Does Disease Cause Vaccination? Disease Outbreaks and Vaccination Response*

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Abstract

Parental fear of vaccines has limited vaccination rates in the United States. I test whether disease outbreaks increase vaccination using a new dataset of county-level disease and vaccination data. I find that pertussis (whooping cough) outbreaks in a county decrease the share of unvaccinated children entering kindergarten. These responses do not reflect changes in the future disease risk. I argue that these facts are best fit by a model in which individuals are both myopic and irrational. This suggests that better promotion of outbreaks could enhance the response.

1 Introduction

Childhood vaccinations are a crucial input to disease prevention. In the period from 1920 through 1940, prior to vaccination, the incidence of pertussis (whooping cough) in the US was 150 cases and 6 deaths per 100,000 people (Kutty et al, 2013). By the early 1990s, case counts had dropped to just 1 per 100,000 with typically fewer than 10 deaths per year across the country (Davis et al, 1992). These long run trends in disease reflect trends in vaccination. The current vaccination rate in the US for pertussis among schoolchildren is around 94%.[1]

Vaccination rates in the US are not 100%, however, and under-vaccination is geographically concentrated, leaving some areas with quite low vaccination rates (Omer et al, 2006). Low vaccination rates has contribute to incidence of disease. Pertussis rates in the US

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[1]https://www.cdc.gov/vaccines/imz-managers/coverage/schoolvaxview/data-reports/coverage-reports/2015-16.html

have roughly doubled since 2000, with a corresponding increase in deaths, primarily among infants.[2] Maintaining and increasing vaccination rates in the face of these issues is a goal for both policy-makers and for many practitioners (Yang and Silverman, 2015; Orenstein and Seib, 2014).

Undervaccination largely reflect parental choice and fear about vaccine safety and efficacy (Healy and Paulson, 2015; Glassser et al, 2016; Omer et al, 2012;Omer et al, 2009; Salmon et al, 2005).[3]

US vaccine policy has focused on either (a) educating parents about vaccines or (b) changing school vaccination policies to make it more difficult to enroll unvaccinated children in school. Both policies have limitations. Changing school vaccination rules is effective (Sadaf et al, 2013), but faces significant resistance from both politicians and parents (Constable, Blank and Caplan, 2014; Hoberock, 2017; Associated Press, 2015; Mello et al, 2015; Siepel, 2016). Education campaigns are more palatable in the sense that they preserve parental choice, but they are largely ineffective (Nyhan et al, 2014; Sadaf et al, 2013; Nyhan and Reifler, 2015; Williams et al, 2013).

Recently, there has been anecdotal evidence that suggests that disease outbreaks may increase vaccination rates. In the wake of the 2015 Disneyland measles outbreak, for example, local news in a variety of locations reported more demand for vaccination (Aleccia, 2015; Turkewitz, 2015). However, there is little systematic evidence on whether this is true and, if so, why. Even if the anecdotes do reflect detectable effects, it is difficult to know if they reflect a rational response to increased disease risk (as in Philipson, 1996), or something more behavioral. Differentiating between these may be helpful in identifying policies to encourage vaccination.

This paper brings new data to bear on the relationship between disease outbreaks and vaccination. I combine county-year data on vaccination among kindergarten children with county-year data on outbreaks of disease. The data is an unbalanced panel of roughly 1,000 counties in 12 states over 15 years. I also obtain data on Google searches for terms related to vaccination and disease, local news coverage of disease outbreaks, and information from states on their policy approach to disease reports.

I estimate the response of pertussis vaccination to pertussis outbreaks. I find that vaccination does respond to outbreaks: within a county over time, higher disease rates in the years between birth and kindergarten entry lead to higher vaccination rates at entry.

[2]See evidence from the CDC: http://www.cdc.gov/pertussis/images/incidence-graph-age.jpg

[3]In the late 1990s a now-discredited study was published in the Lancet suggesting a link between vaccines and autism. Although the paper was shown to be fraudulent, its effects on vaccination rates have been long-lasting (Mnookin, 2011). More recently, many parental concerns have focused on worries about toxins and metals being present in vaccines.

Outbreaks in the year of birth and the year before kindergarten seem to be the most significant.

These vaccination responses seem to reflect a pattern of increased information and information seeking. I show that outbreaks also increase Google searches for terms related to pertussis ("pertussis", "whooping cough", "pertussis vaccination"). They also increase the frequency of news coverage of pertussis in local newspapers.

I consider the possible role of local policy in mediating this result. I exploit a survey of health departments to estimate whether the response differs across areas depending on their policy for dealing with outbreaks. In particular, I differentiate between states in which the state health department coordinates outbreak response and those in which each county autonomously deals with outbreaks. I find that the vaccination increase appears only in the states in which the state health department coordinates the outbreak response. These states also show a more substantial response in Google searches.

In summary, the first part of the paper demonstrates that childhood vaccinations do respond to disease outbreaks. In the second part of the paper I explore why this occurs. I first evaluate the extent to which outbreaks provide information about future risks. I show that the pertussis series is stationary within a county, meaning that current year outbreaks are not informative about the future, conditional on the past. There is a correlation across years, however, so someone uninformed about the past could learn from current levels.

I then outline an extremely simple theory of the vaccination decision in which households choose to vaccinate if the perceived benefits of vaccination, in terms of disease avoidance, exceed the perceived costs in terms of vaccine risks, inconvenience or other costs.

I consider three versions of this model. I show first that a benchmark version of this model - in which people are fully informed and fully rational - does not seem consistent with the data. I then allow for the possibility that people are rational but not fully informed. Finally, I consider the general case in which people are not rational.

I argue that distinguishing between the latter two cases empirically is valuable in considering what type of information might be used to change behavior. To do this, I use a simple machine learning approach with a lasso algorithm to evaluate whether variables other than disease rate influence behavior. I find that there are some other features of the disease that matter. This suggests there may be non-rational aspects of the response which policy could be built around.

This paper contributes to the general literature on interventions to increase vaccination rates, well summarized by Sadaf et al (2013). Perhaps the most closely related paper on this topic, Wolf et al (2014), found that a single large outbreak in Washington State did not impact vaccination of young children. This differs markedly from my findings, which may be because I am able to look at a large number of outbreaks, or because my data focuses on school-age children and not younger children. More supportive of my findings, Cacciatore, Nowak and Evans (2016) find that the 2014-2015 Disneyland measles outbreak did increase confidence in vaccines, although they are not able to look at actual vaccination behavior.

The paper also contributes to the literature on economic epidemiology (e.g. Philipson, 1996; Geoffard and Philipson, 1996; Geoffard and Philipson, 1997; Philipson, 2000; Kremer, 1996; Adda, 2016; Aguero and Beleche, 2016). Philipson (1996) finds that states with more measles in the late 1980s also had higher vaccination rates in that period. The direction of the effect is consistent with my findings, although the argument in Philipson (1996) is that the response is a rational one, given that measles was more common in this period.

The rest of the paper is organized as follows. Section 2 discusses background. Section 3 presents the data and empirical strategy. Section 4 presents the primary results on the changes in vaccination behavior in response to outbreaks. Section 5 discusses mechanisms for this effect and Section 6 concludes.

2 Background on Pertussis

This paper focuses on pertussis, commonly called whooping cough.[4] Pertussis is a very contagious bacterial disease. It begins with symptoms similar to a cold, but then evolves into a severe cough which can last for months. Coughing fits are often followed by a characteristic "whoop" sound while gasping for air, hence the name. Pertussis can be treated with a course of antibiotics, and even without this most older children and adults make a full recovery.

Pertussis can be much more serious for children under a year old, who are more likely to develop complications like pneumonia. Pertussis can be fatal, and in a typical year it is responsible for 10 to 20 deaths, most among very young babies. Prior to the introduction of vaccination for pertussis in the 1940s there were approximately 10,000 deaths a year in the US due to the disease.

Pertussis rates have declined dramatically in the US in the wake of vaccination, but the disease continues to be endemic. Vaccination protection wanes 3 to 5 years after vaccination and is typically completely gone after 12 years. In addition, the disease is extremely contagious. As a result, outbreaks continue at a low level despite high rates of vaccination overall in the US.

The standard vaccine schedule for pertussis is 2 months, 4 months, 6 months and 15 to 18 months. A fifth dose is typical for children between ages 4 and 6. Depending on the school system and timing a child with either four or five doses is considered fully vaccinated. Recent

[4]Details about pertussis here are drawn from Kliegman et al (2011) unless otherwise specified.

recommendations also suggest pregnant women should get a pertussis booster, as this enhances immunity among children younger than two months.

Pertussis is a notifiable disease, which means doctors and county health department are required to report identified cases to the CDC. In 2014 (the most recent year with available data), 32,971 cases were reported; this is up 15% from 2013.[5]

Isolated cases of pertussis are treated individually, but a cluster of cases - typically defined as two or three cases together, depending on the county - are considered an outbreak. The CDC, along with individual counties, issues guidelines about behavior during outbreaks. These guidelines include suggested interventions by school and day care centers, information provision by doctors and, in some cases, county-led vaccination campaigns.[6] During an outbreak, older children and adults that have not been vaccinated in some time are typically recommended to receive booster vaccination.

Pertussis vaccination rates in the US are high but not 100%. Based on National Immunization Survey data from the CDC, approximately 84% of children have 4 or more doses of the pertussis vaccine, as recommended by the CDC (Hill et al, 2016).

3 Data

3.1 Data

This paper uses a number of data sets. I discuss each in turn.

The data on vaccination rates comes from individual states. The goal was to collect county-level vaccination data from as many states as possible. Some states do not collect their own data on vaccinations, relying instead on the National Immunization Survey. For states which do have their own data collection, data is from one of two sources. In some cases data comes from annual school surveys, aggregated to the county level. In others, states use immunization registries. In the latter, only a subset of the registries are mandatory and optional registries tend to have quite poor coverage.

For data quality reasons, I use data from states that either have a mandatory registry or provide data from school reports.[7] I use the vaccination data at kindergarten entry because it provides consistent data for the largest number of locations. I focus on pertussis since this is the only illness with a significant number of outbreaks. In an appendix I will show results for older children and for measles vaccinations. Summary statistics for the states used in the

[5]https://www.cdc.gov/pertussis/outbreaks/trends.html

[6]https://www.cdc.gov/pertussis/outbreaks/about.html

[7]The school reports will include private schools but will not include students who are home schooled. Home schooling accounts for only about 3% of children so any bias from this is likely to be small.

analysis appear in Panel A of Table 1. The years of coverage for states varies. I have the longest time series for California, from 1991 to 2011. The shortest time series is for Missouri, with coverage only in 2011. Vaccination rates are generally high, although they are below 95% (a typical herd immunity level) in many states.

The vaccination data measures the share of children with complete vaccination uptake, as measured by the standards of the state. In some state-years this is four vaccines, and in others it is five. In some states it would be possible to differentiate between completed vaccinations and any vaccinations, although for much of the sample the only reporting is on the share of children with completed vaccinations.

Vaccination rates have declined over the period covered by the data, going down approximately 4 percentage points from a high in the late 1990s.[8] There is also substantial variation across space. This is illustrated in Figure 1, which shows the distribution of county vaccination rates in the most recent year of data. Although many counties have vaccination rates at or close to 100, there is a long tail of low vaccination rates. 7.8% of county-years have pertussis vaccination rates below 80%, and 12% have rates below 90%. These areas of very low vaccination are especially at risk for disease outbreaks (Phadke et al, 2016).

The second data set covers disease outbreaks by county over time. These data are available from the Center for Disease Control (CDC) through the National Notifiable Diseases Surveillance System (NNDSS). The NNDSS is a nation-wide collaboration, run by the CDC, for public health departments at various levels (state, local) to share information about a set of notifiable diseases, of which pertussis is one. Reporting of these diseases is judicially mandated. The data provides counts, by county-year, of disease cases. It is likely that these figures are an understatement of total cases, especially for pertussis, but I expect them to be correlated with the true counts.

Merging disease counts with county-level population data produces disease rates. Panel B of Table 1 summarizes the rates of pertussis by state. Pertussis cases per 100,000 people range from 2 to almost 10 per year. The median county-year has zero cases of pertussis; even at the 75th percentile of county-years, there are only 4 cases.

The third data set is from Google trends. These data report the volume of Google searches for various terms within a location over time. I focus on three categories of searches. The first are searches for terms related to pertussis ("pertussis" or "whooping cough"), the second are searches related to the vaccines ("pertussis vaccination"), and the third are searches related to vaccine risks (either "vaccine injury" and related terms or "autism and vaccines"). The full list of search terms in each category appears in Table B.1 in the Appendix.

An issue in constructing the Google trends data is that the data are subject to privacy

[8] This figure is based off of estimated time dummies in a regression including county fixed effects.

thresholds. It is not possible to generate data from rare search terms. To get around this, I use a technique from Stephens-Davidowitz (2014). In broad terms, this involves searching for the term of interest along with another common word (for example, "joke" or "sponge") and then searching for the common word alone and subtracting the two. Details of the implementation appear in Appendix B.

I use two sets of Google data. First, I use DMA-level measures which I average over the entire period from 2004 to 2015. These data indicate which areas have the overall highest interest in a particular term over this period. They do not adjust for domain-specific search volume so I also collect data on searches for non-vaccination-related health terms (cancer, diabetes) and generate area-level residuals with respect to these terms.

Second, I use Google trend data at the state-month level to estimate search response to disease outbreaks. The Google trends data are merged with disease outbreak data at the state-month level from the NNDSS system.[9]

The fourth dataset is on news reports. I scrape news coverage of pertussis at the county-year level from InfoWeb, a source which includes online and offline newspapers, blogs and other news sources. I generate counts of articles by county-year. These data are used to evaluate whether news coverage responds to outbreaks. I do not restrict the articles to those which cover outbreaks, so there will certainly be a variety of topics covered in the articles captured, but as we will see they do correlate with disease incidence.

Finally, I use a survey of state and county health departments to understand their policies for dealing with outbreaks. The primary finding from this survey exercise was that states differ in their coordination of outbreak response. In four of the states, any outbreaks are centrally coordinated by the state health department; while in the other eight, counties have their own control. The analysis will separate these groups to learn whether variations in policy alter the patterns of results.

Data Validation

The vaccination data used in this paper – from school vaccination reports – comes from the same source that the CDC uses in their summary of school vaccination rates.[10] The CDC typically summarizes the data at the state level, and does not limit to states with comprehensive reporting, but this provides some confidence in the validity of this data source. A second CDC source for vaccination data is the National Immunization Survey, which

[9]In the period prior to 2011, there is an excess mass of reported cases in December, seemingly due to a policy of listing all cases with unknown timing as occurring in the last week of the year. I will therefore drop December from this monthly analysis.

[10]See, for example, the CDC discussion at this site: https://www.cdc.gov/vaccines/imz-managers/coverage/schoolvaxview/index.html

surveys parents of children 19 to 35 months about their children's vaccination status. These data cover a different age group and the data collection method is different. Nevertheless, there is a significant correlation between the two series at the state-year level. A regression of our measure of vaccination on the NIS measure of coverage of the pertussis vaccine yields a coefficient of 0.48, significant at the 5% level.

4 Estimation Strategy

I use a simple empirical model. There is a birth cohort b in county c and we observe the vaccination rate for this cohort at age 5. Denote this vaccination rate as v_{bc}.

At each age leading up to 5, there is a realization of disease state. Denote a vector of disease measures over this period as $\mathbf{r_{bc}}$ where the subscripts indicate the relevance to birth cohort b in county c. The elements included in this vector could include various measures of disease, such as disease rate, or counts, or other metrics. Note importantly that this is not the disease rate among cohort b. Rather, it is the disease profile experienced by this cohort up to age 5. The disease rate is a function of the entire population.

We model household i as vaccinating their child (who is in birth cohort b in county c) if the perceived benefits B_{bci} exceed the perceived costs C_{bci}. The benefits of vaccination come in the form of disease avoidance. I assume these benefits may be a function of $\mathbf{r_{bc}}$, either due to changes in the perceived risk of contracting the disease or changes in the perceived dangers of the disease. Vaccination occurs if $B_{bci}(\mathbf{r_{bc}}) > C_{bci}$. In this case, vaccination rate v_{bc} will be a function of $\mathbf{r_{bc}}$. It will also be a function of other variables, assuming (for example) that the perceived vaccination cost is a function of county or time characteristics.

I model vaccination rate as a function of disease measures and other variables. Denote the elements of $\mathbf{r_{bc}}$ as r_{kbc} for $k = 1, ..., n$. In addition, consider that there is a set of variables $\mathbf{X_b}$ which capture (possibly unobserved) birth cohort characteristics and $\mathbf{X_c}$ which capture (possibly unobserved) county characteristics. These factors could contribute, for example, to differences in perceived cost of vaccination or differences in perceived benefits, either of which could impact vaccination rates in this simple framework. In general, we can then write $v_{bc} = f(\mathbf{X_c}, \mathbf{X_b}, \mathbf{r_{bc}})$.

A first question in moving to estimation is the appropriate functional form for $f(.)$. I note that v_{bc} is bounded between 0 and 1 and, in practice, most values are close to 1. Given this, a linear function for $f(.)$ may not fit the data well. As is common with this type of variable, I assume $f(.)$ is an inverse logit function. I can then model the logit transform of v_{bc} (namely, $log\left(\frac{v_{bc}}{1-v_{bc}}\right)$) as a linear function of $\mathbf{X_c}, \mathbf{X_b}, \mathbf{r_{bc}}$. Denote the transformed variable $\mathring{v}_{bc}$. The linear regression of interest is then:

$$\mathring{v}_{bc} = \alpha + \mathbf{\Psi X_c} + \mathbf{\Phi X_b} + \sum_k \beta_k r_{kbc} + \epsilon_{bc} \tag{1}$$

Here note that we can in principle include a rich set of functions of disease in the vector $\mathbf{r_{bc}}$ so this doesn't restrict us, for example, to assuming that vaccination is a linear function of disease rates.

For the standard reasons - namely, that we do not necessarily observe the elements of $\mathbf{X_b}$ and $\mathbf{X_c}$, I cannot run this regression directly and generate unbiased estimates of $\beta_{k.}$ It seems likely that disease outbreaks are correlated with other county characteristics, including the whole history of vaccination, so a regression which excludes $\mathbf{X_b}$ and $\mathbf{X_c}$ will be subject to omitted variable bias.

We solve this issue with the inclusion of county and cohort fixed effects. These fixed effects will fully control for the vectors $\mathbf{X_b}$ and $\mathbf{X_c}$ and will then identify the impact of disease on vaccination by looking for variation in vaccination rates which lines up with variations in disease risk. Formally, Equation (2) below specifies the fixed effect regression we run in a standard form:

$$\mathring{v}_{bc} = \alpha + \gamma_c + \delta_b + \eta p_{ct} + \sum_k \beta_k r_{kbc} + \varepsilon_{bc} \tag{2}$$

where γ_c is a county fixed effect and δ_b is a birth cohort fixed effect. The variable p_{ct} measures the population in county c in year t. This is not captured fully by county fixed effects since it may vary over time. The coefficients of interest are still the β_k values.

In the primary regressions I consider several sets of variables in $r_{kbc.}$ These include averages of the disease rate or counts over the previous five years (i.e. during the life of the child), the maximum rate or count over this period, and rates or counts by year for this period. In Section 6, I explore a larger set of variables and try to infer more about the functional form of this relationship.

Reverse Causality The fixed effect framework addresses concerns about omitted variables at the county level. However, here is still the potential for an issue of reverse causality. In particular, we may worry that deviations in vaccination rate for cohort b will drive deviations in disease rate.

This is possible because some of the vaccination of cohort b occurs at earlier ages. If higher disease rates at (say) the age of 1 increase vaccination rates, then this may impact disease rates when the child is (say) 3 and also will (mechanically) impact the observed vaccination rate. This will bias the estimated coefficients downward, making it more difficult to pick up our hypothesized positive impacts.

Any bias from this source is likely to be small in the fixed effect model. In particular, the disease rate is the rate among the whole population, and we are considering vaccination rates in a single cohort. Movement in one cohort's vaccination rates have only a small impact on total vaccination rates and, therefore, are likely to have, at most, a very tiny impact on disease outbreak. Moreover, given the average level of vaccination in this data, most of the variation in disease rate here is simply random.

We can, however, test this directly by regressing disease outbreaks in a given period on vaccination rates for a single cohort in that period using fixed effects. In particular, take the disease rate which is realized at the age of 5 - in the year *after* our measure of vaccination - and regress it on the vaccination rate among the entering kindergarten class. This relationship is subject to omitted variable bias, which we can address using the fixed effects. Note that it is not, however, subject to the same reverse causality concerns since this cohort vaccination rate is by definition determined before the disease outbreak.

This regression simply asks whether there is any evidence that deviations from the average vaccination rate in a single cohort seem to be reflected in future deviations from the average in disease. To the extent this relationship is close to zero, it suggests a limited scope for bias.

Appendix Table A.1 shows this analysis. The relevant estimate is small and insignificant, suggesting this bias is not quantitatively important. If concerns about this bias remain, the results should be seen as a lower bound on the impacts.

Google and News Estimation

In addition to vaccination rates, I also analyze the reaction of news coverage and Google trends to outbreaks. In the case of news, the observations are at the county-year level. Denote news coverage in county c in year t as n_{ct}. I regress n_{ct} on outbreaks in county c in year t. County and year fixed effects are included to address omitted variable bias concerns and a control for county-year population is included. The regression is specified in Equation (3).

$$n_{ct} = \alpha + \gamma_c + \delta_t + \eta p_{ct} + \Phi r_{ct} + \varepsilon_{ct} \tag{3}$$

The coefficient of interest is Φ.

In the case of Google, the data is observed at the state-month level. The geographic scope is therefore larger, but we have finer timing. This is merged with data on outbreaks at the state-month level. Denote the volume of Google searches in state s in month m as g_{sm} and the outbreaks in that state-month as $r_{sm.}$ The fixed effect equation is specified in Equation (4).

$$g_{sm} = \alpha + \gamma_s + \delta_m + \Psi r_{sm} + \varepsilon_{sm} \tag{4}$$

5 Results: Vaccination Behavior and Disease Outbreaks

This section presents the baseline results for the response of pertussis vaccination to disease outbreaks. The first subsection describes vaccination response. The second subsection describes the Google trend results. The third subsection analyzes variation in the vaccination response across space.

5.1 Vaccination Response to Outbreaks

Primary Results

Table 2 shows the primary results in the paper. The outcome in each column is the transformed vaccination rate measure. Each column includes a different pertussis measure. Columns (1) - (3) show impacts of pertussis measured in the disease rate. Column (1) shows the impact of the average pertussis rate over the preceding five years and Column (2) shows the impact of the maximum outbreak over the period. Column (3) shows the impact of the rate in each year.

Columns (4) through (6) show the same results but with counts of cases rather than with the rate.

The message in all of the columns is similar. More pertussis outbreaks in early childhood lead to higher vaccination rates in kindergarten. These effects are significant in all columns. Columns (3) and (6) reveal that these effects are driven by outbreaks in the year before kindergarten entry and outbreaks in the first year of life. This is not surprising given that these are the times at which parents are most likely to be consider whether to vaccinate. Vaccination for pertussis starts in the first year of life and in the year before kindergarten parents must either vaccinate or obtain an exemption.

Figures 2a and 2b show a graphical interpretation of the relationship, designed to be more interpretable in terms of magnitudes. To create these graphs, I divide outbreaks (measured either by the average rate or the average counts) into seven groups and regress vaccination on dummies for each group. In addition, to facilitate interpretation I use the vaccination rate (rather than the transformation) as the outcome. I divide the sample into high and low vaccination counties..

Both graphs show a positive relationship between outbreaks and vaccination rate. These figures also give some sense magnitudes. Based on Figure 2b, being in the highest pertussis group during early childhood will prompt an increase in vaccination rate of about 1.5 percentage points among low vaccination counties. On average, 92 percent of children in this group are vaccinated, so this increase accounts for 20 percent of unvaccinated children becoming vaccinated.

Tables 3 and 4 show four robustness checks, replicating Table 2. First, in Panel A of Table 3, I limit the data to county-years with 10 or fewer pertussis cases. This represents 88% of the data and 75% of positive outbreaks, although it eliminates many of the large outbreaks. The effects remain significant. This helps avoid the concern that these impacts are driven by the few very large outbreaks which would be widely noticed and publicized.

Second, in Panel B of Table 3 I include a control for future pertussis cases.[11] Disease in the year following the vaccination measurement does not impact vaccination rates. The loss in sample size (due to having to look forward for future years) also affects some of the main coefficients, but in the case of counts these remain significant and can be statistically distinguished from the future impacts.

Third, in Panel A of Table 4, I include county-specific trends in the analysis. The coefficients are still positive, but lose their significance, perhaps due to the very large set of controls. As has been pointed out elsewhere (Wolfers, 2006) these controls may be too conservative in this type of setup.

Finally, in Panel B of Table 4, I weight the data by population counts. This change to the analysis may be appropriate if we think that each person should have the same weight; on the other hand, this changes the composition of the population, increasing the weight on large cities and relatively poorer places. Empirically, these locations are less likely to harbor vaccine resistance, which impacts the identification in the data. The changes in composition alone are likely to change the results. Nevertheless, the patterns are similar, if slightly less significant.

Overall these results provide some comfort, although the issues of precision do illustrate the limitations of the data in this setting.

Secondary Results

The primary results focus on the response of pertussis vaccination to pertussis outbreaks within a small geographic area. Here, we present a few auxiliary results. Tables for this section are included in the Appendix.

[11] This panel excludes the estimation for the maximum rate and count as these did not seem comparable to the future measure.

Geographic Reach of Outbreaks Appendix Table A.2 shows the impact of state-level pertussis rate on county vaccinations. The regressions suggest that outbreaks elsewhere in the state also significantly impact vaccination rates. In the case of the pertussis rate, the impacts are much larger for the state, likely reflecting the fact that a larger number of cases translates to a smaller rate change. When we turn to counts, in Column 2, we find that counts of cases in the individual county are more important in magnitude terms than those in the state.

Older Children, Measles I focus on pertussis for kindergarten students because this is the age group with the best data coverage and this is the disease with the most frequent outbreaks. However, to the extent possible we would like to confirm that these effects are not limited to this setting. Appendix Table A.3 shows two additional tests. First, Column (1) shows the same regressions - pertussis vaccination on pertussis rate - but for 11-year-olds. Due to data limitations, I look back only five years - as done for the five year olds - and in general there is less data for this age group. However, we do see a large positive response in this group, as well.

Column (2) shows the impact of measles outbreaks on measles vaccination for kindergartners. Measles outbreaks are rare even relative to the pertussis outbreaks, so the effects here are identified off of a very small number of outbreaks. Despite this, we do see evidence that a higher measles rate prompts increases in vaccination. Both of these provide some helpful confirmation that the results are not limited to a single specification.

Other Vaccinations Do pertussis cases also impact vaccination for other diseases? Appendix Table A.4 shows the impact of pertussis outbreaks on measles vaccinations (all measles vaccine and MMR vaccines). There is some evidence of cross-vaccine response, although the effects are smaller than the own-vaccine response and less significant. Still, this suggests that there is some more general re-evaluation of vaccination.

5.2 Google and News Response to Outbreaks

The above results show that vaccinations respond to disease outbreaks. We turn now to whether we see a response in either Google searches or news mentions.

Figure 3a and 3b show the impact of outbreaks in a state-month on Google searches for information about the disease, information about vaccination and searches for terms related to vaccine dangers. Figure 3a estimates the impact of the number of cases. Figure 3b estimates the impact of cases measured in standard deviations from the mean in the county.

The results in either case are the same. Outbreaks prompt a significant increase in searches for information on the disease and for information on the vaccine. Both of these effects are short lived - they last a month or two before dissipating. The effects are reasonably large. In the case of searches for pertussis, a one standard deviation increase in cases increases searches by 0.2 standard deviations. These results show that information about outbreaks is reaching the population.

In contrast there is no evidence that outbreaks increase searches for vaccine injury terms or for terms that link vaccines to autism. This is despite the fact that, in general, these searches move together. In other words, although it is generally the case that increases in searches for pertussis vaccination also increase searches for terms related to vaccine dangers, the increase in vaccine searches that is prompted by outbreaks does not seem to be accompanied by an increase in interest in vaccine risks.

Table 5 estimates the impact of pertussis on news reporting about the disease. The outcome measured here is a count of articles in newspapers in the county that mention pertussis or whooping cough. The results show consistent evidence that outbreaks increase news coverage of pertussis. As with the Google evidence, this suggests that information about outbreaks does get disseminated.

5.3 Variation in Vaccination Response across Local Areas

From a policy standpoint, the key follow-on question to the results above is what - if anything - magnifies the impact of pertussis cases. Identifying the size of the largest effects may give a better sense of whether this is a productive avenue for policy.

I focus in this analysis on variation in response across local areas.

Based on a survey of county and state health departments, I identified an important cross-state difference in the approach to outbreaks. Specifically, a subset of states centrally coordinates responses, while the remainder coordinate at a county level. The full sample in the paper includes 12 states: Alabama, Arizona, California, Kansas, Kentucky, Michigan, Missouri, New York, North Carolina, North Dakota, Oregon and Texas. In four of these states - Alabama, North Dakota, Oregon and Michigan - the response to disease outbreaks is coordinated directly by either the state or, in the case of Michigan, regional health offices. In these states the counties may play a role in disseminating information about disease outbreaks but they do so at the direction of the state or regional office. In the other eight states counties have autonomy with respect to their response to disease outbreaks. The counties may notify the state and ask for help, and the state may provide some guidelines, but the counties ultimately decide their own policies.

In principle, both structures have advantages. State-coordinated response could dominate since those dealing with outbreaks will have more experience in this sphere (a state overall experiences many more outbreaks than individual counties) and the state may have a better ability to see the whole picture, including cross-county spread, etc. On the other hand, locally-sourced responses may allow for better targeting of the response to the individual county circumstances.

Columns (1) through (4) of Table 6 show the primary regressions in the paper (replicating Columns (1), (2), (4) and (5) of Table 2), separating the effect by areas with central coordination versus those with county autonomy. All four columns make clear that the effects are driven by states with centralized responses. The effect in this group is much larger, and is statistically distinguishable from the effect in the other group.

Columns (5) of Table 6 shows the evidence on the response of Google searches for "pertussis" (and related terms) in the two groups of states. This is the search term which was most responsive to outbreaks. Consistent with the evidence on vaccination response, the Google search response on both terms is substantially higher for the centrally coordinated states.

An important caveat to these results is that they rely on cross-state variation, and it is difficult to know whether differences across states should be attributed to the particular issue of county autonomy. There may well be other state-level differences which are driving the results. To the extent that we can attribute these differences to the structure of outbreak management, there is an open question of what these states are doing well. The increase in Google interest suggests states must be driving consumer behavior in some way. More evidence on the specifics of this behavior could drive policy responses. At a minimum, these results suggest fairly sizable vaccination responses are possible.

6 Mechanisms Behind Response

The previous section shows that vaccination rates respond to disease outbreaks. In this section I try to understand the mechanisms behind this response. This section assumes that vaccination decisions are ultimately made by the household. This seems to be a reasonable assumption, but it is worth saying that when I discuss mechanisms here I am not taking a stand on how the information is conveyed to people. It may be that information on disease is spread around by individual schools, by state governments, by doctors office or others. These are all consistent with the idea that households get information from a variety of sources and make decisions based on this information.

The most straightforward explanation for increased vaccination rates is that they are a rational response to an increase in disease risk; this would be consistent with the explanation in (for example) Philipson (1996) who studies measles in an earlier period. The first section below evaluates the information content in the outbreak, asking whether an outbreak indicates an increase in future disease risk.

Section 6.2 then discusses a decision framework for the problem and suggests that we may learn about the mechanisms through the functional form of the relationship between disease outbreaks and vaccinations. In Section 6.3 I use a simple machine learning approach to identify functional form.

6.1 Information in Outbreak

To begin, I evaluate the extent to which current outbreaks are informative about future disease risk.

I do this in two ways. First, I ask simply whether outbreaks in the current year are correlated with outbreaks in future years. I find that they are: The correlation between the current year and the previous year is close to 0.20, and regressing current year rate on previous year rate (with no other controls) leads to a significant coefficient of 0.15. This suggests that if you knew nothing about the overall risk of disease in the area, then observing a higher rate in the current year would be informative. It is notable that the correlation is short lived: outbreaks two years ago do not predict current outbreaks.

A more rigorous question is whether observing a high pertussis rate in a given county in a given year should lead one to think that this will result in a permanent increase in pertussis. Effectively, this asks whether there is a unit root in the rate series. I test for this using a Dickey-Fuller test. The test strongly rejects the null of a unit root, suggesting the rate series within a county is stationary.

In terms of speaking to the question of information, this suggests two things. First, for someone who sees the complete past time path of rates, there is no information conveyed by the current year's pertussis cases; if anything, current cases predict fewer cases in the slightly more distant future. Second, and in contrast to the first, for someone who is uninformed - who does not know about the general pertussis situation in the county - observing cases in the current year is somewhat predictive of the future.This predictive power is fairly limited.

One interpretation of the lack of a unit root is that when there are outbreaks, the vaccination rate goes up, and this prevents future outbreaks. Given the scope of the responses estimated here, that force is probably not sufficiently large to actually drive this result. Regardless, from the standpoint of any individual household what matters for their decision - given that they are a small part of the vaccination rate - is the realized stationarity of the series, not why it is stationary.

I turn now to incorporating these facts into a decision framework.

6.2 Decision Framework

I return to the basic framework in which parents choose to vaccinate their children if the perceived benefits exceed the perceived costs. As above, denote the perceived costs of vaccination for household i in location c as C_{ci}.[12] These costs could include the true monetary costs of vaccination, any inconvenience costs, and any perceived or actual vaccine risks. The benefits of vaccination come in the form of disease avoidance, either due to changes in disease risk or changes in perceived loss from contracting the disease. I denote the benefits B_{ci} and indicate their dependence on disease measures $\mathbf{r_c}$ by writing $B_{ci}(\mathbf{r_c})$.

A household will choose to vaccinate if $B_{ci}(\mathbf{r_c}) > C_{ci}$. Note that as written, $\mathbf{r_c}$ can contain various measures of disease, including the number of cases, the disease rate, deviations from normal and so on. For ease of notation, however, denote r_c^1 as the actual disease risk in the county.

Fully Informed Model Consider first the model of a fully informed and fully rational individual. For this person, the decision problem simplifies to

$$r_c^1 B_{ci} > C_{ci}$$

That is, they vaccinate if the disease risk multiplied by the loss from the disease exceeds the cost.

For someone fully informed, the loss to the disease is known, as is the cost of vaccination. In Section 6.1 we observe, again, that if you are fully informed, r_c^1 - the true future disease risk - is not informed by the current disease level. As a result, for this type, there should be no response to disease outbreak, and these events will not increase the degree of vaccination. This stylized model - which would be in the spirit of Philipson (1996) - does not, therefore, seem consistent with the data.

Partially Informed Rational Model Consider now a second version of the above model in which the household is still fully rational with the same decision problem but they are not fully informed about the probability of disease in their area. Instead, these households perceive disease risk as equal to some other r_c^m element of the vector. In this model, we restrict that this element is also some observed measure of disease risk, although it may not be the true risk. A simple version of this is one in which r_c^m is just the risk of disease in the previous year. In this model, vaccination occurs if $r_c^m B_{ci} > C_{ci}$.

[12] Since we are now discussing individual households in a decision framework, I drop the b subscript for birth cohort; obviously it would be straightforward to include that.

This captures someone who knows the costs of vaccination (or their perceived costs) and knows the downsides of pertussis but is not informed about the disease risk in their area. This may be a practical model, since this is a sufficiently rare event that people may not know disease details. For an uninformed person, the evidence in Section 6.1 on correlations shows that observing disease outbreaks in the current year does predict future outbreaks. Effectively, people are learning something about the overall area disease risk. The model is rational in the sense that people are thinking specifically about disease risk, with a known benefit and cost, but they are simply not using the fully informed risk estimate.

To the extent that people observe a r_c^m which is higher than they anticipated, they may react by vaccinating their children. In particular, although r_c^1 is not dependent on outbreaks, r_c^m may depend on recent observed risks. This would be trivially the case if r_c^m was the previous year disease risk.

In this case, increases in the disease risk in a given year will increase vaccination rates. Note importantly that this model puts restrictions on this dependence. Households in this model may respond to changes in disease rate, but they should not respond to other features of disease, controlling for the rate. This is the sense in which they are rational.

Non-Rational Model We can contrast the above with the general case in which we do not restrict the functional form. That is, we simply model behavior as households vaccinate when $B_{ci}(\mathbf{r_c}) > C_{ci}$. In this model the benefits can depend on arbitrary function of disease - if we think that $\mathbf{r_c}$ has k elements, the models above restrict the dependence of behavior to a subset of these elements, and this model does not. It allows for the possibility that perceived risk of disease depends on various aspects of outbreaks, and also for the possibility that the loss associated with the disease depends on outbreaks. This could occur if people hear about the consequences of pertussis as a result of local cases.

Distinguishing Models Distinguishing between these models may be important for creating policy to change vaccination rates. Under the fully informed model, efforts to inform individuals about disease risk would have no impact on vaccination rates. In this case, other polices (for example, changes in school exemption policy) would be a better option. Under the partially informed model there may be scope for informing people about the pertussis rate. From a policy standpoint, however, this is limited in the sense that the response is constrained by the rate. To the extent that the data is best described by the non-rational model, there is the greatest scope for policy intervention. If, for example, there is some vaccination response to having any cases of pertussis, policy could take advantage of this more frequently.

As noted above, the data seem less consistent with the fully informed model, given the assumptions stated.

Thus far, however, what we observe would be consistent with either of the other models articulated. What distinguishes between these models is the functional form of the relationship between pertussis outbreaks and vaccination behavior. In the rational case, the disease rate should be sufficient to predict vaccination response. In the non-rational case, it will not be. In the next section I use a simple application of machine learning methods to estimate this.

It is important to note that this model does not take into account heterogeneity across individuals in types. That is: I allow households to vary in C_{ci} – their vaccination costs – so this model can accommodate the fact that some people believe vaccines are more costly than others. But I do not allow that there may be some people who are fully rational and others who are not. In practice, however, the test suggested here boils down to a test of whether some non-trivial fraction of the population falls in to the non-rational group. If there are some rational people and some non-rational people, then we could still see some responses to disease outbreaks.

6.3 Estimation

The discussion above suggests that we consider distinguishing between models by modeling the functional form of the relationship between vaccination and disease. We recall Equation (1) above. In that equation, I specify that the vaccination rate may depend on any of the k elements of $\mathbf{r_{bc}}$. In the estimation above I focus on simple measures - the disease rate by year or disease counts - but do not include them together.

The goal here is to include in the $\mathbf{r_{bc}}$ a rich set of measures of pertussis, and observe the functional form of the relationship.

An issue with estimation in practice is that if $\mathbf{r_{bc}}$ includes many variables, this estimation is subject to concerns about over-fitting. To address this, I use a lasso algorithm. The lasso selects a subset of variables that are above a threshold level of predictive power for predicting the outcome from a large set of possible factors.

I feed into the lasso a large number of measures of disease – rates, counts, smaller measures of counts, etc.

The lasso selects four variables as significant determinants of vaccination rate. They are: (1) the maximum rate over the five year period, (2) an indicator for any cases two years before entry (this enters negatively), (3) an indicator for more than 1 case in the year of birth and (4) an indicator for more than 5 cases in the year of birth. Table 7 shows the primary regression in the paper using only these measures. They are individually significant. The final row of the table gives the p-value for the joint test of all of the non-rate measures being significant; they are jointly significant.

These results provide some suggestive evidence that characteristics of the disease other than the disease rate may influence behavior. If true, this suggests progress may be made by promoting *any* disease outbreak, even if it is small. For example, the data indicates that there is some response to even a single case of pertussis in the year of birth, which is a sufficiently common occurrence that there would be many instances in which this might be used to influence behavior.

7 Conclusion

Anecdotal evidence suggests that vaccine-resistant parents can be swayed toward vaccination by disease outbreaks. This paper provides evidence suggesting those anecdotes are borne out in the data. Using a data set of county-year vaccination rates and outbreaks, I show that vaccination rates among entering kindergartners are increased by outbreaks of disease. For large outbreaks, these effects are sizable.

It is difficult to fit these facts with a fully informed model in which households react to disease risk. Instead, I suggest the data may be better fit by a model in which households are both myopic and have some behavioral biases in processing information. For these households, recent disease cases have an out-sized effect and disease matters beyond the disease rate.

The key policy issue motivating this paper is how to increase childhood vaccination rates. The paper shows that disease outbreaks may be a powerful motivator and, in particular, that outbreaks may be a useful motivation even if they are not actually informative. I show that the structure of outbreak response across counties and states can importantly influence the size of this response. In particular, states which coordinate their response through state health departments are much more effective at promoting vaccination response than those which coordinate at the county level. This may reflect better general management.

It is important to note that this paper is not able to identify the specific policies which are effective. It is possible that the effects are driven by changes in how doctors approach the conversation with patients in light of an outbreak. It is possible the effects are driven by pressure applied within schools against children who are not vaccinated. Future work could elucidate these mechanisms in an effort to more fully take advantage of them.

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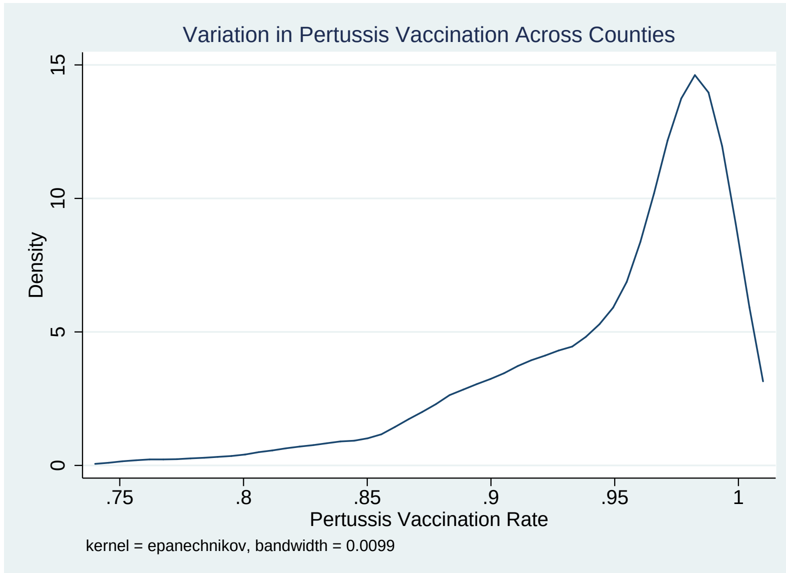
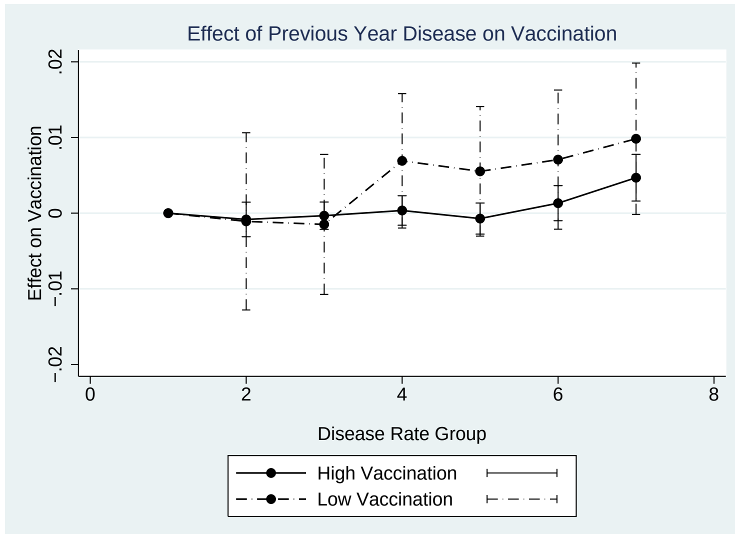
Figure 1: **Pertussis Vaccination Rate Variation Across Space**



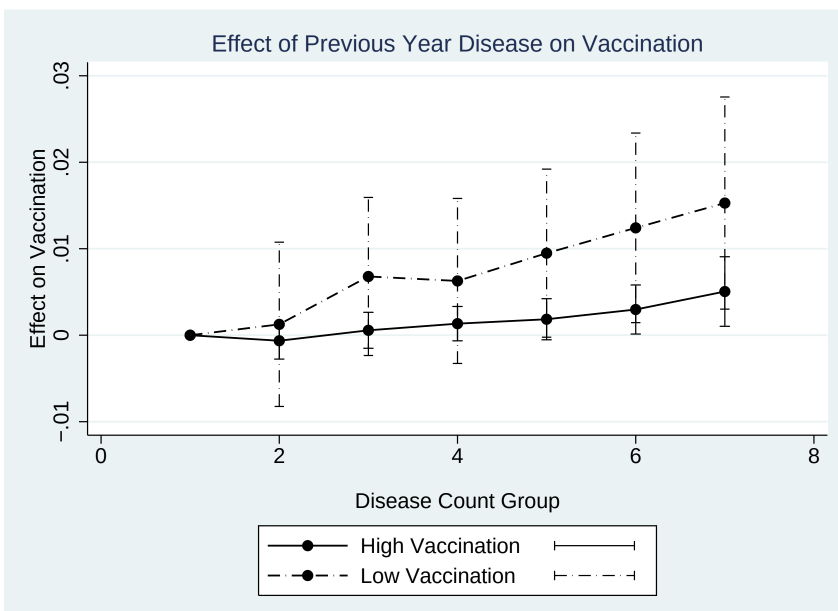
Notes: These figures show the density of vaccination rates across counties in the 2010-2011 period. I average vaccination rates for 2010 and 2011 and drop the bottom 1% of counties.

Figure 2: **Impact of Pertussis on Vaccination**

(a) Groups Based on Disease Rate



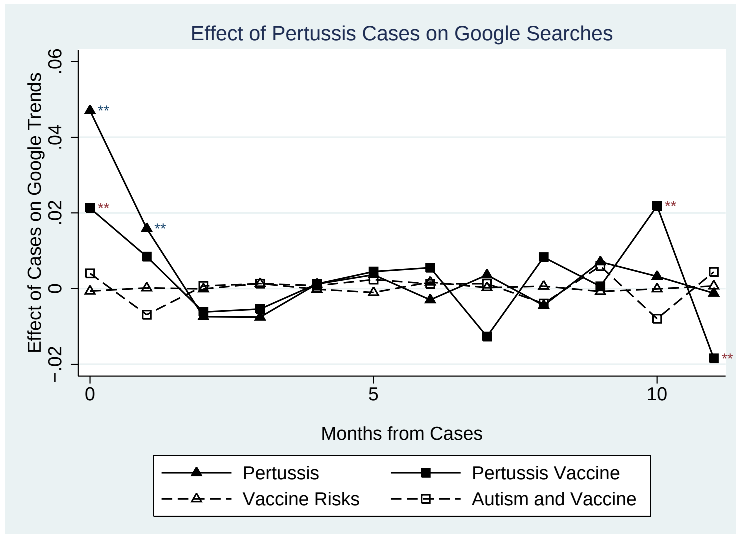
(b) Groups Based on Counts



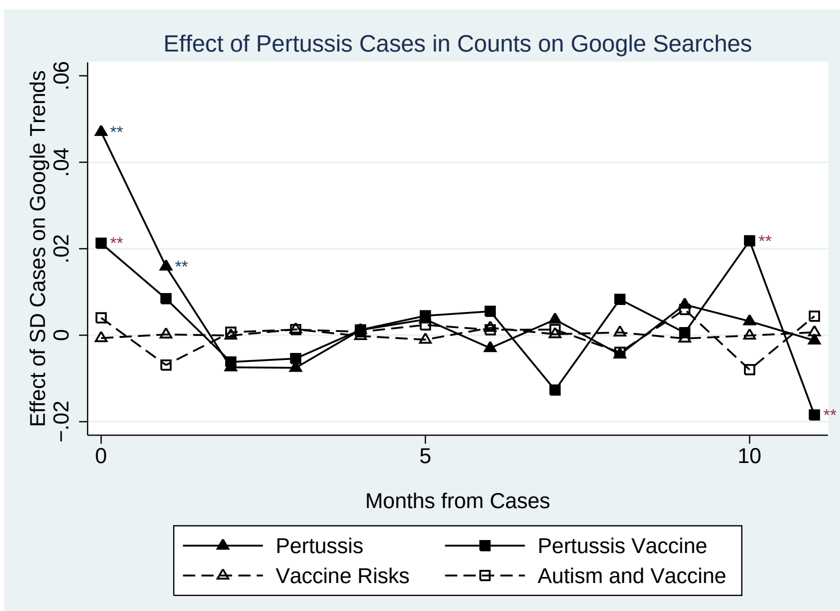
Notes: This figure shows the relationship between pertussis outbreaks in year $t-1$ and vaccination in year t. All points shown are regression coefficients from regressions with county and year fixed effects and population controls. Sub-figure (a) groups cases based on the average disease rate over the previous five years. Sub-figure (b) groups cases based on average case counts. 90% confidence intervals are shown.

Figure 3: **Impact of Pertussis Cases on Google Searches**

(a) Count of Cases



(b) Std. Dev of Cases Relative to Mean



Notes: These figures show the impact of outbreaks on Google searches for four groups of terms: terms related to the disease, “pertussis vaccine” and related, “vaccine risks” and related and “vaccine and autism”. The graph maps out the impact in the month in which the cases occur, the following month, the month after and so on up to a year after the outbreak. All coefficients are from regressions which include state and month fixed effects. Sub-figure (a) shows the impact of a linear control for number of cases. Sub-figure (b) shows the impact of cases measured in standard deviations from the local mean.

Table 1: **Summary Statistics**

			Vaccination Rates	Pertussis	
State	Years of Coverage	Sample Size	Mean (SD)	Pertussis Rate Per 100,000 Mean (SD)	Pertussis Cases Mean (SD)
Alabama	2007-2011	304	.977 (.042)	3.50 (6.13)	2.61 (4.78)
Arizona	2009-2011	45	.944 (.033)	4.75 (5.55)	37.55 (122.18)
California	1991-2011	1218	.934 (.041)	4.88 (12.1)	22.39 (64.29)
Kansas	2009-2011	314	.869 (.087)	6.90 (25.3)	1.81 (5.49)
Kentucky	2004-2011	886	.965 (.051)	3.07 (8.84)	1.33 (5.07)
Michigan	2004-2011	662	.906 (.034)	8.71 (30.8)	7.48 (21.74)
Missouri	2011-2011	115	.966 (.027)	2.95 (9.86)	3.80 (22.75)
New York	2002-2011	682	.991 (.013)	2.07 (10.47)	1.73 (5.28)
North Carolina	1999-2011	1293	.937 (.085)	6.51 (20.45)	1.11 (4.06)
North Dakota	2005-2011	352	.976 (.057)	9.73 (22.48)	16.62 (31.35)
Oregon	1992-2011	660	.958 (.032)	4.52 (18.75)	5.10 (15.54)
Texas	2007-2011	1260	.973 (.041)	5.04 (18.42)	8.14 (54.28)

Notes: This table shows summary statistics on pertussis vaccination and disease rates by state. Disease rates are quoted in rates per 100,000 people. As throughout the paper, vaccination rates are the share of children entering kindergarten with a completed pertussis series.

Table 2: **Impacts of Pertussis Outbreaks on Vaccination**

Outcome:	*Pertussis Vaccination Rate Measure, 5-year-olds, year t*					
Disease Measure:	Pertussis Rate			Pertussis Counts		
	(1)	(2)	(3)	(4)	(5)	(6)
Previous 5 Year Average	908.0 ***			0.0049***		
	(328.3)			(0.002)		
Previous 5 Year Max		223.5***			0.0012***	
		(78.3)			(0.0004)	
Year $t-1$			266.3*			0.0008**
			(147.6)			(0.0004)
Year $t-2$			25.6			0.0008**
			(117.8)			(0.0004)
Year $t-3$			127.4			0.0007
			(118.1)			(0.0005)
Year $t-4$			192.1			0.0007
			(145.9)			(0.0005)
Year $t-5$			248.8**			0.0023***
			(104.7)			(0.0005)
County FE, Year FE	YES	YES	YES	YES	YES	YES
Population Control	YES	YES	YES	YES	YES	YES
R-squared	0.61	0.61	0.61	0.61	0.61	0.61
Number of Observations	7135	7135	7135	7135	7135	7135

Notes: This table shows the impact of pertussis outbreaks on vaccination rates. Denoting vaccination rate in county c for birth cohort b as v_{bc}; the outcome variable is the logit transformation of this variable which we denote $\mathring{v}_{bc}$. The estimating equation is $\mathring{v}_{bc} = \alpha + \gamma_c + \delta_b + \eta p_{ct} + \sum_k \beta_k r_{kbc} + \varepsilon_{bc}$. The measures included in the vector $\mathbf{r_{bc}}$ vary by column as indicated. Robust standard errors in parentheses, clustered at the county level. * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 3: **Impacts of Pertussis Outbreaks on Vaccination, Robustness**

Outcome:	*Pertussis Vaccination Rate Measure, 5-year-olds, year t*					
Disease Measure:	Pertussis Rate			Pertussis Counts		
	Panel A: Limited Number of Cases					
Previous 5 Year Average	1307.7 *			0.116***		
	(784.1)			(0.046)		
Previous 5 Year Max		347.7*			0.029*	
		(192.6)			(0.017)	
Year $t-1$			435.7			0.033**
			(309.7)			(0.015)
Year $t-2$			-38.8			-0.0008
			(269.8)			(0.015)
Year $t-3$			320.3			0.018
			(202.8)			(0.016)
Year $t-4$			344.7			0.025
			(245.7)			(0.016)
Year $t-5$			243.5			0.039***
			(241.3)			(0.015)
Number of Obs.	5611	5611	5611	5611	5611	5611
	Panel B: Including Future Cases					
Previous 5 Year Average	365.1			0.006***		
	(410.1)			(0.002)		
Year $t-1$			227.5			0.0005
			(183.2)			(0.0004)
Year $t-2$			-69.9			0.0018***
			(130.6)			(0.0004)
Year $t-3$			51.9			0.0008
			(129.1)			(0.0005)
Year $t-4$			107.8			0.001*
			(163.9)			(0.0005)
Year $t-5$			64.2			0.002***
			(104.5)			(0.0005)
Year $t+1$	-198.4		-187.1	0.0003		0.0002
	(190.0)		(189.6)	(0.0002)		(0.0003)
p-value, Previous vs. Fut	0.15			0.0005		
p-value, $t-1$ vs $t+1$			0.08			0.57
p-value, $t-5$ vs $t+1$			0.20			0.01
Number of Obs.	6085		6085	6085		6085

Notes: This table shows some robustness checks. Denoting vaccination rate in county c for birth cohort b as v_{bc}; the outcome variable is the logit transformation of this variable which we denote $\mathring{v}_{bc}$. The estimating equation in both panels is $\mathring{v}_{bc} = \alpha + \gamma_c + \delta_b + +\eta p_{ct} + \sum_k \beta_k r_{kbc} + \varepsilon_{bc}$. In Panel (A) the data is limited to county-years with 10 or fewer cases. In Panel (B) I include future cases in the regression. Both panels include county and year fixed effects, and population controls. Robust standard errors in parentheses, clustered at the county level. * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 4: **Impacts of Pertussis Outbreaks on Vaccination, Robustness**

Outcome:	*Pertussis Vaccination Rate Measure, 5-year-olds, year t*					
Disease Measure:	Pertussis Rate			Pertussis Counts		
	Panel A: County-Specific Trends					
Previous 5 Year Average	256.2			0.002		
	(472.3)			(0.0014)		
Previous 5 Year Max		87.2			0.0004	
		(120.1)			(0.0003)	
Year $t-1$			129.8			0.0003
			(175.5)			(0.0002)
Year $t-2$			-103.9			0.0006
			(157.5)			(0.0004)
Year $t-3$			-78.2			-0.0004
			(163.8)			(0.0005)
Year $t-4$			-16.2			-0.0009
			(174.5)			(0.0005)
Year $t-5$			156.8			0.0006
			(130.2)			(0.0006)
Number of Obs.	7135	7135	7135	7135	7135	7135
	Panel B: Weighted by Population					
Previous 5 Year Average	457.4			0.002*		
	(343.3)			(0.0009)		
Previous 5 Year Max		117.9*			0.0004**	
		(73.8)			(0.0002)	
Year $t-1$			23.1			0.0001
			(81.7)			(0.0001)
Year $t-2$			50.8			0.0003
			(89.9)			(0.0002)
Year $t-3$			-10.3			0.0002
			(103.2)			(0.0004)
Year $t-4$			91.7			0.0004
			(104.0)			(0.0003)
Year $t-5$			331.6***			0.0014***
			(138.9)			(0.0004)
Number of Obs.	7135	7135	7135	7135	7135	7135

Notes: This table shows some robustness checks. Denoting vaccination rate in county c for birth cohort b as v_{bc}; the outcome variable is the logit transformation of this variable which we denote v°_{bc}. The estimating equation in Panel A is $v^{\circ}_{bc} = \alpha + \gamma_c + \delta_b + \tau_c + \eta p_{ct} + \sum_k \beta_k r_{kbc} + \varepsilon_{bc}$, where τ_c is a county-specific trend. In Panel (B) I weight by the population in the county-year. Both panels include county and year fixed effects, and population controls. Robust standard errors in parentheses, clustered at the county level. * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 5: **Impacts of Pertussis Outbreaks on News Stories**

Outcome:	*Count of News Stories about Pertussis in County*	
Pertussis Rate	317.5***	
	(90.8)	
Count of Cases		0.014***
		(.0048)
County FE, Year FE	YES	YES
Population Control	YES	YES
R-squared	0.19	0.40
Number of Observations	7792	7792

Notes: This table shows the impact of pertussis outbreaks on local news stories about pertussis. The outcome is the count of local news stories mentioning "pertussis" or "whooping cough" in the headline.We denote this count in county c in year t as n_{ct}. The estimating equation is $n_{ct} = \alpha + \gamma_c + \delta_t + \eta p_{ct} + \Phi r_{ct} + \varepsilon_{ct}$ where γ_c and δ_t are county and year fixed effects, and p_{ct} is a control for population in county c in year t. Robust standard errors in parentheses, clustered at the county level. Note that these regressions are contemporaneous: we estimate the impact of current cases on current news coverage. * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 6: **Impacts of Outbreaks by Local Response Coordination**

Outcome	*Pertussis Vacc. Rate Measure*				*Searches:Pertussis*
Disease Measure:	Pertussis Rate		Pertussis Counts		
	(1)	(2)	(3)	(4)	(5)
Previous 5 Year Average, Autonomy	607.2		0.001***		
	(523.8)		(0.0004)		
Previous 5 Year Average, Centralized	933.5**		0.002**		
	(438.7)		(0.0009)		
Previous 5 Year Max, Autonomy		150.8		0.0046***	
		(119.5)		(0.002)	
Previous 5 Year Max, Centralized		255.6**		0.0098***	
		(114.4)		(0.004)	
Pertussis Cases, Current Month, Autonomy					0.050***
					(0.003)
Pertussis Cases, Current Month, Centralized					0.267***
					(0.014)
p-value, autonomy vs. centralized	0.03	0.03	0.03	0.005	0.0000
County, Year FE, Population Controls	YES	YES	YES	YES	NO
State, Month FE	NO	NO	NO	NO	YES
R-squared	0.61	0.61	0.61	0.61	0.76
Number of Observations	7135	7135	7135	7135	1508

Notes: This table shows the impact of outbreaks on vaccination rates and Google searches depending on the government coordination of outbreak response. Columns (1) through (4) look at outbreak impacts. Column (5) looks at Google search responses. Robust standard errors in parentheses, clustered at the county level. States with state or region coordinated responses are Alabama, North Dakota, Michigan and Oregon. * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 7: **Impacts of Outbreaks on Vaccination, Lasso Selected Variables**

Outcome:	*Pertussis Vaccination Rate Measure, 5-year-olds, year t*
Previous 5-Year Max Rate	212.5***
	(78.7)
Any Cases, $t-2$	-0.115**
	(0.053)
More than 1 case, $t-5$	0.123**
	(0.054)
More than 5 Cases, $t-5$	0.111*
	(0.058)
p-value, non-rate vars.	0.0002
County FE, Year FE	YES
Population Control	YES
R-squared	0.61
Number of Observations	7135

Notes: This table shows the impact of pertussis outbreaks on vaccination rates. The variables in the regression are selected using a lasso where the inputs include a wide range of functions of the previous year's pertussis cases. Denoting vaccination rate in county c for birth cohort b as v_{bc}; the outcome variable is the logit transformation of this variable which we denote v°_{bc}. The estimating equation is $v^{\circ}_{bc} = \alpha + \gamma_c + \delta_b + \eta p_{ct} + \sum_k \beta_k r_{kbc} + \varepsilon_{bc}$. Robust standard errors in parentheses, clustered at the county level. * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Appendix: Online Publication Only

Appendix A: Figures and Tables

Table A.1: **Impact of Vaccination Rates on Outbreaks**

	Pertussis Rate, t	Pertussis Count, t
Vaccine Rate in 5-year old Cohort, t	-0.000047	-1.76
	(0.00005)	(4.42)
County, Year FE	YES	YES
Population Control	YES	YES
R-Squared	0.27	0.53
Number of Observations	7472	7472

Notes: This table shows the relationship between contemporaneous vaccine rates in the entering kindergarten class and population disease rates. This regression is intended to test for the possibility of reverse causality bias significantly affecting our results. * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table A.2: **Geographic Reach: Effects Outside of County**

Outcome:	*Pertussis Vaccination Rate Measure, 5-year-olds*	
	(1)	(2)
State (excl. County) Pertussis Rate, Five Year Average	5003.6***	
	(1185.8)	
County Pertussis Rate, Five Year Average	324.4	
	(372.9)	
State (excl. County) Pertussis Count, Five Year Average		0.0009***
		(0.0001)
County Pertussis Count, Five Year Average		0.002*
		(.001)
County, Year FE	YES	YES
Population Control	YES	YES
R-squared	0.54	0.58
Number of Observations	7135	7472

Notes: This table shows the impact of pertussis cases outside of the county - else where in the state - on vaccination rates. Robust standard errors in parentheses, clustered at the county level. * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table A.3: **Auxiliary Effects: Older Children, Measles Vaccination**

Outcome:	*Pertussis Vacc, 11-year-olds*	*Measles Vacc: 5-year-Olds*
	(1)	(2)
Pertussis Rate, Five Year Average	1177.5**	
	(552.1)	
Measles Rate, Five Year Average		2596.9**
		(1282.2)
County, Year FE	YES	YES
Population Control	YES	YES
R-squared	0.71	0.66
Number of Observations	1249	7451

Notes: This table shows the impact of pertussis outbreaks on vaccination among 11-year-olds (Column (1)) and the impact of measles cases on vaccination rate of entering kindergartners. Robust standard errors in parentheses, clustered at the county level. * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table A.4: **Impacts of Pertussis Outbreaks on Other Vaccination Rates**

Outcome:	*All Measles Vacc.*	*MMR. Vacc.*
	(1)	(2)
Pertussis Rate, Five Year Average	619.0**	561.7*
	(268.5)	(325.1)
County, Year FE	YES	YES
Population Control	YES	YES
R-squared	0.66	0.69
Number of Observations	7451	6267

Notes: This table shows the impact of pertussis outbreaks on vaccination for measles (either any measles vaccine or the MMR vaccine in particular). In both cases the outcomes is measured as the logit transform of the outcome variable. * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Appendix B: Google Trends Data Production

Google Trends reports data in two ways. First, they report changes in search interest over time within an area. This is reported relative to the time in that area with the highest search interest. Second, they report differences in search interest across space within a given time period. This is relative to the area with the highest search interest. Our estimation is identified off of changes within a location over time so we focus on the first type of data. These data are generated in the following way:

First define the search rate for a query ($[query]$) in a given area z at time y:

$$\theta_{y,z} = \frac{\text{Number of searches for } [query] \text{ at time } y \text{ in area } z}{\text{Total number of searches at time } y \text{ in area } z}$$

Then trend data (τ) for a given area z over a time period $Y = \{y_1, ..., y_n\}$ can be expressed as:

$$\tau_{y,z} = \frac{\theta_{y,z}}{\max\limits_{y \epsilon Y}(\theta_{y,z})} \times 100$$

Note that Google Trends only calculates these values on a random sample of searches, and so the values may change depending on the time the website was accessed.

The trends data ranges from 0 to 100. A score of 0 however does not usually indicate no searches for the query; instead, it usually indicates that the volume of searches for the query did not meet Google's privacy threshold. While I do not know the exact cut-off for the threshold, in general data is easier to produce for more common queries, larger time periods (i.e. months versus weeks) and larger areas. The data also improves over time.

Many of the terms I am searching do not meet the privacy restrictions. I take two steps to overcome this. First, Google Trends allows me to use an 'or' connector so I can combine many queries (up to 30 words) related to a common topic, which then reports the sum of their trend scores. This still does not fully solve the problem so the second step uses elements of the method described in Stephens-Davidowitz (2014).

The methodology is straightforward. I take a common word that is unrelated to our terms of interest (this common word should meet the privacy threshold by itself). I then search for two terms in the same query: the common word ($[word]$), and the common word or the term of interest ($[word + term]$). For example, if our term was "pertussis" and the common word was "joke", I would search for "joke" and "joke or pertussis" at the same time. The difference between the two trends gives the trends for "pertussis". Note that the scores are still given from 0-100, but the data-point with the 100 score is now given to the relative highest search rate across both terms.

There are trade-offs with how to select the common word. As the common word becomes more popular it is more likely to consistently pass the privacy threshold, even in smaller areas and shorter time periods. However, this also increases the probability of having a small (or zero) difference between $[word]$ and $[word + term]$. This is because Google Trends are reported on a relative scale, so the term of interest's score becomes smaller relative to the common word's score as the popularity of the common word increases.

With this as the general background, I follow the detailed steps below.

1. Scrape the data for [$word$] and [$word + term$] together at the area-month level
2. Collapse both queries to the year level (mean monthly trend)
3. Recode both queries in a given year as missing if:
    (a) One of them has a mean monthly trend equal to zero (i.e. every month in that year was below the privacy threshold)
    (b) [$word$] trend is greater than [$word + term$] trend (i.e. a negative difference, which can occur due to the random sampling and is more likely if the term of interest trend score is relatively small)
4. Eliminate any area with less than two non-missing year observations
5. Re-scale the trends relative to the highest area-year score within each area and across both queries
6. Take the difference between the scaled [$word + term$] and [$word$] - this generates the trends for [$term$]
7. Re-scale again relative to the highest area-year score within each area

To balance the popularity trade off, I repeat these steps using five common words with varying levels of popularity (sponge, joke, fax, chair, rainbow). I then repeat this process over three different days and average the results of the 15 scrapes. I do this at the state-month level for the time period 2004-2015 ($Y = \{2004, ..., 2015\}$). The search queries I scraped are listed in Table B.1.

Table B.1: **Google Trend Search Queries**

Topic	**Search Queries**	**Example Captured Searches**
Whooping Cough	“pertussis”, “whooping cough”	“what is pertussis”, “whooping cough symptoms”
Whooping Cough Vaccine	“pertussis vaccine”, “pertussis vaccines”, “whooping cough vaccine”, “whooping cough vaccines”, “pertussis vaccination”, “whooping cough vaccination”, “pertussis immunization”, “whooping cough immunization”, “dtap”, “tdap”, “dpt vaccine”, “dtp vaccine”	“pertussis vaccine age”, “whooping cough immunization side effects”
Vaccine Risk	“vaccine injury”, “vaccine danger”, “vaccine dangers”, “vaccines risk”, “vaccines risks”, “vaccine side effects”, “vaccine side effects”, “mercury vaccine”, “mercury vaccines”, “thimerosal vaccine”, “thimerosal vaccines”, “vaccine ingredient”, “vaccine ingredients”	“mmr vaccine side effects”, “vaccines mercury content”
Autism-Vaccine Link	“autism vaccine”, “autism vaccines”, “autism immunization”, “autism immunizations”, “autism mmr”, “autism measles”, “mercury autism”, “thimerosal autism”	“vaccines autism study”, “do vaccines cause autism”, “immunization linked to autism”

Notes: This table shows the collection of search queries run for each topic, where each query is written within quotation marks. Google Trends searches for the exact word written (e.g. “vaccine” is different to “vaccines”), but searches are not case sensitive. A comma in the table above indicates an ‘or’ connector (e.g. “Term 1”, “Term 2”’ means “Term 1” or “Term 2”, which gives us “Term 1” trends plus “Term 2” trends). Google Trends captures all searches that include all the words within a query, in any order, and with any words before, after, or between them.