, the results from these yearly data varied from year to year and there was no consistency in the results of any media variable. Such findings, probably, are on expected line as mortality reduction occurs through behavioral change and behavioral change through media use is a slow process. Using data over three months or 784 days in a year to study media effect on mortality is too short to see such changes. Hence, I present the results from the pooled panel data in the paper.

6.1 Summary Statistics

Table 3 shows the definition and summary statistics of the main variables used for estimating the models. The average death has been 0.027 per day while the highest percentage of victims is drawn from among the males and the elderly people in the 60 plus age group. The variation in data is more within districts than between districts except for the socio-economic variables for which the within district variation is minimal as these values are interpolated from the census years. On a daily basis, the advertisement on heat wave awareness is broadcast at least twice by radio and 1.5 times by television though only 0.008 times in newspapers. Thus, the frequency of the heat wave advertisement in newspapers is much less compared to those on radio or television. In terms of accessibility, the percentage of television owners is higher than that of radio owners or newspaper readers which implies that television advertisements reach more people than advertisements through the other two media.

6.2 Regression Results

6.2.1 Fixed Effect Poisson Results

First, I estimated a minimal model (model 1) using the time trend, population, maximum temperature of the same day and the two previous days (heat waves continuing for a minimum of two to three days' duration) and humidity. Next I estimated model 2 where other controls like month and year dummies, per capita income, forest cover etc. were added to variables of model 1 and then a model 3 where policy variables (media variables) were added to variables of model 2. First fixed effect OLS estimates were derived using per capita death as dependant variable and then fixed effect Poisson estimates were derived using number of deaths as dependant variable. The main results are shown in Table 4 and 5 without reporting the month and year dummy coefficients. Table 4 reports the fixed effect Poisson estimates and Table 5, the OLS estimates. The signs and magnitudes of estimated Poisson coefficients match very strongly with OLS estimates putting confidence on the results. These models were estimated repeatedly taking different types of deaths, like males, females, elderly, young, etc. as dependent variable and all results, especially with regard to media variables, were found very similar to ones shown in Table 4 and 5 except for children and young people (in the age group of 15 to 40). As heat wave victims have been mostly elderly people, not young people or children that explain these results.

Of the three media variables, only the cumulative number of advertisements comes out negative for all the three types of media, but significant only for television and newspapers, not radio, in reducing heat wave mortalities. Moreover, same day media use does not seem to affect the death occurrences. This means repeated exposure to media over a period of time has helped to reduce deaths. All media variables come out jointly significant. The inclusion of media variables does not affect the results on other variables which are similar to the ones in model 1 and 2 which means effect of repeated use of media on death is significant and independent of other variables' influences.

Next to find out how many days of exposure can affect behavior and help reduce deaths, model 3 was re-estimated using different cumulative media variables like cumulative use in last one year, cumulative use in last one month, last one week, etc. Table 6 shows the fixed effect Poisson and fixed effect OLS estimates of only cumulative media variables. There is no consistency in results for shorter periods except radio which seems to have some effect after one year of use, not others. This means exposing people to media campaign for a shorter duration like one week, one month, or even one year do not seem to bring any intended effect. Only longer exposure over years seems to have resulted in reduced deaths. Thus, the robustness of result on cumulative media use over long period, as shown in Table 4, is examined.

6.2.2 Linear and Other Alternative Specification Results

I test the robustness of the results of model 3 (table 4) by estimating it using pooled Poisson estimates with robust clustered standard errors, PCSE and AMG estimates (Pesaran and Smith, 1995). Both PCSE and AMG estimates are improved versions of panel OLS estimates as mentioned before. All these models include the full set of district dummies. Table 7 shows the results on only policy variables.

PCSE and AMG being more suitable for linear model or continuous data, per capita deaths were used as dependent variable to derive these estimates. Table 7 strongly supports the cumulative use of the video media as the most effective medium to reduce heat wave mortality. The media variables were jointly significant in all such models. Both pooled Poisson and PCSE estimates also show that cumulative use of print media reduces deaths though its coefficient has a positive sign in case of AMG estimation. The cumulative use of audio also reveals a negative sign throughout and is significant in two cases. Thus, while media use on the same day may not affect behavior or mortality rate the same day, their repeated use over a longer period is significant in changing behavior and reducing mortality occurrences. This finding is the most robust vis-à-vis the use of television channels to disseminate IEC materials. These results strongly hold when I estimated a Zero Inflated Poisson model with the pooled data (or any spilt sample) and full set of district, year, month dummies and other variables. Electricity availability and supply are not seen as limiting variables in this study as people buy television only if they have electricity connection and Government advertisements are likely to be aired when there is no load shedding in the area, electricity being under government control in the state.

The results are similar for video and print media if I use males, the 40 plus age group or 60 plus age group as dependant variables in place of total deaths. However, the fixed-effect Poisson models do not converge when I use female deaths as dependant variables though other estimates support the above results, especially on video media. These results are not shown, but can be shared on request.

6.2.3 Dynamic Model Specification Results

As discussed above, there could be learning effects from deaths or from media exposure previous days and lagged values of dependant variable could be influencing the results. Thus, I estimated a dynamic Poisson panel (Wooldridge, 2005) by adding the lagged values of dependant variables (total deaths on a day) and deaths that occurred in the year 1998 in the district as the initial condition (Eq. 8). First, I selected the lag period for each district on the basis of the final prediction error (FPE), Akaike information criterion (AIC) and Bayesianinformation criterion (BIC) and it varied from one day to 10 days from district to district. Thus, I used 10 days' lagged values in the final model. I estimated equations 8 using a random effect Poisson panel (see last paragraph of section5) and then pooled Poisson estimates with 29 district dummies and robust standard errors clustered over weeks. Both produced similar results. Table 8 presents these estimates for only media variables of equation 8, which shows the results on policy variables to be very similar to the ones in non-dynamic specifications of the models. The results show that the cumulative uses of television and print media have significantly reduced heat wave mortality. While the advertisements in these channels on any particular day do not seem to influence behavior on the same day, they appear to do so over a period with repeated use. In a dynamic set up, print media on the same day comes out significant with a negative sign which indicates that the print media has some effect on same-day death occurrences unlike audio and video although this result is not robust.

Results on the policy variables are also supported when I estimate the Equation 8 using either deaths of males, or deaths of females, or the deaths of elderly people (60 years of age or above) as dependent variable. These results too show that the cumulative use of print and television has reduced the death occurrences of males and elderly people who form the maximum number of victims of heat waves. Though such results on different death categories are not shown, they can be shared if desired.

7. Conclusions and Policy Recommendations

Research has shown that media use in public health communication, especially the ones that target an entire population, to be effective in changing the health behavior of the public in many cases. However, few studies examine the effectiveness of individual media and the effect of media on human behavior in the case of developing or emerging economies such as India. The present study examines the role of the individual media (audio vs. video vs. print) used in heat-wave awareness-raising campaigns by the Government of Odisha, one of the states in India, in order to reduce the adverse health impacts of heat waves.

The results show that the cumulative use of video and print media over time have significantly reduced the death toll in the state, which means that media variables affect behavior with repeated use and help in averting casualties from severe heat. However, this effect was visible over long run, not in the short run as the effect of cumulative use of different media in last year, in last month and in last week on heat wave mortality was not found to be negative and significant consistently across different models. IEC material disseminated in the media mainly emphasizes changes in behavior to avert heat stroke and this probably is happening with repeated hearing as the cumulative number of uses, rather than use on the same day, seems to have a significant effect. The results with regard to both television and newspapers are robust and remain unchanged with different model specifications. The paper addresses various econometric issues including endogeneity between media reporting and death occurrences by estimating dynamic models and estimating both linear and non-linear models. The results hold under every specification.

Radio channels are the most economical media type compared to video and newspapers, as reported by the health institute officials of Odisha and, hence, the government has intensified its use over the years. However, there is no robust finding to support the effectiveness of radio in reducing heat wave mortalities in the long run, even though the cumulative use of radio has a negative sign throughout. Recently, I conducted household surveys on media effectiveness for cyclone warning dissemination for some of the districts of coastal Odisha and found television messages to have been the most used and trusted, inducing communities to believe in the cyclone warning and evacuate to the shelter. Not a single household replied to have read or believed the short warning messages send by government through cell phones.[17] Thus, primary field based evidence supports the findings of the present study, which is based on secondary data.

Poor economies face monetary constraints in educating the public to adapt to various climate extremes and, hence, the selection of effective media is important. In this context, the findings of the present study can help policy makers make a better selection in terms of the different types of media availablefor public health communication. In spite of so many years of awareness campaign, the state is still witnessing heat wave related mortalities and they all seem to be elderly people. May be the awareness campaign that emphasizes on traditional eating habits, clothing etc. is not having much impact on them as they usually follow such life style. A more focused intervention targeting elderly care may bring out better outcome. A survey based household level study shows behavioral adaptations to heat waves to be high among high and medium income people and low among low income people (Das, 2015). Present study also shows district with high per capita income witnessed fewer deaths. This means economic compulsion could be forcing people to expose more during heat waves and thus, interventions targeting poor people are necessary.

There are many limitations to this analysis, particularly related to the data available for analyses and econometric modeling. Thus, such research needs to be supported by more primary data based analyses and theoretical advances.

8. Acknowledgements

This paper is the second working paper from the project “Adaptation to Heat Waves: Evaluating the Role of Awareness Campaigns as an Effective Strategy to Avert Health Risk” financed by the South Asian Network for Development and Environmental Economics (SANDEE). I sincerely thank the program director, E. Somanathan and the former program director, Priya Shyamsundar, and the SANDEE secretariat for their support. I also thank Jeffrey Vincent, Subhrendu Pattanayak, K. L. Krishna, Jaya KrishnaKumar, Mani Nepal, Jean Marie Baland and Enamul Haque for their valuable guidance and help. I sincerely acknowledge the help of Sarat Sahu, Director of the Indian Meteorological Department, Bhubaneswar, Bholanath Mishra of OSDMA, and Bijayeen Mohapatra and Pradyumn Mishra of SIHFW in data collection. Ruchika Khanna provided very efficient research assistance and it was a pleasure to work with her. Many thanks to Ruchika.

[17] Report submitted to Odisha State Disaster Management Authority regarding “Lessons Learnt from Cyclone Phailin on Community Preparedness, Response and Role of State Institution: Outlining the Resilience Building Approach to Disaster Management for the State of Odisha”on 30th October 2014.

References

Anderson, J. A. and T. P. Meyer (1988), *Mediated Communication: A Social Action Perspective*, Newbury Park: SAGE Publications.

Balraj, V. and T. J. John (1986), 'Evaluation of a Poliomyelitis immunization campaign in Madras City', *Bulletin of the World Health Organization* **64** (6): 861–865.

Beck, N. and J.N. Katz (1995), "What To Do (and Not To Do) with Time-Series Cross Section Data," *American Political Science Review* **89** (3), 634–647

Das, S. (2015), "Temperature increase, labour supply and cost of adaptation in developing economies: Evidence on urban workers in informal sectors", *Climate Change Economics* **6** (2): DOI: 10.1142/S2010007815500074

Das, S. (2012), 'Do awareness campaigns save lives? Assessing the Odisha government's efforts to reduce the impacts of heat waves?', Policy Brief Number 64-12, (South Asian Network for Development and Environmental Economics), Kathmandu, Nepal.

Das, S. and S. C. Smith (2012), 'Awareness as an adaptation strategy for reducing mortality from heat waves: evidence from disaster risk management program in India', *Climate Change Economics* **3** (2): DOI: 10.1142/S2010007812500108

Eberhardt, M. and S. Bond (2009): *Cross-section dependence in non-stationary panel models: a novel estimator*. ,[Available at] http://mpra.ub.uni-muenchen.de/17870/, accessed on 11th June 2015

Eberhardt, M. and F. Teal (2009), A Common Factor Approach to Spatial Heterogeneity in Agricultural Productivity Analysis (CSAE Working Paper, WPS/2009-05), Centre for the Study of African Economies, Department of Economics, University of Oxford.

Ebi, K.L., F.J. Teisberg, L.S. Kalkstein, L. Robinson, and R.F. Weiter (2004), 'Heat watch/warnings systems save lives: estimated cost and benefits for Philadelphia 1995-98', *Bulletin of the American Meteorological Society* **85**: 1067–68.

Glanz, K., B. K. Rimer, and K. Viswanath (2008). *Health Behavior and Health Education: Theory, Research, and Practice*, San Francisco, CA: Wiley & Sons, pp. 592.

Gerbner, G. (1998), 'Cultivation analysis: an overview', *Mass Communication and Society* 3/4: 175–94.

Guimarães, P. (2008), 'The fixed effects negative binomial model revisited', *Economics Letters* **99**: 63-66.

Guo, Y., A. G. Barnett, X. Pan, W. Yu, and S. Tong (2011), 'The impact of temperature on mortality in Tianjin, China: a case-crossover design with a distributed lag nonlinear model', *Environmental Health Perspective* **119**: 1719–25., [Available at] http://dx.doi.org/10.1289/ehp.1103598.

Hornik, R. C. (2002), 'Public health communication: making sense of contradictory evidence', In R. C. Hornik (ed.), *Public Health Communication: Evidence for Behavior Change*, New York: Routledge, pp. 1-19.

IPCC, 2014: Summary for policymakers. In: *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea,T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken,P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press, Cambridge, United Kingdom.

IPCC, 2012: Glossary of terms. In: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation [Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (eds.)]. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, Cambridge, UK, and New York, NY, USA, pp. 555-564.

Jalan, J. and E. Somanathan (2008), 'The importance of being informed: experimental evidence on demand for environmental quality', *Journal of Development Economics* **87** (1): 14–28.

Levin, A., C. F. Lin, and C. S. J. Chu (2002), 'Unit root tests in panel data: asymptotic and finite-sample properties', *Journal of Econometrics* **108**: 1–24.

M. Madajewicz, Pfaff, A. van Geen, J. Graziano, I. Hussein, H. Momotaj, R. Sylvi and H. Ahsan (2007), 'Can information alone change behavior? Response to arsenic contamination of groundwater in Bangladesh', *Journal of Development Economics* **84**: 731–54.

Matthies, F., G. Bickler, N.C. Marin, and S. Hales (eds.) (2008), 'Heat health action plans: guidance', [Available at] http://www.euro.who.int/data/assets/pdf_file/0006/95919/E91347.pdf

McCombie, S., R.C. Hornik, and J. K. Anarfi (2002), 'Effects of mass media campaign to prevent AIDS among young people in Ghana', In R. C. Hornik (ed.), *Public Health Communication: Evidence of Behavior Change*, New York: Routledge, pp. 147–63.

McGregor, G., P. Bessemoulin, K. Ebi., and B. Menne (Eds), (2010), 'Heat waves and Health: Guidance on warning system development', Report submitted to World Meteorological Organization and The World Health Organization.

Newbold, K.B. and S. Campos (2011), 'Media and social media in public health messages: a systematic review', McMaster Institute of Environment &Health Publication, Hamilton, Ontario, Available at: http://www.mcmaster.ca/mieh/documents/publications/Social%20Media%20Report.pdf, [Accessed on 10 January, 2014].

Pattanayak, S.K. and A. Pfaff (2009), 'Behavior, environment, and health in developing countries: evaluation and valuation', *Annual Review of Resource Economics* **1**: 183–217.

Pesaran, M.H. and R.P. Smith (1995), 'Estimating long-run relationships from dynamic heterogeneous panels', *Journal of Econometrics* **68**: 79–113.

Pierce, P. J., P. Macaskill, and D. Hill (2002), 'Long term effectiveness of early mass media led anti-smoking campaigns in Australia', In R. C. Hornik (ed.), *Public Health Communication: Evidence of Behavior Change*, New York: Routledge, pp. 57–73.

Roccella, E.J. (2002), 'The contributions of public health education towards the reduction of cardiovascular disease mortality: experiences from the national high blood pressure education program', In R. C. Hornik (ed.), *Public Health Communication: Evidence of Behavior Change*, New York: Routledge, pp. 73-85.

Trivedi, P. K. (2010), 'Recent developments in panel models for count data', Available at: www.stata.com/meeting/mexico10/mex10sug_trivedi.pdf [Accessed on 10 January, 2014].

Verbeek, M. and Th.E. Nijman (1996), 'Incomplete panel and selection bias', In L. Matyas and P. Sevestre (eds.), *The Econometrics of Panel Data, A Handbook of the Theory with Applications*, 2nd revised edition, Dordrecht, The Netherlands: Kluwer Academic Publishers, pp. 449–90.

Wooldridge, J. (2005), 'Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity', *Journal of Applied Econometrics* **20**: 39–54.

Tables

Table 1: Heat wave days and heat wave deaths in Odisha

Year	Heat Wave Days (HWD)*	Deaths due to Heat Waves	Average Deaths per HWD
1998	28	2042	72.9
1999	25	91	3.6
2000	18	29	1.6
2001	12	25	2.1
2002	21	41	2.0
2003	28	68	2.4
2004	8	45	5.6
2005	29	236	8.1
2006	4	21	5.3
2007	8	47	5.9
2008	12	68	5.7
2009	29	85	2.9
2010	38	100	2.6
2011	12	22	1.8
2012	30	61	2.0

*Heat wave days are counted using the heat wave day definition of India Meteorological Department.

Table 2: Annual aggregate frequency* of different media used in awareness campaign of Odisha Government

	State Institute of Health and Family Welfare (SIHFW)				Orissa State Disaster Management Authority			
	Frequency of Advertisements in a year			Number of Posters Printed	Frequency of Advertisements in a year			Number of Posters Printed
Year	Print (News Papers)	Video (Television channels)	Audio (Radio channels)		News papers	Television	Radio	
2005	96	12	4	30000	0	0	0	50000
2006	27	0	0	60000	0	0	0	50000
2007	17	66	52	0	7	0	30	100000
2008	27	107	76	0	16	60	30	100000
2009	32	80	358	0	14	66	50	100000
2010	27	60	250	0	15	5	8	100000
2011	37	280	797	0	0	0	0	100000
2012	76	280	905	0	16	0	0	100000

**Annual aggregate frequency for each type of media is measured as* $\sum_m \sum_i \sum_j n_{ij} m_j$ *, where* m *is type of media (print, audio or video),* i *is month (March to June),* j *is a particular newspaper or radio or television channel and* n *is the number of times this* j^{th} *channel was used in* i^{th} *month. As mentioned before, print media included 15-20 newspapers, audio media covered four radio channels (All India Radio and three FM channels) and video media covered six television channels (one government-owned and the rest private). Using the daily use data, I calculated the annual frequencies for each year for each media.*

Table 3: Definition and summary statistics of variables

Name of the Variable	Definition of Variables (N = 23,520, n = 30, T = 784)	Mean	Standard Deviation[b]			Min	Max
Death Variables			Overall	Within group	Bet group		
Total Death	Total number of deaths due to heat waves	0. 027	0.216	0.027	0.214	0	8
Males	Number of males in total deaths	0.021	0.17	0.019	0.169	0	5
Females	Number of females in total deaths	0.006	0.095	0.008	0.094	0	5
Elderly	Number of old people (age> 60 years) in total deaths	0.014	0.148	0.015	0.147	0	7
Middle aged	Number of middle aged people (age 41 to 60 years) in total deaths	0.0091	0.105	0.01	0.104	0	3
Young	Number of young people (age 15 to 40 years) in total deaths	0.0035	0.06	0.005	0.06	0	2
Children	Number of children (age < 14 years) in total deaths	0.0006	0.027	0.001	0.027	0	2
Weather Variables							
Temperature	Daily maximum temperature in ^{0}C	38.10	3.69	1.487	3.395	12.9	47.6
Humidity	Daily humidity as measured at 11AM of each day	54.38	18.22	8.61	16.14	5	100
Socio-economic and Media Access Variables							
Total Population	Total population of the districts as interpolated from 2001 and 2011 census (in million)	1.3	0.7	0.71	0.05	0.3	3.5
Forest Cover	Total forest cover of the districts (in 000 sq. km)	1.6	1.38	1.41	0.015	0.013	5.48
NDDP	Net district domestic product (in billion INR)	320.31	213.63	207.23	64.19	47.41	990.28
Per Capita Income	District per capita income at constant prices (in 000 INR)	23.53	9.67	9.12	3.62	11.52	57.12
Radio Owners	Share of households owning radio	0.14.	0.06	0.05	0.03	0.03	0.29
Television Owners	Share of households owning television	0.22	0.10	0.10	0.03	0.06	0.53
Matriculates	Share of population who are matriculate or above	0.072	0.027	0.027	0	0.02	0.14
Media (Policy) Variables							
Total Audio Media	Total number of times radio channels are used on a day	2.05	4.12	1.17	3.96	0	20
Cumulative Audio Media	Cumulative number of times radio channels were used from 15 March 2005	469.22	586.26	273.38	521.01	0	2893
Total Video Media	Total number of television channels used on a day	1.49	2.96	0	2.96	0	20
Cumulative Video Media	Cumulative number of TV channels used from 15 March 2005	292.98	282.83	0	282.83	0	1168
Total Print Media	Total print media used on a day* share of district in total print of Samay[a]	0.008	0.042	0.011	0.04	0	1.16
Cumulative_ Print_Media	Cumulative number of total print media used since 15 March 2005	2.96	4.769	3.81	2.95	0	38.61

Table 4: Coefficient estimates of media variables on total heat wave deaths over time

(Fixed effect poisson estimates: Dependent variable = total number of deaths)

Control Variables	Model 1	Model 2	Model 3
DaysTime_trend	-0.0004 (0.0002)	0.02 *** (0.003)	0.027*** (0.006)
Total_Population	0.08 (0.464)	-1.02 * (0.621)	-0.540 (0.459)
temperature	0.29*** (0.095)	0.14* (0.080)	0.091 (0.069)
tempr_lag1	0.074* (0.038)	0.065 * (0.034)	0.058* (0.034)
tempr_lag2	0.12*** (0.039)	0.095*** (0.028)	0.097*** (0.029)
humidity	0.028 (0.060)	-0.07 (0.047)	-0.119*** (0.038)
temperX humidity	-0.0006 (0.001)	0.002 (0.001)	0.003*** (0.0009)
Forest_Cover		-0.003 (0.007)	0.010* (0.006)
Net District Domestic Product (nddp)		0.012*** (0.004)	0.016*** (0.002)
Per capita nddp		-21.39*** (7.366)	-23.577*** (5.721)
Total _audio _media			0.029 (0.030)
Total _video _media			0.072 (0.050)
Total _print_media			0.364 (0.845)
cum _audio _media			-0.0003 (0.0003)
cum_video_media			-0.004*** (0.001)
cum_print_media			-0.123*** (0.033)
audio_exposed			0.113 (0.216)
tv_exposed			-0.184 (0.154)
print_exposed			-0.571 (0.989)
Year dummies (2005 to 2012)		Yes	Yes
Month dummies (March to May)		Yes	Yes
DRMdummies[a]		Yes	Yes
log pseudo likelihood	-2219.7091	-2107.41	-2060.99
Number of observations	23040	23040	23040
Wald statistics	Wald Chi2 (7) = 2404.78 (P=0.000)	Wald Chi2 (7) =10748.36 (P=0.000)	Wald Chi2 (29)= 426503.14 (P=0.000)
Joint test of all media variable being zero in model 3			Chi 2 (9) = 283.77***

Level of significance: ***1%, **5%, *10%. (Coefficient estimates with Standard errors in parenthesis)

[a]DRM dummies: Dummy for districts under Government of India-UNDP Disaster Risk Program

Table 5: Coefficient estimates of media variable on total heat wave deaths over time

(Dependent variable = deaths per 100 million population)

Control Variables	Model 1	Model 2	Model 3
Days	-0.001** (0.0004)	0.451*** (0.011)	0.07*** (0.017)
Total_Population	——	——	——
temperature	1.096*** (0.322)	0.841*** (0.285)	0.86*** (0.277)
tempr_lag1	0.205*** (0.052)	0.203*** (0.053)	0.197*** (0.053)
tempr_lag2	0.164*** (0.048)	0.158*** (0.049)	0.166*** (0.053)
humidity	0.485*** (0.166)	0.294** (0.142)	0.311** (0.137)
temperX humidity	-0.013*** (0.005)	-0.009** (0.004)	-0.009** (0.004)
Forest_Cover		-0.016 (0.019)	-0.009 (0.016)
Net District Domestic Product (nddp)		0.008 (0.009)	0.021** (0.009)
Per capita nddp		-21.621 (17.069)	-32.835* (18.528)
Total _audio _media			0.121 (0.141)
Total _video _media			-0.076 (0.116)
Total _print _media			8.353 (11.957)
cum _audio _media			-0.001 (0.001)
cum_video_media			-0.014*** (0.003)
cum_print_media			-0.270** (0.109)
audio_exposed			-0.052 (0.893)
tv_exposed			0.319 (0.373)
print_exposed			14.41 (85.502)
Year dummies (2005 to 2012)		Yes	Yes
Month dummies (March to May)		Yes	Yes
DRM dummies[a]		Yes	Yes
Constant	-37.117*** (10.640)	–755.98*** (87.584)	-1171.583*** (281.589)
Number of observations	23040	23040	23040
F statistics	F (6, 29) = 5.92***	F (19,29) = 6.67***,	F (28, 29)=74.53***,
Joint test of all media variable being zero in model 3			F(9, 29) = 10.84***

significance: ***1%, **5%, *10%. (Coefficient estimates with Standard errors in parenthesis)

Table 6: Comparing the effect of cumulative use of media over different period of time on heat wave mortality

Name of the cumulative media variable	Poisson fixed effect coefficient estimates	OLS fixed effect coefficient estimates
Cum_audio_media	-0.0003 (0.0003)	-0.001 (0.001)
Cum_video_media	-0.004*** (0.001)	-0.014*** (0.003)
Cum_print_media	-0.123*** (0.034)	-0.270*** (0.109)
Cum_audio_last_year	-0.002*** (0.0008)	-0.006*** (0.002)
Cum_video_last_year	-0.002 (0.002)	-0.009*** (0.003)
Cum_print_last_year	0.311*** (0.095)	1.580*** (0.583)
Cum_audio_last_month	-0.002* (0.001)	0.005 (0.004)
Cum_video_last_month	0.005*** (0.002)	-0.007*** (0.003)
Cum_print_last_month	0.297*** (0.096)	2.291*** (0.64)
Cum_audio_last_week	0.005 (0.005)	-0.011 (0.012)
Cum_video_last_week	-0.012* (0.007)	-0.061* (0.022)
Cum_print_last_week	1.045*** (0.289)	14.758*** (4.712)

The numbers shown are estimated coefficients with standard errors in parenthesis

Table 7: Estimated coefficients of media variables on heat wave mortalities under different specification of the model

Media Variables	Type of Estimates[a]				
	Pooled Poisson with district dummies and clustered st error (clustering by weeks)	PCSE estimates with assumption of no auto correlation	PCSE estimates with assumption of common AR1 auto correlation for all panels	PCSE estimates with assumption of panel specific AR1 auto correlation	AMG Estimates (coefficients are averages across districts)[b]
total_audio_media	0.028 (0.029)	0.121 (0.148)	0.091 (0.165)	0.011 (0.151)	0.595 (0.647)
total_video_media	0.072*** (0.029)	-0.076 (0.103)	-0.076 (0.112)	-0.057 (0.108)	-5.467*** (1.414)
total_print_media	0.365 (0.524)	8.352 (8.520)	0.785 (0.575)	-2.607 (6.485)	34.594 (23.64)
cum_audio_media	-0.0003 (0.0002)	-0.001* (0.0007)	-0.001* (0.0008)	-0.0006 (0.0007)	-0.017*** (0.003)
cum_video_media	-0.004*** (0.001)	-0.014*** (0.004)	-0.013*** (0.004)	-0.012*** (0.004)	-0.013*** (0.005)
cum_print_media	-0.123*** (0.026)	-0.275*** (0.068)	-0.264*** (0.081)	-0.252*** (0.078)	16.932*** (4.268)
Exposedtoaudio media	0.113 (0.164)	0.052 (0.711)	0.116 (0.814)	0.054 (0.745)	-2.805 (5.835)
Exposedtovideo media	-0.184* (0.104)	0.032 (0.425)	0.329 (0.472)	0.375 (0.426)	22.574*** (6.262)
Exposedtoprint media	-0.571 (1.534)	14.40 (19.174)	28.512 (44.606)	19.651 (38.290)	-303.773 (260.691)

[a]XTPCSE and AMG models have per capita death as dependant variable. [b]Pesaran& Smith (1995) Mean Group estimator; Level of significance: ***1%, **5%, *10%. (Coefficient estimates with Standard errors in parenthesis)

Table 8: Estimated coefficients of media variables on heat wave mortality under dynamic poisson specification (Dependent variable = total deaths)

Name of the Variables	Random Effect Poisson Estimates	Pooled Poisson Estimates with Cluster Robust Standard Errors and District Dummies
total_audio_media	0.036 (0.027)	0.024 (0.025)
Total_video_media	0.039 (0.027)	0.040 (0.033)
total_print_media	-1.204 (0.828)	-1.174** (0.547)
cum_audio_media	-0.0001 (0.0002)	-0.0002 (0.0002)
cum_video_media	-0.004*** (0.001)	-0.004*** (0.001)
cum_print_media	-0.085*** (0.019)	-0.108*** (0.022)
audio_exposed	0.073 (0.158)	0.139 (0.130)
tv_exposed	0.002 (0.076)	-0.021 (0.143)
print_exposed	3.499 (5.115)	3.620 (2.680)
_cons	-331.208*** (101.027)	-338.323** (162.323)
Log likelihood	-2120.2924	-2064.5153
Wald chi2(40)	1297.16, P=0.00	Missing
Likelihood-ratio test of alpha=0:	chibar2(01) = 126.57, P=0.00	Pseudo R2 = 0.3107
N	21120	21120
Joint test of all media variable being zero	Chi 2 (9) = 52.78***	Chi 2 (9) = 196.49***

Level of significance: ***1%, **5%, *10%. (Coefficient estimates with standard errors in parenthesis)

Figures

Figure 1: Average death per heat wave day in Odisha (1999–2012)

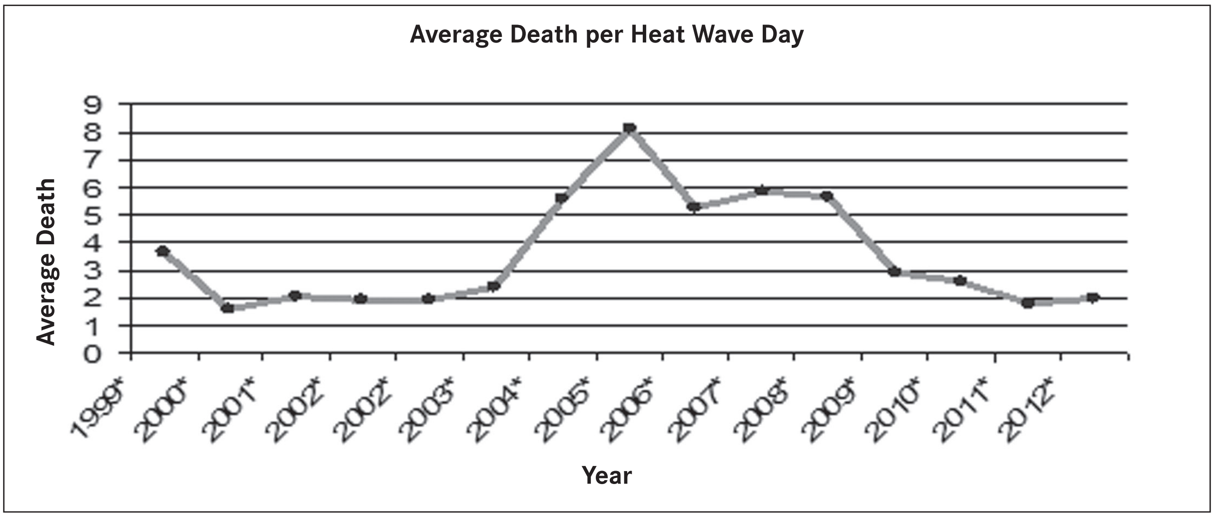
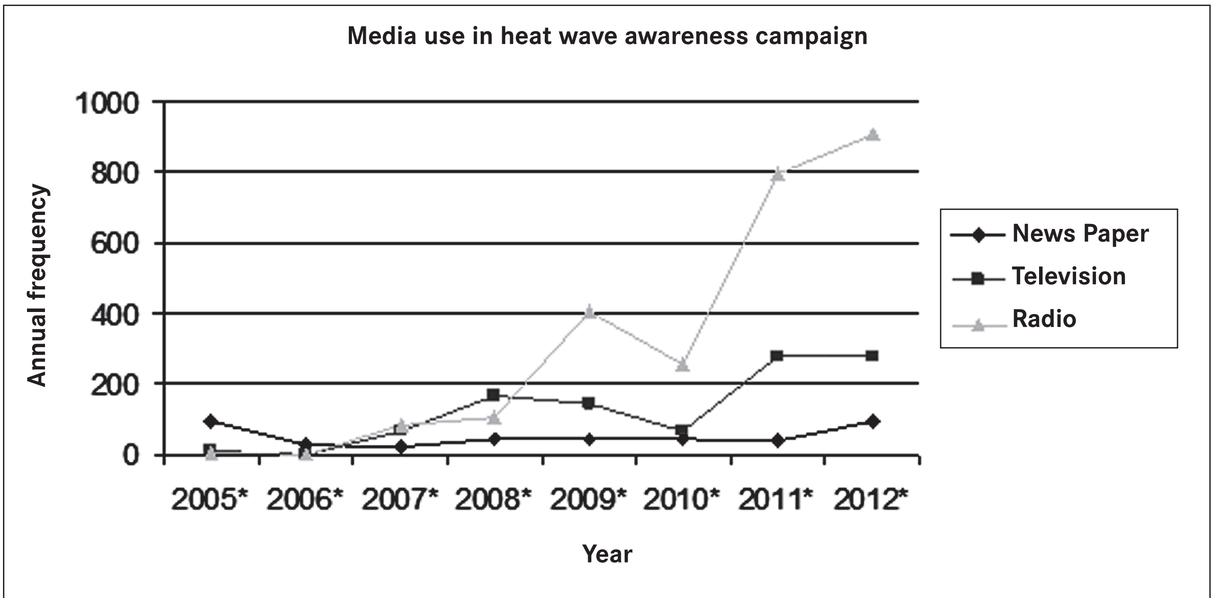


Figure 2: Annual frequencies of audio, video and print media



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