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DEATH AND THE MEDIA:
ASYMMETRIES IN INFECTIOUS DISEASE REPORTING DURING THE HEALTH TRANSITION

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ABSTRACT

In the late 19th Century, cities in Western Europe and the United States suffered from high levels of infectious disease. Over a 40 year period, there was a dramatic decline in infectious disease deaths in cities. As such objective progress in urban quality of life took place, how did the media report this trend? At that time newspapers were the major source of information educating urban households about the risks they faced. By constructing a unique panel data base, we find that news reports were positively associated with government announced typhoid mortality counts and the size of this effect actually grew after the local governments made large investments in public goods intended to reduce typhoid rates. News coverage was more responsive to unexpected increases in death rates than to unexpected decreases in death rates. Together, these facts suggest that consumers find bad news is more useful than good news.

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In the early twentieth century, typhoid fever, a water-borne illness for which there was no cure, ravaged US cities. Five years prior to the filtration and chlorination of Philadelphia's water, weekly deaths from typhoid fever averaged 1.09 per 100,000. Five years after both filtration and chlorination, weekly deaths averaged 0.15 per 100,000. Typhoid rates in Philadelphia, which drew its water from the contaminated river, were unusually high. But even in New York City, where some but not all areas had access to clean water, weekly death rates from typhoid were 0.33 per 100,000 prior to the construction of the New Croton Dam. After the further construction of the Ashokan Reservoir and Catskill Acqueduct, weekly death rates fell to 0.06 per 100,000.[1] Declines in the level and variance of a disease which killed 10-20% of its victims and affected all age groups were rapid after the introduction of clean water technologies (Cutler and Miller 2005; Troesken 1999).

How did the media react to changes in typhoid death rates? The media may both provide readers with the information they want (Gentzkow and Shapiro 2008) and carry out public health campaigns in the editorial and news pages. In neither case will news reports be unbiased, i.e. coverage determined purely by death or case rates. If readers want sensationalist stories newspapers will focus on the unusual and thus over-emphasize low-risk causes of death (as found in Frost, Frank, and Maibach 1997). If consumers find "bad" news more useful than "good" news then increases rather than decreases in mortality will be emphasized. Editors' desire to nudge politicians on public health expenditures and readers on private measures of self-protection may lead to "over-reporting." Newspaper campaigns in 1894 and 1895 contributed to the public acceptance of diphtheria antitoxin and to public funding for antitoxin (Hammonds 1999 93-117). Case studies suggest that recent media campaigns have reduced smoking, cocaine use by teenagers, HIV infection rates, and deaths from Reye's syndrome (Hornik 2008) but that the media also spread sensationalist misinformation about vaccines (Freed, Katz, and Clark 1996). The clearest evidence

[1] Mortality rates are estimated from the data used in the paper.

of the impact of media on behavior comes from studies of the effect of the media on voter turnout (Gentzkow 2006; Gentzkow, Shapiro, and Sinkinson 2011), but some evidence also exists on the impact of the media on voting outcomes (DellaVigna and Kaplan 2007; cf., Gentzkow, Shapiro, and Sinkinson 2011).

We have created a database of weekly counts of articles mentioning typhoid from major US newspapers from 1890 to 1938 to document how news reports responded to weekly death rates in 6 US cities. We focus on typhoid because weekly data are readily available; because there were sharp declines in typhoid case and death rates after the clean water interventions thus allowing us to examine news reports under very different mortality regimes; and because individuals had a clear self-interest in knowing what the trends were so they could protect themselves against typhoid outbreaks, and by the 1890s they knew how to do so.

We find that although news reports were positively associated with mortality and case rates, coverage was biased and not just because of public health campaigns. The responsiveness of news reporting to changes in typhoid mortality and case rates differed before the clean water interventions compared to after the clean water interventions. News coverage also was more responsive to unexpected increases in death rates than to unexpected decreases in death rates. Several hypotheses could explain our results. Although we cannot distinguish between them, all of the hypotheses emphasize that what mattered was how useful the information was to consumers. After the clean water interventions, individuals probably cut back on costly self-protection actions. Knowledge of disease outbreaks may thus have been more valuable after the interventions because the returns to self-protective actions were greater. Knowledge of disease outbreaks may also have been more valuable after the intervention if the stigma of a disease transmitted through contaminated fecal matter was greater after the intervention, thus making costly self-protection measures even more valuable. After the interventions, both the mean and variance of death and case rates fell, thus making any information more informative in a classical signal extraction model. Our findings on asymmetries in reporting are consistent either with high gains in survival probabilities to making the correct self-protection choices or with prospect and psychological theories of reference points in which information on “bad” events is more useful than information on “good” events.

Our findings have implications for the economic incidence of urban public health improvements. If improvements are common knowledge both to incumbent city residents and to non-residents, then standard no arbitrage compensating differentials logic implies that landowners in the cities and neighborhoods that experienced the largest reduction in death would enjoy the windfall of higher prices. But, if outsiders are unaware of the localized quality of life improvements then incumbent renters could gain the windfall. In standard compensating differential models it is assumed that households have full information about the attributes of each choice at each point in time. However, in the case of endogenous dynamic attributes such as typhoid death rates this assumption appears to be extreme. With dynamic and stochastic disamenities, the media may play a key role in spreading information about the shifting location of specific attributes. With asymmetries in media coverage, outsiders may be unaware of progress. This suggestion of “segmented” markets recasts the standard urban locational choice problem as one where information frictions could generate rents for incumbents. If the media devoted extra coverage to deaths during good times, then the public may perceive a higher risk of infectious disease risk than was actually present.

1 Economic Framework

We assume that consumers demanded typhoid information. In recent times the number of newspaper articles on topics of concern to consumers such as crime, inflation, and disease closely track self-reports of concern in polls and ameliorative actions by consumers (Lowenstein and Mather 1990). Why did consumers demand typhoid information?

Typhoid spread primarily through drinking water contaminated with the wastes of infected individuals. Other modes of transmission were direct contact with a contaminated privy, with the wastes of a typhoid patient, with food prepared by a typhoid carrier, or indirect contact with a contaminated privy through flies. Precautions individuals could take included using individual water filters, bringing water to a roiling boil, pasteurizing milk, thoroughly cooking all vegetables, peeling fruit, disinfecting privies and homes, and sealing privies and homes from flies.

An individual's probability of survival p thus depends on self-protection measures, S, such as filtering or boiling water and on water, W_s, in state s. We are assuming that there is a stochastic component to water quality. Water quality is a random variable, ranging from polluted to clean. Individuals do not know the probabiilty distribution but they update their subjective assessment of the severity of the water pollution risk based on announced death and case rates reported in news reports. In our empirical work below, we assume that such news reports are urbanites' main source of information concerning the evolving threat of infectious disease.

We also assume that health, H depends on self protection measures and on water in state s, $H(S, W_s)$ and that self-protection and clean water are substitutes. The consumer's utility in state of world s is weighted by the survival probability

$$p(S_O, S_N, W_s) \times U(H(S, W_s, C) \tag{1}$$

and must satisfy the budget constraint

$$I = p_S S_O + p_W W_s + p_c C. \tag{2}$$

where I is income and p_S, p_W, and p_c are the prices of self-protection, water, and consumption goods. In the linear case, we can re-write the probability of survival as an index function

$$Y^* = \gamma_1 S + \gamma_2 W_s \tag{3}$$

where an individual survives if Y^* is greater than 0.[2] One plausible assumption is that individuals maximize expected utility, similar to the framework of Ehrlich and Becker (1972). News stories convey information about recent changes in water quality and this should affect household self-protection levels.

During the time period we study, many cities made major investments in water treatment and other public goods with the intent of reducing infectious disease. Households are assumed to be aware of the dates of these investment regime shifts. Such local public goods investment should reduce the probability that a water pollution outbreak occurs. Anticipating this fact, such public investments may crowd out private investment in costly self protection. Because H is concave, the returns to increasing self-protection are greater at lower levels of self-protection, i.e. after the clean water interventions. Information about poor water quality is more valuable after the clean water interventions because at lower levels of self-protection, the rates of return to increasing self-protection measures is greater. Such information also may be more valuable after the clean water interventions because individuals can better interpret deviations from trend. A change in mortality rates, whether high or low, represents a sharper deviation from trend in the low level and low variance regime which prevailed after the clean water intervention (the classical signal extraction problem). This phenomenon has been noted in the literature about inflation expectations, where disagreement about the future path of inflation tends to rise both with inflation and with sharp

[2]We are modeling a household's self protection choice as if its location within a city is not a relevant factor. In a more realistic model, households would select a residential neighborhood and neighborhoods would differ with respect to their disease risk. Real estate rents should be lower in high risk neighborhoods. Once a person has selected a neighborhood, one's infection risk would be a function of overall water quality, neighbor self protection investments and one's own investments. Self protection by neighbors would be especially important in cases where people live in high density areas.

inflation changes (Mankiw, Rise, and Wolfers 2004).

Our model could be modified to account for the stigma or fear effects of a disease. Because typhoid was transmitted through the fecal-oral route, stigma may have been greater after the intervention when the disease was rarer. For example, there is a cancer premium for the value of a statistical life either because cancer is a dreaded disease or because of the accompanying morbidity (Viscusi, Huber, and Bell 2014).

Our model also implies that "bad" news is more important than "good" news. "Bad" news will lead individuals to revise upwards their probabilities that the water supply is dirty. Because there is a high gain in the probability of survival if individuals make the correct self-protection choices, accurately weighting "bad" events is more important than accurately weighting "good" events.

Both prospect theory and psychological theories also imply that individuals react more to an increase in mortality rates than to declines. Kahneman and Tversky (1979) argued that individuals care more about loss in utility than gain. The psychology literature argues that asymmetries arise because of differences in perceptions and because individuals are mildly optimistic. If impressions are based on reference points, the loss is felt more keenly (Helson 1964). If more attention is given to new or novel information, which is extreme information, then negative information is given more weight (Fiske 1980). In examining inflation expectations Carroll (2003) found that not only did the volume of news matter, but also news that represented sharp and negative break from the past.

We therefore hypothesize that

1. An increase (decrease) in typhoid death or case rates will lead to more (less) news reports.

2. An increase (decrease) in typhoid death or case rates will lead to more (less) news reports about typhoid after clean water interventions than before these interventions. This could arise either because of diminishing rates of return to self-protection before the intervention, increased stigma after the intervention, or a clearer signal from change in death and case

rates after the intervention.

3. An unexpected change in typhoid death or case rates will have a bigger impact on news reports when the change is an unexpected increase. This phenomemon could arise either from endowment or reference point effects or from bad news being more valuable in a world where there are high gains in the probability of survival to making the correct self-protection choices.

2 Econometric Specifications

As discussed above, we seek to document whether the urban media was responsive to changes in ”objective reality”. Put simply, when the death count increased from infectious disease, did the media cover the story? We then seek to test whether the media’s response differs before and after the major local public health interventions. To study this, we estimate count models of how the number of weekly news reports (r) depends on current weekly death or case rates (d), the clean water intervention (I), and the interaction between the clean water intervention and the death rate. In a linear form, we have

$$r = \gamma_1 d + \gamma_2 I + \gamma_3 (d \times I).$$

Our second hypothesis, that the media reacts asymmetrically to increases and decreases in death rates, implies that the the number of weekly news reports depends on the unexpected change in expected death or case rates (D) and on whether this change is an unpleasant surprise,

$$r = \delta_1 D + \delta_2 (D \times (\text{Dummy=1 if bad news}).$$

We adopt a simple forecasting model to determine whether “good” and “bad” news are treated asymetrically. Urban households having read past newspapers are aware of past trends in typhoid death rates. We posit that households act as if they use all of the recent typhoid past data and fit a trend line to predict the current death rate from typhoid. For example during a time when typhoid death rates are declining, it may not be ”new news” that typhoid death rates are low. In such a setting, new ”bad news” would be if the typhoid death rate in that week is larger than would be expected given the recent time trend. We test whether the media was more responsive to such ”unexpected bad news”.

To operationalize our explanatory variable measuring ”new news”, we assume that expectations about current typhoid death or case rates are determined in one of two ways.

1. Individuals de-trend death or case rates, accounting for intercept changes caused by clean water interventions. A surprise in death or case rates is a deviation from trend. Thus, in current time period i, the deviation from death rate trend (D) is

$$D_i^0 = \hat{d}_i - d_i \tag{4}$$

   where $\hat{d}_i$ is the predicted death rate and d_i is the death rate. The death rate is predicted at each date i by running a regression using all prior death rates (from 2 years of data to all years in the final period),

$$\hat{d}_i = \alpha + \beta_1 t_i + \beta_2 t_i^2 + \beta_3 t_i^3 + \sum_{k=0}^{n} \delta_k I_k$$

   where d is the death rate, t is time, and I_k is a set of dummy variables indicating that intervention k has occurred.

2. Individuals de-trend as above but then adjust for the standard deviation of death rates ($\hat{\sigma}$),

that is

$$D_i^1 = (\hat{d}_i - d_i)/\hat{\sigma}_i. \tag{5}$$

We specify the relationship between the count of articles and death rates or unexpected deviations in death rates using a negative zero inflated binomial model to account for excess zeros and over-dispersion. Assume that the observed count of articles y_i is the product of two latent variables, z_i and y_i^*,

$$y_i = z_i y_i^*$$

where z_i is binary variable with values 0 or 1, and y_i^* has a negative binomial distribution. Then,

$$\begin{aligned}
\Pr(y_i = 0) &= \Pr(z_i = 0) + \Pr(z_i = 1, y_i^* = 0) \\
&= q_i + (1 - q_i)f(0) \\
\Pr(y_i = k) &= (1 - q_i)f(k), k = 1, 2, ...
\end{aligned}$$

where q_i is the probability of no article and $f(\cdot)$ is the negative binomial probability distribution for y_i^*. We model the binary process z_i using a logit model. We perform Vuong tests to determine if the excess number of zeros leads us to prefer a zero-inflated negative binomial model to a standard negative binomial model (a statistically significant statistic suggests yes). Assuming that we reject the negative binomial model in favor of the zero-inflated negative binomial model, we will then test whether the dispersion parameter (α) is 0 (or the logarithm of α is negative infinity). A statistically insignificant dispersion parameter suggests that we instead should be using a Poisson model. We estimate our zero-inflated negative binomial regression models with robust standard errors, clustered on the city.

We specify the logit part of the zero-inflated negative binomial regression as

$$\Pr(y=0) = L(\text{dummy=1 if news event}, \text{dummy=1 if holiday week}, \text{city and year fixed effects}) \quad (6)$$

We specify the negative binomial part of the zero-inflated binomial regression model in three different ways. In our first specification, Equation 4 below, we examine differential reactions to typhoid death or case rates before and after the clean water interventions. Our specification includes typhoid death or case rates (d), two clean water interventions (I_1 and I_2), and interactions between deaths rates and the clean water interventions.

$$\Pr(y=k) = F(d, I_1, I_2, I_1 \times d, I_2 \times d, \text{number of total articles}) \quad (7)$$

When possible (i.e. when convergence was not an issue), we also control for city and year fixed effects.

In our other two specifications, Equations 5 and 6 below, of the negative binomial part of the zero-inflated binomial regression model, we examine differential reactions to better and worse than expected typhoid death or case rates. We include either D^0 or D^1, our deviations from expected death or case rates specified in Equations 1 and 2, the interaction between either D^0 or D^1 and a dummy variable indicating whether D^0 or D^1 are positive (and thus death or case rates are greater than expected),

$$\begin{aligned} \Pr(y=k) &= F(D^0 \times (\text{Dummy=1 if } D^0 > 0), \text{number of total articles}) & (8) \\ \Pr(y=k) &= F(D^1 \times (\text{Dummy=1 if } D^1 > 0), \text{number of total articles}). & (9) \end{aligned}$$

3 Data

We created a panel data set from newspaper articles and from weekly typhoid death and case rates for New York City, Baltimore, Boston, Chicago, Washington DC, Philadelphia. Weekly deaths and cases for New York City are from our digitization of Emerson and Hughes (1941), which provides continuous data from 1890 until 1938. Weekly deaths and cases for our other cities are from Project Tycho (https://www.tycho.pitt.edu/), which digitized data from the weekly national publication, *Public Health Reports*. These data are incomplete; the number of cases only begins to be published in 1906 and both deaths and cases are more likely to be missing once typhoid deaths have fallen to close to zero. Deaths are available up to 1932. We have used data from the published censuses of population to estimate yearly city populations (adjusted for city annexations of neighboring communities) and thus yearly death and case rates.

We obtained daily counts of the total number of newspaper articles and the number of newspaper articles mentioning typhoid and also typhoid and the city using mechanized searches of *The New York Times*, *The Baltimore Sun*, *The Boston Globe*, *The Chicago Tribune*, *Washington Post* and *The Philadelphia Inquirer*.[3] These were the major "serious" newspapers within each city (their rivals have not been digitized and indexed). We aggregated our daily counts to the weekly level. Reports include all types of news, including reports from local public health officials, stories of outbreaks, society news, obituaries of well-known individuals, editorials, and appeals to charity.

Cities had to have both digitized and indexed newspapers and good weekly typhoid death data to be included in our panel data set. Our final panel data set has data for New York City for all weeks for 1890-1938, and, with some weeks missing, for Chicago for 1896-1932, Baltimore for 1900-1932, Boston for 1890-1932, Philadelphia for 1901-1922, and Washington DC for 1890-1932. We also created dummy indicators for a holiday during that specific week and for a major

[3] The first five newspapers are available from Proquest Historical Newspapers. *The Philadelphia Inquirer* is available from Readex America's Historical Newspapers.

news event that week. What constituted a major news event was a judgement call. Recurring events such as the day after elections and the World Series were labeled major news events, as were outbreaks of war and major war events, natural disasters, New York City ticker tape parades and the events meriting these parades, new world records, and famous trials, murders, and kidnappings.

Figure 1 compares our mechanized searches of *The New York Times* for typhoid fever with manual searches for 1900-1932. Except for some learning by doing by data inputters in the early manual searches, peaks and troughs in the percentage of articles mentioning typhoid coincide across the two samples. However, the mechanized searches for mentions of local typhoid fever yield a consistently greater percentage than the manual searches. The mechanized searches also capture deaths or illnesses of New Yorkers outside of the city.

4 Typhoid Death and Case Rates

The major interventions in each of our cities (see Table 1) take the form either of cleaning up the water supply obtained from the nearby river through chlorination or filtration or of obtaining new, clean sources of water. For each city we could identify two interventions from Cutler and Miller (2005) for Chicago, Baltimore, and Philadelphia and from histories of local water supply systems for New York City, Boston, and Washington, DC. (Although we could identify a third for New York City, the effect of this intervention was negligible.)

Figure 2, which also shows missing data, and Table 2 suggest that the inteventions were effective in lowering typhoid mortality and case rates. In the sample as a whole, typhoid death rates per 100,000 were 0.8 prior to any intervention, 0.4 after the first intervention but before the second, and 0.1 after the second intervention. Prior to the first intervention, death rates per 100,000 varied widely across cities with highs of 1.0 and 1.5 in Philadelphia and Washington, DC, respectively and a low of 0.4 in New York City. After both interventions, death rates per 100,000 varied from a high of 0.2 in Baltimore to a low of 0.03 in New York City. Case rates also fell after an intervention and converged across cities.

These interventions were statistically significant negative predictors of death rates, controlling for a year trend (see Table 3). In all cities, the first intervention was a statistically significant predictor of death rates. Controlling for the effects of the first intervention, in all cities except for Washington DC the second intervention was a statistically significant predictor of death rates and the combined effect of both interventions was statistically significant in all cities except for Washington DC. The inclusion of lagged death rates in the specification also yielded statistically significant effects of the interventions (results not shown).

Figure 3 plots the deviation from the expected death rates adjusted for the standard deviation of death rates in each city. In all cities deviations were high prior to any interventions and then narrow after both interventions.

5 Results: Death and the Media

Figure 4, which shows smoothed plots of typhoid death rates and of the percentage of typhoid articles, suggests that while on the whole reports of typhoid followed mortality patterns, with more reporting in a high mortality regime than in a low mortality regime, an increase in city death rates led to more news reports in a low than in a high mortality regime. For example, in New York City, the up-tick in typhoid mortality rates in the 1920s is associated with an increase in news reports that is greater than the increase in the early 1890s when typhoid mortality rates spiked up higher. The increases in reporting that are not related to city death rates were often associated with world events such as concern over typhoid epidemics during the Spanish-American War and World War I.

We find that the media are more likely to report changes in typhoid after the clean water interventions than before. Table 4 shows that increases in typhoid death rates increase reporting both pre- and post-intervention but there is a stronger positive effect after both interventions. Prior to any intervention, a half standard deviation increase in post first intervention typhoid death rates (0.141) leads to an increase of at least 0.05 in the count of the logarithm of typhoid articles (=0.141 $\times$ 0.335). After both interventions, this half standard deviation increase of 0.141 in death rates yields an additional increase in the count of the logarithm of typhoid articles of 0.06 (=0.141 $\times$ 0.417) to 0.20 (=0.141 $\times$ 1.422). Table 5, which gives the marginal effects, implies that this half standard deviation increase of 0.141 in death rates increases the number of typhoid articles by at least 0.14 (=0.141 $\times$ 1.023) prior to any interventions. After both interventions, this half standard deviation increase raises the number of typhoid articles by an additional 0.18 to 0.61. The total increase of 0.32 to 0.75 represents an 11 to 26% increase relative to the mean number of articles. Although the interaction between death rates and the second intervention is not statistically significant when both the count and zero article part of the negative binomial include both city and fixed effects, the joint effect of both interventions interacted with the death rate becomes statistically significant when Philadelphia (which has few observations after the intervention) is excluded. Excluding Philadelphia and including both city and year fixed effects in both parts of the negative binomial (not shown), yields an additional, statistically significant increase of 0.242 in the number of articles after both interventions.

Media responses to death rates after the two interventions are even greater, and are always statistically significant, when we examine local typhoid articles (see Tables 6 and 7). Prior to any intervention, an increase in the death rate of 0.141 leads to an increase of at least 0.06 (=.141 $\times$ .418) in the number of local typhoid articles. After both interventions, this increase in the decrease rate leads to an additional increase of 0.10 (=0.141 $\times$ 0.742) to 0.19 (=0.141 $\times$ 1.350) in the number of typhoid articles. The total increase of 0.16 to 0.25 represents a 15 to 17% increase in the number of local news articles relative to the mean.

We find that the media respond more to “bad” than to “good” news. Our specifications for mortality expectations were based on deviations from trend, both unadjusted and adjusted for the standard deviation of death rates, and these show that an unexpected increase in death rates (a positive residual) leads to more news reports than an unexpected decrease in death rates (see Tables 8 and 9). A half standard deviation change in the deviation from expected death rates (0.188 over all time periods) leads to a statistically insignificant decrease of 0.062 (=0.188 $\times$ -0.329) in the logarithm of the total number of articles and of 0.202 (=0.188 $\times$ -1.072) in the total number of articles when the change leads to mortality rates being lower than expected. When mortality rates are higher than expected, a half standard deviation change leads to a statistically significant increase of 0.185 (=0.188 $\times$ 0.982) in the logarithm of the number of articles and of 0.600 (=0.188 $\times$ 3.194), a 21% increase relative to the mean, in the number of articles. Effects on the number of local typhoid articles are not statistically significant. However, when we modeled expectations as deviations from the trend adjusted for the standard deviation of death rates we found statistically significant effects both for all and local typhoid articles. A half standard deviation change in the deviation from expected death rates adjusted for the standard deviation of death rates (0.334 over all time periods) produces a statistically significant decrease of 0.09 (=0.334 $\times$ -0.256) in the logarithm of the total number of articles and of 0.267 (=0.334 $\times$ -0.798) in the total number of articles when the change leads to mortality rates being lower than expected. When mortality rates are higher than expected, a half standard deviation change leads to a statistically significant increase of 0.20 (=0.334 $\times$ 0.586) in the logarithm of the number of articles and of 0.610 (=0.334 $\times$ 1.826) in the number of articles, a 21% increase relative to the mean. When we examined local articles, we found statistically insignificant effects when mortality rates were lower than expected but a statistically significant effect of 0.22 articles (=0.334 $\times$ 0.663), a 20% increase, for a half standard deviation increase in expected mortality rates adjusted for the standard deviation of mortality.

We examined how accurately our three different specifications predicted the mean number of articles to determine if how we modeled expectations of mortality rates made a difference. The difference between the observed mean and the predicted mean was 0.002 for all newspaper articles and 0.008 for local newspaper articles when we included the death rate and intervention interactions. When we used deviations from expected death rates we found that the difference between the observed and predicted means was 0.199 for all news and 0.005 for local news. When we adjusted deviations from expected death rates by the standard deviation of death rates we found that the differences were 0.076 and 0.004, for all news and local news, respectively. We interpret these results as indicating that using deviations from expected death rates alone is the least preferred specification.

Controlling for case rates, newspapers were more likely to report on typhoid after the clean water interventions, when case rates were lower. We found statistically significant effects of both intervention case rate interactions, even controlling for year fixed effects in both the count and the logit part of the negative binomial (see Tables 10 and 11). After the first intervention, the standard deviation of case rates was 1.682. A half standard deviation increase in case rates increased logarithm of the number of articles after both interventions by at least an additional 0.10 (=0.841 $\times$ 0.114) relative to the pre-intervention period and the number of articles by an additional 0.25, a 35% increase relative to the mean. The increase in the number of local articles was at least 0.10 (=0.841 $\times$ 0.119), a 12% increase.

We also found that newspapers were more likely to report on typhoid when case rates deviated from expected case rates (see Tables 12 and 13). A half standard deviation change in the deviation from expected case rates (0.601 over all time periods) leads to a statistically significant decrease of 0.12 (=0.601 $\times$ -0.200) in the logarithm of the total number of articles and of 0.305 (=0.601 $\times$ -0.507) in the total number of articles when the change leads to case rates being lower than expected. When case rates are higher than expected, a half standard deviation change leads to a statistically significant increase of 0.16 (=0.601 $\times$ 0.269) in the logarithm of the number of articles and of 0.409 (=0.601 $\times$ 0.681), a 17% increase relative to the mean, in the number of articles. When we adjusted the deviation in expected case rates for the standard deviation of case rates we found that a half standard deviation change leads to a statistically significant decrease of 0.33 (=0.325 $\times$ -1.022) in the number of articles when case rates are lower than expected and to statistically significant increase of 0.45 (=0.325 $\times$ 1.382) when case rates are higher than expected. We observe the same asymmetry when we examined the number of local articles.

A newspaper article on typhoid was more likely when there was a news event. The effect was statistically significant when we examined unexpected deviations in typhoid death or case rates (see Tables 8, 9, 12, and 13.) Because large news events such as wars or natural disasters were associated with typhoid outbreaks (or fear of such outbreaks), we interpret this effect as dominating the displacement of typhoid news from a sensational trial or murder case. In some of our specifications, holidays also had a statistically significant, positive effect on news reports. We would expect a positive effect either if articles about typhoid can be written ahead of time or if appeals to charity (e.g. the New York's Neediest column) are more likely during holidays.

6 The Editorial Page's Response to Death Rates

Was newspaper reporting on typhoid fever determined by editors' campaigns favoring the adoption of clean water technologies? If yes, we would expect more editorials on typhoid prior to the intervention. This "campaign" effect would therefore counteract our first hypothesis.

Figure 5 shows that only in Chicago was there a large number of editorials prior to the first intervention – the closing of the sewer outfalls of Lake Michigan. There were many editorials on the incompetence of the city for delays in sanitary reforms. The upsurge in editorials in New York City and in Boston prior to the sanitary reforms was associated with worries about typhoid during the Spanish-American War and the building of the Panama Canal. The editorials in Washington DC after the first intervention were largely articles about clean water interventions in other cities. The editorials in Boston after the second intervention focused on the dangers of typhoid on vacation. There were no editorials in Baltimore about typhoid.

7 Robustness: Diphtheria and the Media in New York City

We test the robustness of our findings by comparing results for typhoid articles in New York City with diphtheria articles. Diphtheria, an upper respiratory tract infection, is spread through physical contact or breathing the aerosolized secretions of infected individuals. In New York City, diphtheria death rates fell rapidly once antitoxin became widely available in 1895 (it was provided by the City). We would therefore not expect a positive effect of the interaction between typhoid death rates and typhoid interventions on the number of diphtheria articles. However, we would expect a more positive response to death rates after diphtheria antitoxin became widely available.

Tables 14 and 15 show that in New York City the effect of typhoid death rates on all and local typhoid news reports is greater after the second intervention but that there is no effect on diphtheria news reports. Diphtheria death rates, however, have a greater effect on diphtheria news reports once antitoxin become widely available. In New York City, the standard deviation of typhoid deaths after the first clean water intervention was 0.096 and the standard deviation of diphtheria deaths was 0.563 after antitoxin became widely available. A half standard deviation increase in typhoid deaths led to an increase of 0.11 (=0.048 $\times$ 2.404) in the total number of articles and an increase of 0.073 (=0.048 $\times$ 1.514) in the number of local articles before any intervention and to an additional increase of 0.430 total articles (=0.048 $\times$ 8.956) and 0.23 local articles (=0.048 $\times$ 4.781) after both interventions. These last two increases were, respectively, increases of 15% and 23%. Typhoid interventions interacted with typhoid death rates were not statistically significant predictors of diphtheria news reports. A half standard deviation increase in diphtheria death rates had a statistically insignificant effect on diphtheria reports prior to the intervention and led to a statistically significant increase of 0.09 (=0.282 $\times$ 0.304) in the total number of local articles, a 17% increase.[4]

8 Conclusion

At a time before television, radio and the Internet, newspapers played a central role in disseminating information and thus guiding their readers' choices and viewpoints. The availability of weekly typhoid death and case reports permits us to test how major urban newspapers responded to emerging public health trends during a key time in urban history.

Between 1880 and 1940, today's developed countries experienced a major urban public health transition (see Haines 2001 on the US, Kestzenbaum and Rosenthal 2011 on France, and Brown 2000 on the UK and Germany). How does the media cover the emerging story during a time of rapid progress? Studies of newspapers in the economics literature have focused on political bias (e.g. Gentzkow and Shapiro 2008). We instead have focused on news stories about a disease. We found that news reports were positively associated with typhoid death and case rates but that the size of the effect grew after cities cleaned up their water supplies. In addition, we also found that news coverage was more responsive to bad news (i.e., unexpected increases in death rates) than to good news (unexpected decreases in death rates). The losses to individuals of not knowing bad news are likely to outweigh the losses of not knowing good news. Not knowing good news may lead to too much time and money spent on self-protection. Not knowing bad news may lead to death if not enough time and money is spent on self-protection.

[4] We could not estimate a similar specification for all articles because of convergence problems.

References

[1] Brown, John C. 2000b. Wer bezahlte die hygienische Stadt? Finanzielle Aspekte der sanitären Reformen in England, USA, und Deutschland um 1910 [Who Paid for the Sanitary City? Issues and Evidence Ca. 1910]. In Jörg Vögele and Wolfgang Woelk, eds. Stadt, Krankheit, und Tod. Berlin: Duncker and Humblot: 237-257.

[2] Cutler, David and Grant Miller. 2005. The Role of Public Health Improvements in Health Advances: The Twentieth-Century United States. *Demography*. 42(1): 1-22.

[3] Cutler, David and Grant Miller. 2006. Water, Water Everywhere: Municipal Finance and Water Supply in American Cities. In Glaeser and Goldin, Eds., *Corruption and Reform: Lessons from America's Economic History*.

[4] DellaVigna, Stefano and Ethan Kaplan. 2007. The Fox News Effect: Media Bias and Voting. *Quarterly Journal of Economics*. 122(3): 1187-234.

[5] Ehrlich, Isaac and Gary Becker. 1972. Market Insurance, Self-Insurance, and Self-Protection. *The Journal of Political Economy*. 80(4): 623-48.

[6] Emerson, Haven and Harriet E. Hughes. 1941. *Population, Births, Notifiable Diseases, and Deaths, Assembled for New York City, NY: 1866-1938*.

[7] Fiske, Susan T. 1980. Attention and Weight in Person Perception: The Impact of Negative and Extreme Behavior. *Journal of Personality and Social Psychology*. 38(6): 889-906.

[8] Freed, Gary L., Samuel L. Katz, Sarah J. Clark. 1996. Safety of Vacciantions: Miss America, the Media, and Public Health. *Journal of the American Medical Association*. 276(23): 1869-1872.

[9] Frost, Karen, Erica Frank, and and Edward Maibach. 1997. *American Journal of Public Health*. 87(5): 842-45.

[10] Gentzkow, Matthew, Edward Glaeser, and Claudia Goldin. 2006. The Rise of the Fourth Estate: How Newspapers Became Informative and Why It Mattered. In Glaeser and Goldin (Eds), *Corruption and Reform: Lessons from America's Economic History*.

[11] Gentzkow, Matthew, Nathan Petek, Jesse M. Shapiro, and Michael Sinkinson. 2015. Do Newspapers Serve the State? Incumbent Party Influence on the US Press, 1869-1928. *Journal of the European Economic Association*. 31(1).

[12] Gentzkow, Matthew and Jesse M. Shapiro. 2008. Competition and Truth in the Market for News. *Journal of Economic Perspectives*. 22(2): 133-54.

[13] Gentzkow, Matthew, Jesse M. Shapiro, and Michael Sinkinson. 2011. The Effect of Newspaper Entry and Exit on Electoral Politics. *American Economic Review*. 101(7): 2980-3018.

[14] Gentzkow, Matthew, Jesse M. Shapiro, and Michael Sinkinson. 2014. Competition and Ideological Diversity: Historical Evidence from US Newspapers. *American Economic Review*. 104(10): 3073-3114.

[15] Gentzkow, Matthew, Jess M. Shapiro, and Daniel F. Stone. Forthcoming. Media Bias in the Markeplace: Theory. In Anderson, Strömberg, and Waldfogel, Eds., *Handbook of Media Economics*. Elselvier.

[16] Haines, Michael. R. 2001. The Urban Mortality Transition in the United States, 1800 to 1940. *Annales De Démographie Historique*. 1: 33-64.

[17] Hammonds, Evelynn Maxine. 1999. *Childhood's Deadly Scourge: The Campaign to Control Diphtheria in New York City, 1880-1930*. Baltimore and London: Johns Hopkins University Press.

[18] Helson, H. 1964. *Adaptation-level Theory*. New York: Harper.

[19] Hornick, Robert C. (Ed.) 2002. *Public Health Communication: Evidence for Behavior Change*. Mahwah, NJ: Lawrence Erlbaum Associaes, Inc.

[20] Kahneman, Daniel and Amos Tversky. 1979. Prospect Theory: An Analysis of Decision Under Risk. *Econometrica*. 47(2): 263-92.

[21] Kesztenbaum, Lionel, and Jean-Laurent Rosenthal. 2011. ”The health cost of living in a city: The case of France at the end of the 19th century.” *Explorations in Economic History*. 48 (2):207-225.

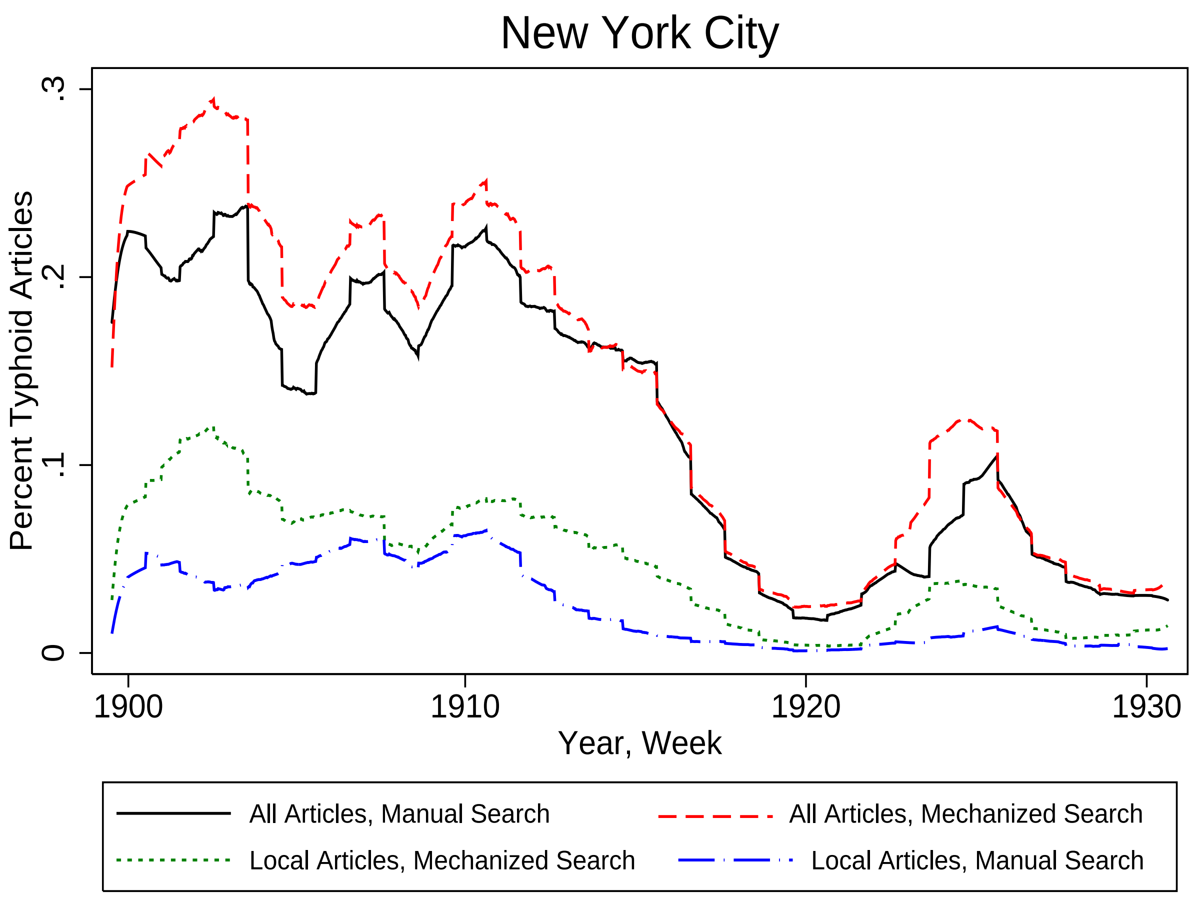
[22] Mankiw, N. Gregory, Ricardo Reis, and Justin Wolfers. 2004. Disagreement about Inflation Expectations. In Gertler and Rogoff (Eds), *NBER Macroeconomics Annual 2003, Volume 18*.

[23] Troesken, Werner. 1999. Typhoid Rates and the Public Acquisition of Private Waterworks, 1880-1920. *Journal of Economic History*. 59(4): 927-948.

[24] Troesken, Werner. 2004. *Water, Race and Disease.* MIT Press, Cambridge, MA.

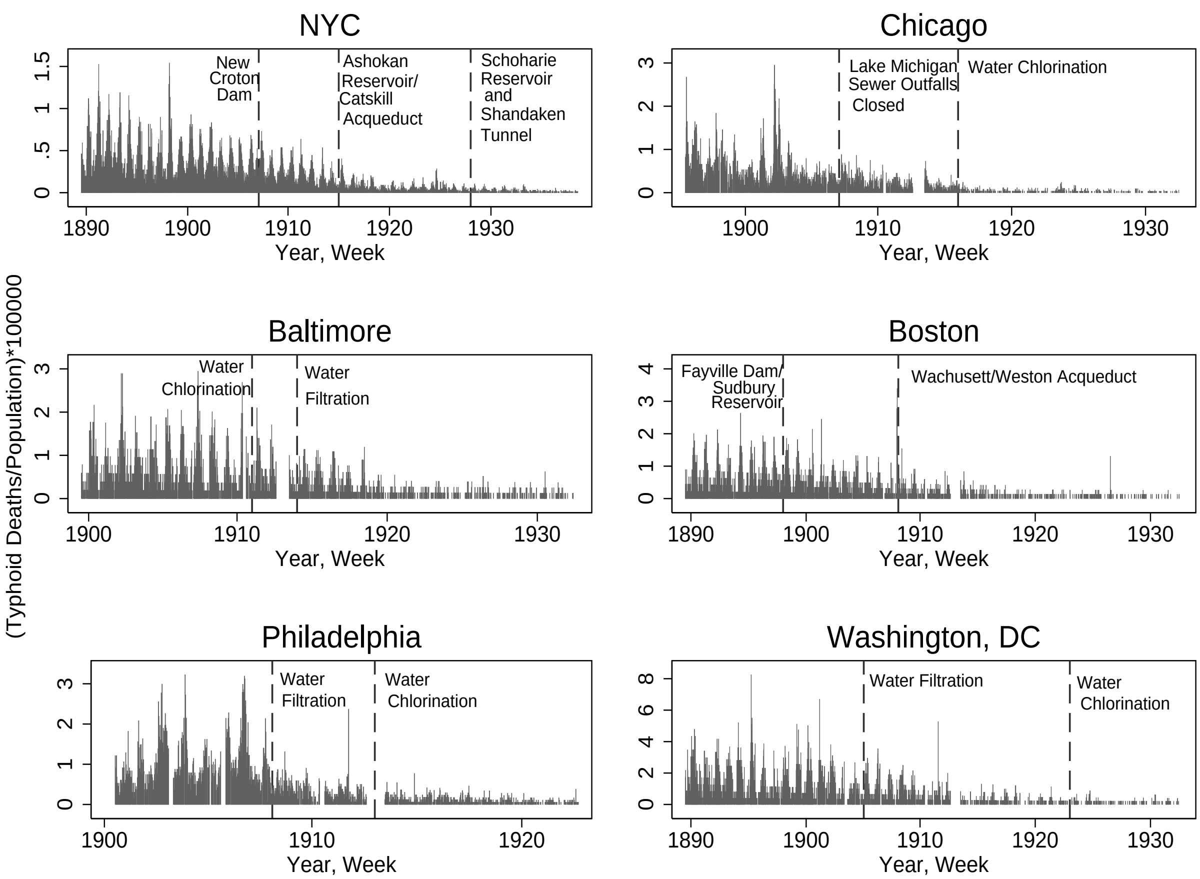
[25] Villarreal, Carlos. 2014. Where the Other Half Lives: Evidence on the Origin and Persistence of Poor Neighborhoods from New York City 1830-2012. Unpublished MS. https://sites.google.com/site/carlosrvillarreal/

Figure 1: Comparison of Manual and Mechanized Searches, *The New York Times* 1900-1932



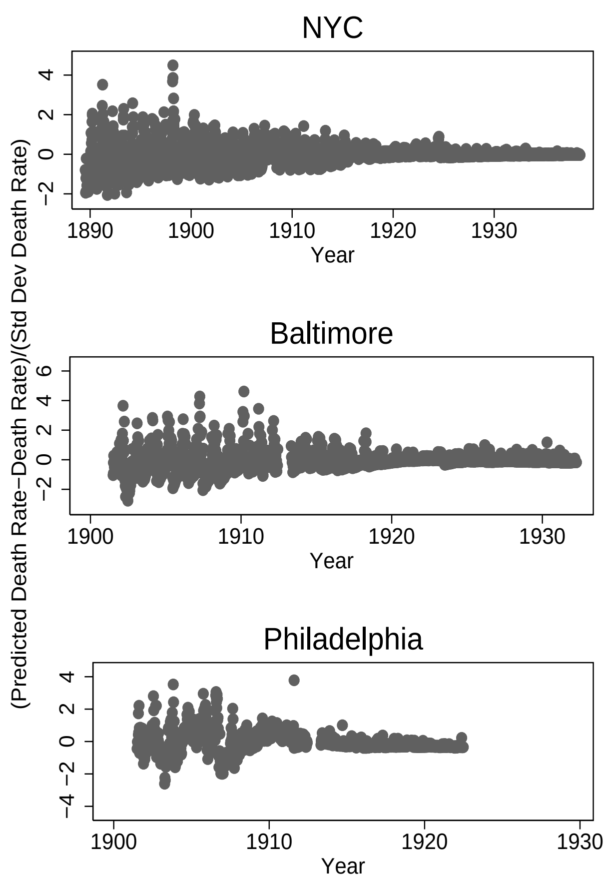
Source: *The New York Times*. See the text for details.

Figure 2: Weekly Typhoid Death Rates by City



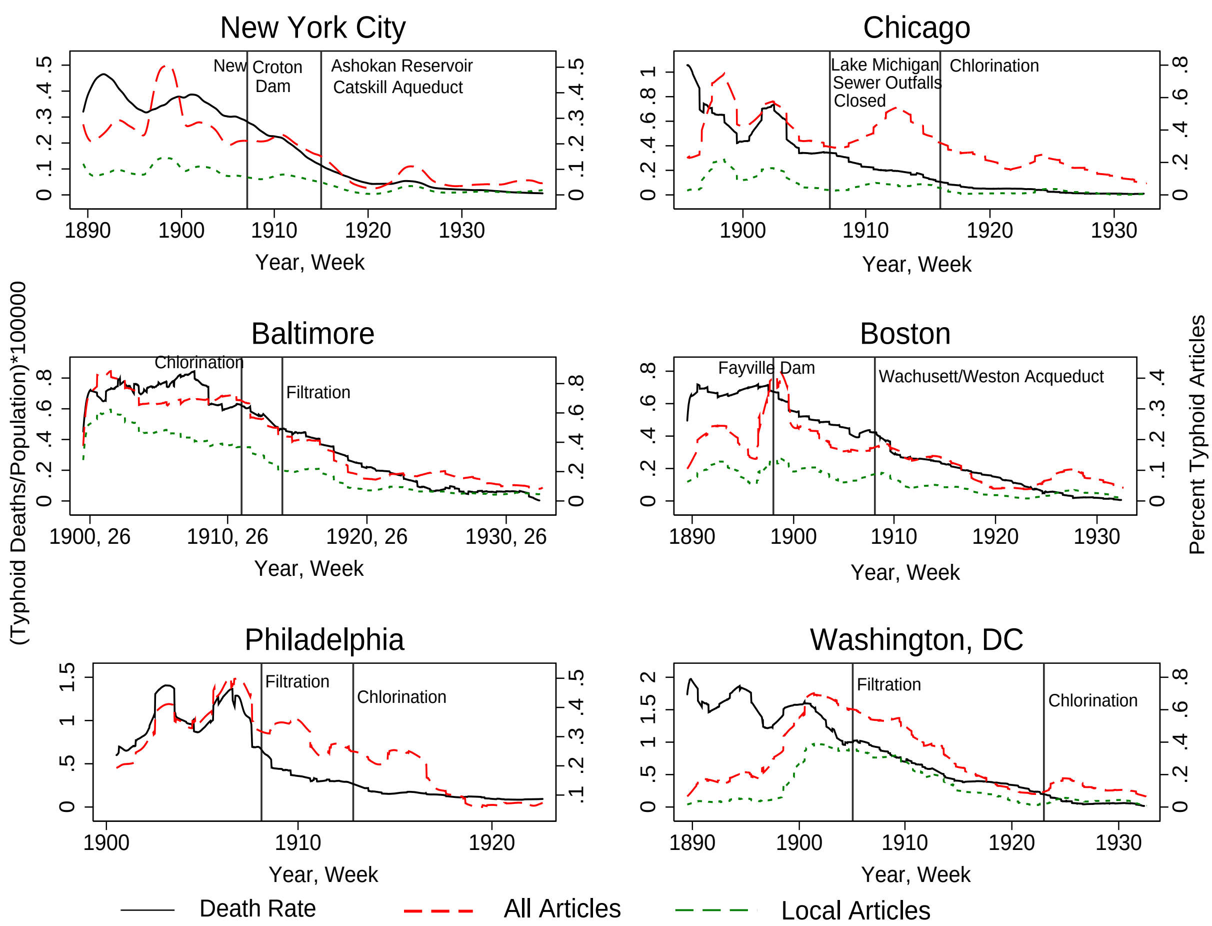
See the text for sources.

Figure 3: Deviations from Expected Typhoid Death Rates Adjusted for the Standard Deviation of Typhoid Death Rates



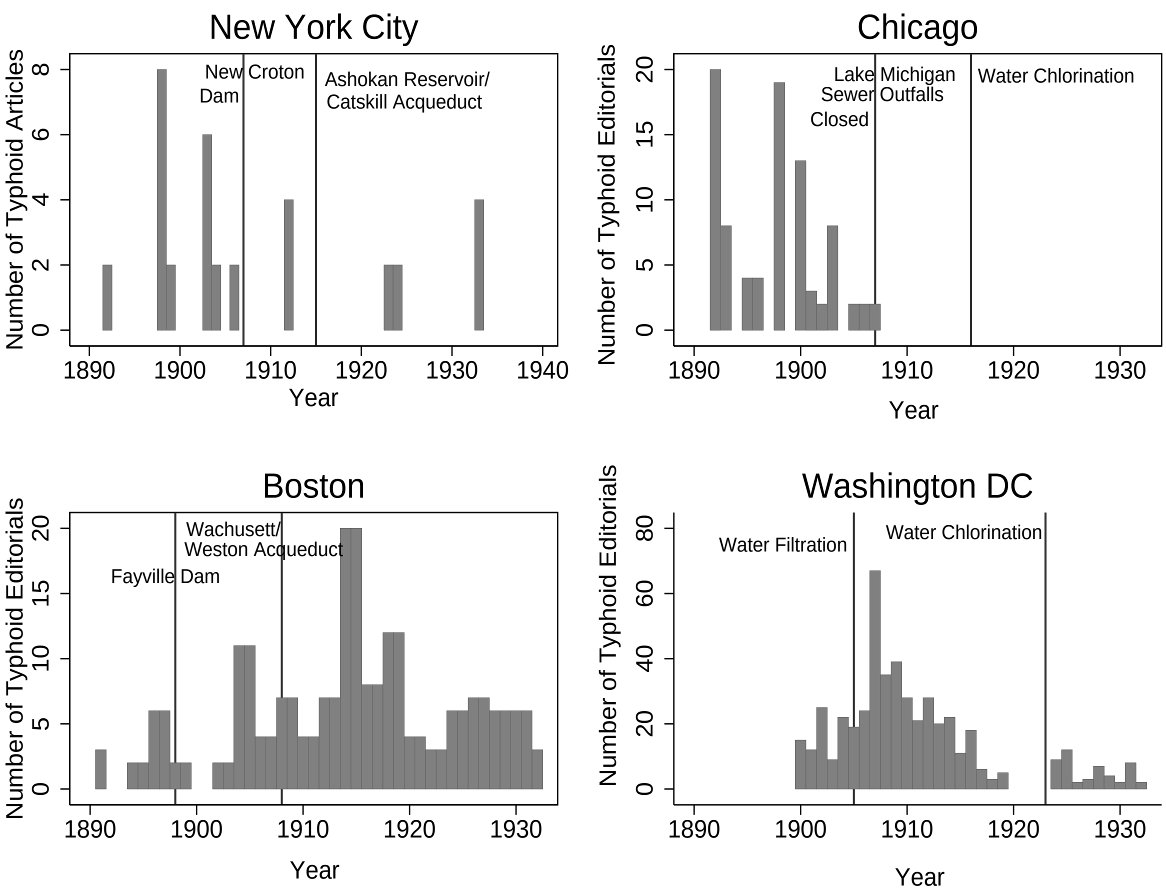
Estimated using Equation 2. See the text for details.

Figure 4: Weekly Typhoid Death Rates and Percentage of Typhoid Articles by City



See the text for sources. Death rates and the percentage of articles were smoothed using a lowess estimator.

Figure 5: Number of Typhoid Editorials by City



Editorials could not be identified for Philadelphia. There were no editorials in Baltimore.

Table 1: Clean Water Intervention Dates

City	Intervention	Intervention
Baltimore	1911	1914
	water chlorination	water filtration
Boston	1898	1908
	Fayville Dam/Sudbury Reservoir	Wachusett/Weston Acqueduct
Chicago	1907	1916
	Lake Michigan sewer outfalls closed	water chlorination
New York City	1907	1915
	New Croton Dam	Ashokan Reservoir/Catskill Acqueduct
Philadelphia	1908	1913
	water filtration	water chlorination
Washington DC	1905	1923
	water filtration	water chlorination

Table 2: Mean Death and Case Rates, Before, Between, and After Interventions

	Before First Intervention		Between Interventions		After Second Intervention	
	Death Rate	Case Rate	Death Rate	Case Rate	Death Rate	Case Rate
Baltimore	0.726	4.437	0.490	2.843	0.156	0.878
	(0.525)	(4.921)	(0.311)	(2.410)	(0.198)	(1.282)
Boston	0.687		0.489	3.358	0.110	0.629
	(0.461)		(0.390)	(5.253)	(0.150)	(0.819)
Chicago	0.554	0.471	0.199	1.231	0.026	0.156
	(0.403)	(0.440)	(0.135)	(1.053)	(0.034)	(0.199)
New York City	0.366	1.444	0.185	1.243	0.034	0.266
	(0.231)	(1.112)	(0.118)	(0.972)	(0.040)	(0.292)
Philadelphia	0.971	6.949	0.343	2.141	0.131	0.664
	(0.600)	(5.746)	(0.252)	(1.596)	(0.089)	(0.579)
Washington DC	1.494		0.596	2.662	0.061	0.324
	(1.072)		(0.538)	(3.091)	(0.124)	(0.429)
All Cities	0.765	2.449	0.382	2.067	0.080	0.484
	(0.717)	(3.409)	(0.385)	(2.596)	(0.129)	(0.772)

See text for death and case rate sources. Standard deviations in parentheses. Case rates are not available for Boston and Washington DC prior to the first intervention.

Table 3: OLS Regression of Effect of Clean Water Interventions on Typhoid Death Rates

	NYC	Chicago	Baltimore	Boston	Philadelphis	DC
1st intervention	-0.116***	-0.158***	-0.080*	-0.075**	-0.614***	-0.257***
	(0.010)	(0.020)	(0.042)	(0.030)	(0.056)	(0.084)
2nd intervention	-0.073***	0.088***	-0.112***	-0.127***	-0.197***	0.050
	(0.009)	(0.021)	(0.039)	(0.030)	(0.046)	(0.060)
Combined interventions	-0.189***	-0.070**	-0.192**	-0.202***	-0.811***	-0.207
	(0.013)	(0.035)	(0.043)	(0.037)	(0.090)	(0.132)
Observations	2,548	1,538	1,387	1,588	904	1,558
R^2	0.517	0.503	0.391	0.396	0.476	0.428

All regressions include a linear time trend and constant term. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Negative Binomial Regression of Effect of Typhoid Death Rates on Newspaper Reports

	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Number of Typhoid Articles						
Death rate	0.335**	0.158	0.386***	0.122	0.350***	0.086
1st intervention	-0.296*	0.151	-0.159	0.098	-0.278***	0.092
2nd intervention	-0.639***	0.067	-0.537***	0.127	-0.121	0.146
1st intervention x death rate	0.107	0.230	0.153	0.166	0.173*	0.092
2nd intervention x death rate	1.316***	0.205	0.617***	0.214	0.244	0.264
Number of total articles	0.014**	0.006	0.006	0.007	0.005	0.006
Constant	1.133***	0.215	1.409***	0.124	0.834***	0.279
City Fixed Effects	N		Y		Y	
Year Fixed Effects	N		N		Y	
Dummy=1 if no typhoid article						
Dummy=1 if big news event	-0.742	0.453	-0.936**	0.434	-0.823**	0.340
Dummy=1 if holiday week	-0.292*	0.166	-0.453	0.461	-0.908***	0.186
Constant	-20.318***	5.659	-6.177	8.369	-30.486	28.637
City Fixed Effects	Y		Y		Y	
Year Fixed Effects	Y		Y		Y	
Both interventions	-0.935***	0.135	-0.697***	0.204	-0.398*	0.214
Both intervention death rate interactions	1.422***	0.217	0.769***	0.198	0.417	0.318
ln(alpha)	-0.798***	0.148	-0.914***	0.229	-1.335***	0.136
Vuong test, z=	9.22***		7.55***		7.771***	
Observations	9,492		9,492		9,492	
Zero observations	2,127		2,127		2,127	

The dependent variable for the count part of the negative zero-inflated binomial is number of typhoid articles. The dependent variable for the logit part of the model is a dummy equal to 1 if there was no typhoid article. Robust standard errors in parentheses, clustered on the city. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Marginals from Negative Binomial Regression of Effect of Typhoid Death Rates on Newspaper Reports

	$\frac{\partial y}{\partial x}$	Std. Err.	$\frac{\partial y}{\partial x}$	Std. Err.	$\frac{\partial y}{\partial x}$	Std. Err.
Death rate	1.023*	0.539	1.174***	0.385	1.062***	0.269
1st intervention	-0.905*	0.482	-0.485	0.298	-0.842***	0.290
2nd intervention	-1.952***	0.359	-1.633***	0.404	-0.367	0.445
1st intervention x death rate	0.326	0.691	0.464	0.499	0.526*	0.280
2nd intervention x death rate	4.022***	0.852	1.875***	0.661	0.740	0.807
Number of total articles	0.043***	0.015	0.018	0.021	0.016	0.017
Dummy=1 if big news event	0.155	0.130	0.147	0.096	0.168	0.125
Dummy=1 if holiday week	0.061	0.051	0.071	0.105	0.186	0.115
City FE in count regression	N		Y		Y	
Year FE in count regression	N		N		Y	
City FE in zero value logit	Y		Y		Y	
Year FE in zero value logit	Y		Y		Y	
Both interventions	-2.857***	0.597	-2.118***	0.632	-1.209*	0.664
Both intervention death rate interactions	4.348***	0.765	2.338***	0.594	1.266	0.971
Mean number of typhoid articles	2.917		2.917		2.917	
Observations	9,492		9,494		9,492	

Marginals are for the regression in Table 4. Robust standard errors in parentheses, clustered on the city. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Negative Binomial Regression of Effect of Typhoid Death Rates on Local Newspaper Reports

	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Number of Typhoid Articles						
Death rate	0.405	0.319	0.373**	0.175	0.366**	0.149
1st intervention	-0.549*	0.303	-0.334***	0.086	-0.274**	0.107
2nd intervention	-0.575***	0.109	-0.774***	0.183	-0.282***	0.072
1st intervention x death rate	0.217	0.361	0.275	0.204	0.244*	0.147
2nd intervention x death rate	0.947***	0.254	0.667***	0.252	0.408***	0.061
Number of total articles	-0.008	0.005	0.003	0.008	-0.000	0.007
Constant	0.778*	0.399	0.328***	0.120	0.507	0.315
City Fixed Effects	N		Y		Y	
Year Fixed Effects	N		N		Y	
Dummy=1 if no local typhoid article						
Dummy=1 if big news event	-0.180	0.236	-0.252	0.339	-0.195	0.290
Dummy=1 if holiday week	0.006	0.164	-0.025	0.289	0.039	0.056
Constant	-15.258***	0.809	-14.551	10.733	-0.766**	0.303
City Fixed Effects	Y		Y		Y	
Year Fixed Effects	Y		Y		Y	
Both interventions	-1.124***	0.405	-1.108***	0.253	-0.556***	0.104
Both intervention death rate interactions	1.164***	0.333	0.942***	0.105	0.651***	0.174
ln(alpha)	-0.494***	0.094	-0.797***	0.278	-0.997***	0.373
Vuong test, z=	19.81***		13.08***		13.50***	
Observations	8,596		8,596		8,596	
Zero observations	3,792		3,792		3,792	

The regressions exclude Philadelphia because we could not mechanically identify local articles. The dependent variable for the count part of the negative zero-inflated binomial is number of typhoid articles. The dependent variable for the logit part of the model is a dummy equal to 1 if there was no typhoid article. Robust standard errors in parentheses, clustered on the city. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: Marginals from Negative Binomial Regression of Effect of Typhoid Death Rates on Local Newspaper Reports

	$\frac{\partial y}{\partial x}$	Std. Err.	$\frac{\partial y}{\partial x}$	Std. Err.	$\frac{\partial y}{\partial x}$	Std. Err.
Death rate	0.470	0.424	0.424**	0.213	0.418**	0.175
1st intervention	-0.637	0.420	-0.380***	0.105	-0.312***	0.120
2nd intervention	-0.667***	0.243	-0.881***	0.233	-0.322***	0.083
1st intervention x death rate	0.252	0.400	0.313	0.228	0.278*	0.163
2nd intervention x death rate	1.099**	0.506	0.759**	0.308	0.465***	0.069
Number of total articles	-0.009	0.006	0.003	0.009	-0.000	0.008
Dummy=1 if big news event	0.036	0.050	0.041	0.066	0.024	0.037
Dummy=1 if holiday week	-0.001	0.033	0.004	0.049	-0.005	0.007
City FE in count regression	N		Y		Y	
Year FE in count regression	N		N		Y	
City FE in zero value logit	Y		Y		Y	
Year FE in zero value logit	Y		Y		Y	
Both interventions	-1.304**	0.643	-1.262***	0.321	-0.634***	0.117
Both intervention death rate interactions	1.350***	0.524	1.073***	0.154	0.742***	0.188
Mean number of typhoid articles	1.097		1.097		1.097	
Observations	8,596		8,596		8,596	

Marginals are for the regression in Table 6. Robust standard errors in parentheses, clustered on the city. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Negative Binomial Regression of Effect of Deviations in Expected Typhoid Death Rates on Newspaper Reports

	All Articles				Local Articles			
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Number of Typhoid Articles								
Predicted - death rate	-0.329	0.383			-0.345	0.491		
(Predicted - death rate) x (Dummy=1 if positive)	1.311*	0.677			1.286	0.937		
(Predicted - death rate)/(Std death rate)			-0.256*	0.143			-0.224	0.241
(Predicted - death rate)/(Std death rate) x (Dummy=1 if positive)			0.842***	0.189			0.802**	0.349
Number of total articles	-0.001	0.010	-0.000	0.010	-0.030***	0.008	-0.030***	0.007
Constant	1.044***	0.276	0.994***	0.254	0.770***	0.241	0.730***	0.204
City Fixed Effects	N		N		N		N	
Year Fixed Effects	N		N		N		N	
Dummy=1 if no typhoid article								
Dummy=1 if big news event	-0.518***	0.119	-0.522***	0.131	-0.263	0.203	-0.265	0.202
Dummy=1 if holiday week	-0.530***	0.150	-0.565***	0.143	-0.085	0.115	-0.108	0.127
Constant	-4.437	2.988	-4.906	3.997	-6.810	100.905	-13.430***	3.108
City Fixed Effects	Y		Y		Y		Y	
Year Fixed Effects	Y		Y		Y		Y	
Total effect of pos(Predicted-death rate)	0.982***	0.001			0.942**	0.477		
Total effect of pos((Predicted-death rate)/Std Dev)			0.586***	0.056			0.578***	0.128
ln(alpha)	-0.545***	0.129	-0.575***	0.150	-0.321***	0.114	-0.376***	0.132
Vuong test, z=	9.54***		9.36***		21.62***		21.62***	
Observations	9,114		9,114		8,269		8,269	
Zero observations	2,040		2,040		4,619		4,619	

The local article regressions exclude Philadelphia. The dependent variable for the count part of the negative zero-inflated binomial is number of typhoid articles. The dependent variable for the logit part of the model is a dummy equal to 1 if there was no typhoid article. Robust standard errors in parentheses, clustered on the city. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9: Marginals from Negative Binomial Regression of Effect of Deviations in Typhoid Death Rates on Newspaper Reports

	All Articles				Local Articles			
	$\frac{\partial y}{\partial x}$	Std. Err.	$\frac{\partial y}{\partial x}$	Std. Err.	$\frac{\partial y}{\partial x}$	Std. Err.	$\frac{\partial y}{\partial x}$	Std. Err.
Predicted - death rate	-1.072	1.375			-0.415	0.705		
(Predicted - death rate) x (Dummy=1 if positive)	4.266	2.790			1.546	1.571		
(Predicted - death rate)/(Std case rate)			-0.798*	0.457			-0.257	0.313
(Predicted - death rate)/(Std case rate) x (Dummy=1 if positive)			2.625***	0.698			0.920*	0.549
Number of total articles	-0.002	0.033	-0.002	0.030	-0.036**	0.015	-0.035**	0.013
Dummy=1 if big news event	0.119**	0.048	0.112**	0.056	0.062	0.066	0.059	0.055
Dummy=1 if holiday week	0.122***	0.043	0.121***	0.030	0.020	0.034	0.024	0.032
City FE in count regression	N		N		N		N	
Year FE in count regression	N		N		N		N	
City FE in zero value logit	Y		Y		Y		Y	
Year FE in zero value logit	Y		Y		Y		Y	
Total effect of pos(Predicted-death rate)	3.194**	1.485			1.132	0.895		
Total effect of pos((Predicted-death rate)/Std Dev)			1.826***	0.324			0.663***	0.248
Mean number of typhoid articles	2.917	3.489	2.917	3.489	1.097	2.019	1.097	2.019
Observations	9,114		9,114		8,269		8,269	

Marginals are for the regression in Table 8. Robust standard errors in parentheses, clustered on the city. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10: Negative Binomial Regression of Effect of Typhoid Case Rates on Newspaper Reports

	All Articles				Local Articles			
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Number of typhoid articles								
Case rate	0.093***	0.022	0.078***	0.019	0.141**	0.057	0.105***	0.034
1st intervention	-0.378***	0.109	-0.285*	0.161	-0.303	0.257	-0.297	0.204
2nd intervention	-0.605***	0.105	-0.128	0.165	-0.660***	0.081	-0.217	0.175
1st intervention x case rate	0.005	0.026	0.010	0.014	-0.026	0.055	0.001	0.026
2nd intervention x case rate	0.213***	0.063	0.104***	0.034	0.171***	0.016	0.129***	0.017
Number of total articles	0.013***	0.003	0.011*	0.005	-0.003	0.004	0.016***	0.006
Constant	1.173***	0.103	0.711*	0.363	0.512	0.388	-0.215	0.370
City Fixed Effects	N		Y		N		Y	
Year Fixed Effects	N		Y		N		Y	
Dummy=1 if no typhoid article								
Dummy=1 if big news event	-0.675***	0.227	-0.993***	0.180	-0.326	0.280	-0.504	0.333
Dummy=1 if holiday week	-0.378**	0.156	-1.001***	0.202	-0.170	0.245	-0.134	0.158
Constant	-5.415***	1.452	-19.704***	1.521	-2.903**	1.380	-0.520***	0.094
City Fixed Effects	Y		Y		Y		Y	
Year Fixed Effects	Y		Y		Y		Y	
Both interventions	-0.984***	0.066	-4.129	0.256	-0.963***	0.326	-0.514*	0.294
Both intervention case rate interactions	0.218***	0.066	0.114***	0.029	0.145***	0.051	0.130***	0.013
ln(alpha)	-1.097***	0.121	-1.523***	0.126	-0.971***	0.177	-1.250***	0.177
Vuong test, z=	8.61***		6.45***		17.32***		11.07***	
Observations	8,214		8,214		7,467		7,467	
Zero observations	2,078		2,078		4,438		4,438	

The local article regressions exclude Philadelphia. The dependent variable for the count part of the negative zero-inflated binomial is number of typhoid articles. The dependent variable for the logit part of the model is a dummy equal to 1 if there was no typhoid article. Robust standard errors in parentheses, clustered on the city. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 11: Marginals from Negative Binomial Regression of Effect of Typhoid Case Rates on Newspaper Reports

	All Articles				Local Articles			
	$\frac{\partial y}{\partial x}$	Std. Err.	$\frac{\partial y}{\partial x}$	Std. Err.	$\frac{\partial y}{\partial x}$	Std. Err.	$\frac{\partial y}{\partial x}$	Std. Err.
Case rate	0.245***	0.056	0.201***	0.051	0.133**	0.056	0.096***	0.033
1st intervention	-0.998***	0.281	-0.736*	0.415	-0.286	0.241	-0.272	0.181
2nd intervention	-1.595***	0.282	-0.332	0.429	-0.623***	0.060	-0.198	0.159
1st intervention x case rate	0.013	0.070	0.026	0.037	-0.024	0.052	0.001	0.024
2nd intervention x case rate	0.561***	0.166	0.269***	0.089	0.161***	0.019	0.118***	0.017
Number of total articles	0.035***	0.007	0.028**	0.014	-0.003	0.004	0.015***	0.005
Dummy=1 if big news event	0.107**	0.054	0.172***	0.039	0.042	0.035	0.049**	0.024
Dummy=1 if holiday week	0.060*	0.033	0.173***	0.034	0.022	0.030	0.013	0.013
City FE in count regression	N		Y		N		Y	
Year FE in count regression	N		Y		N		Y	
City FE in zero value logit	Y		Y		Y		Y	
Year FE in zero value logit	Y		Y		Y		Y	
Both interventions	-2.593***	0.165	-1.068	0.666	-0.909***	0.298	-0.469***	0.260
Both intervention case rate interactions	0.574***	0.178	0.295***	0.077	0.137***	0.050	0.119***	0.011
Mean number of typhoid articles	2.437	2.847	2.437	2.847	0.820	1.483	0.820	1.483
Observations	8,214		8,214		7,467		7,467	

Marginals are for the regression in Table 10. Robust standard errors in parentheses, clustered on the city. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 12: Negative Binomial Regression of Effect of Deviation in Expected Typhoid Case Rates on Newspaper Reports

	All Articles				Local Articles			
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Number of articles								
Predicted - case rate	-0.200***	0.051			-0.193***	0.072		
(Predicted - case rate) x (Dummy=1 if positive)	0.468***	0.059			0.470***	0.055		
(Predicted - case rate)/(Std case rate)			-0.403***	0.148			-0.341	0.295
(Predicted - case rate)/(Std case rate) x (Dummy=1 if positive)			0.948***	0.220			0.893**	0.390
Number of total articles	0.004	0.007	0.003	0.007	-0.013***	0.002	-0.018***	0.003
Constant	0.748***	0.263	0.733***	0.248	0.226	0.153	0.275	0.175
City Fixed Effects	N		N		N		N	
Year Fixed Effects	N		N		N		N	
Dummy=1 if no typhoid article								
Dummy=1 if big news event	-0.486***	0.114	-0.508***	0.126	-0.327*	0.186	-0.348*	0.202
Dummy=1 if holiday week	-0.240	0.175	-0.284*	0.167	-0.084	0.108	-0.106	0.132
Constant	-3.430***	0.896	-4.093***	1.328	-1.483***	0.316	-0.745***	0.094
City Fixed Effects	Y		Y		Y		Y	
Year Fixed Effects	Y		Y		Y		Y	
Total effect of pos(Predicted-case rate)	0.269***	0.035			0.277***	0.038		
Total effect of pos((Predicted-case rate)/Std dev)			0.545***	0.077			0.551***	0.098
ln(alpha)	-0.797***	0.069	-0.798***	0.074	-0.765***	0.084	-2.071**	1.001
Vuong test, z=	10.24***		9.81***		19.44***		20.22***	
Observations	7,706		7,706		7,062		7,062	
Zero observations	2,004		2,004		4,268		4,268	

The local article regressions exclude Philadelphia. The dependent variable for the count part of the negative zero-inflated binomial is number of typhoid articles. The dependent variable for the logit part of the model is a dummy equal to 1 if there was no typhoid article. Robust standard errors in parentheses, clustered on the city. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 13: Marginals from Negative Binomial Regression of Effect of Deviations in Typhoid Case Rates on Newspaper Reports

	All Articles				Local Articles			
	$\frac{\partial y}{\partial x}$	Std. Err.	$\frac{\partial y}{\partial x}$	Std. Err.	$\frac{\partial y}{\partial x}$	Std. Err.	$\frac{\partial y}{\partial x}$	Std. Err.
Predicted - case rate	-0.507***	0.097			-0.169***	0.051		
(Predicted - case rate) x (Dummy=1 if positive)	1.188***	0.168			0.411***	0.050		
(Predicted - case rate)/(Std case rate)			-1.022***	0.377			-0.287	0.261
(Predicted - case rate)/(Std case rate) x (Dummy=1 if positive)			2.405***	0.588			0.750**	0.362
Number of total articles	0.010	0.018	0.007	0.017	-0.012***	0.003	-0.015***	0.003
Dummy=1 if big news event	0.112**	0.046	0.112**	0.051	0.053	0.039	0.058	0.043
Dummy=1 if holiday week	0.055	0.042	0.063*	0.036	0.014	0.019	0.018	0.023
City FE in count regression	N		N		N		N	
Year FE in count regression	N		N		N		N	
City FE in zero value logit	Y		Y		Y		Y	
Year FE in zero value logit	Y		Y		Y		Y	
Total effect of pos(Predicted-case rate)	0.681***	0.143			0.242***	0.056		
Total effect of pos((Predicted-case rate)/Std dev)			1.382***	0.237			0.463***	0.106
Mean number of typhoid articles	2.436	2.847	2.436	2.847	0.820	1.483	0.820	1.483
Zero observations								

Marginals are for the regression in Table 12. Robust standard errors in parentheses, clustered on the city. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 14: Negative Binomial Regression of Effect of Typhoid and Diphtheria Death Rates on Typhoid and Diphtheria Newspaper Reports

	All Articles						Local Articles			
	Typhoid		Diphtheria		Typhoid		Diphtheria		Diphtheria	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Number of articles										
Typhoid death rate	0.806***	0.092	0.221*	0.122	1.507***	0.173	-0.009	0.189		
1st typhoid intervention	-0.080	0.083	-0.395***	0.139	-0.092	0.128	-0.589**	0.252		
2nd typhoid intervention	-0.563***	0.110	-0.160	0.152	-0.540***	0.166	-0.122	0.287		
1st typhoid intervention x death rate	0.430	0.276	-0.466	0.504	0.548	0.412	0.096	0.763		
2nd typhoid intervention x death rate	2.572***	0.844	-1.752	1.201	4.208***	1.562	-0.640	1.883		
Diphtheria death rate									-0.057	0.087
Diphtheria intervention									-0.887***	0.287
Diptheria intervention x death rate									0.599***	0.121
Number of total articles	0.006**	0.003	0.016***	0.003	0.007	0.005	0.018***	0.006	0.019***	0.004
Constant	1.072***	0.065	0.446***	0.081	-0.202*	0.110	-0.308**	0.150	-0.223	0.265
Dummy=1 if no article										
Dummy=1 if big news event	-1.113**	0.464	-0.269	0.274	-1.044**	0.464	-0.106	0.304	-0.141	0.294
Dummy=1 if holiday week	-0.757*	0.400	-0.255	0.228	-0.848**	0.414	-0.397*	0.241	-0.394*	0.230
Constant	-3.669	3.460	-27.033	45,614.242	-1.915	1.670	-1.249	0.819	-1.314	0.858
Year Fixed Effects	Y		Y		Y					
Both interventions	-0.643***	0.106	-0.556***	0.122	-0.632***	0.171	0.711***	0.230		
Both intervention death rate interactions	3.002***	0.810	-2.219**	1.108	4.756***	1.532	-0.544	1.754		
ln(alpha)	-1.507***	0.102	-1.513***	0.134	-0.990***	0.124	-1.805***	0.422	-2.139***	0.590
Vuong test, z=	5.74***		8.51***		5.98***		7.82***		8.08***	
Observations	2,548		2,548		2,548		2,548		2,548	
Zero observations	497		1,607		1,271		1,695		1,695	

The dependent variable for the count part of the negative zero-inflated binomial is number of typhoid or diphtheria articles. The dependent variable for the logit part of the model is a dummy equal to 1 if there was no typhoid or diphtheria article. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 15: Marginals from Negative Binomial Regression of Effect of Deviations in Typhoid Case Rates on Newspaper Reports

	All Articles						Local Articles			
	Typhoid		Diphtheria		Typhoid		Diphtheria		Diphtheria	
	$\frac{\partial y}{\partial x}$	Std. Err.	$\frac{\partial y}{\partial x}$	Std. Err.	$\frac{\partial y}{\partial x}$	Std. Err.	$\frac{\partial y}{\partial x}$	Std. Err.	$\frac{\partial y}{\partial x}$	Std. Err.
Typhoid death rate	2.404***	0.279	0.322	1,086.555	1.514***	0.191	-0.005	0.095		
1st typhoid intervention	-0.239	0.248	-0.576	1,944.205	-0.093	0.128	-0.298**	0.128		
2nd typhoid intervention	-1.680***	0.329	-0.234	788.692	-0.543***	0.168	-0.061	0.145		
1st typhoid intervention x death rate	1.283	0.824	-0.679	2,293.075	0.551	0.412	0.049	0.386		
2nd typhoid intervention x death rate	7.673***	2.522	-2.552	8,617.404	4.230***	1.584	-0.324	0.952		
Diphtheria death rate									-0.029	0.044
Diphtheria intervention									-0.450***	0.147
Diptheria intervention x death rate									0.304***	0.063
Number of total articles	0.017**	0.008	0.024	80.763	0.007	0.005	0.009***	0.003	0.010***	0.002
Dummy=1 if big news event	0.256**	0.104	0.058	405.575	0.110**	0.050	0.014	0.042	0.020	0.042
Dummy=1 if holiday week	0.174*	0.092	0.055	384.324	0.090*	0.049	0.054	0.034	0.056*	0.033
Year FE in zero value logit	Y		Y		Y		Y		Y	
Both interventions	-1.919***	0.316	-0.891	2732.897	-0.636***	0.172	-0.359***	0.118		
Both intervention death rate interactions	8.956***	2.423	-3.232	10910.48	4.781***	1.552	-0.275	0.887		
Mean number of typhoid articles	2.996				1.008					
Mean number of diphtheria articles			1.456				0.505		0.505	
Observations	2,548		2,548		2,548		2,548		2,548	

Marginals are for the regression in Table 14. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$