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The Vaccination Response to Local Measles Outbreaks

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Disease Perception and Preventive Behavior: The Vaccination Response to Local Measles Outbreaks

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CINCH competence in competition + health series

Sarah Hofmann[a]

Disease Perception and Preventive Behavior: The Vaccination Response to Local Measles Outbreaks

Abstract

This paper examines the role of perceived disease risk for vaccination behavior. Using health insurance claims data, I estimate the effect of local measles outbreaks in Germany on first and second dose measles vaccinations in children as well as catch-up vaccinations in adults. In my empirical strategy, I exploit the variation in timing and location of regional disease outbreaks and estimate a two-way fixed effects model with birth cohort and region fixed effects. Basic underlying assumption is that measles outbreaks alter perceptions regarding the disease risk. The robustness of this approach with regard to possible bias due to heterogeneous treatment effects under differential treatment timing is assessed through the use of alternative estimators. The results show that measles outbreaks within a region increase the share of children who receive their vaccination on time by 0.8 percentage points for both the first and second vaccination. This corresponds to a reduction in the share of not timely vaccinated children of about 4.1% and 2.6% for the first and second dose, respectively. They further also increase the rate of monthly catch-up vaccinations in adults by about 15% for the age group 20-30 to up to 46% for those at ages 40-50 in the first six months after an outbreak. One important finding is that regional outbreaks do not lead to increases in vaccinations in other regions even if public attention extends beyond the affected region. This suggests that behavioral responses are driven by affective rather than deliberative risk perception. Also, vaccination effects can be observed only in the few months following the outbreak, which indicates that changes in the perceived disease risk due to a local measles outbreak are short-lived and fade away quickly once the disease outbreak is over.

Keywords: *Vaccinations, Immunizations, Measles, Public Health.*

JEL classification: *I12, I18, C21.*

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1 Introduction

Despite having committed to the elimination of measles, a highly contagious but vaccine-preventable disease, vaccination coverage among children in Germany is still insufficient. While vaccination rates are higher than in other regions of the world, they are still clearly below the 95 % that are considered necessary to ensure herd protection, i.e. protection of unvaccinated individuals by inhibiting the virus from spreading. Further, relatively high average rates at the national level mask strong differences in vaccination rates by region (Rieck et al., 2018). The resulting immunity gaps are reflected by several large measles outbreaks in recent years.

In this paper, I examine whether these local outbreaks of measles lead to changes in vaccination behavior. Assessing vaccination responses to disease outbreaks provides important insight into the role of risk perception for preventive behavior. The basic underlying assumption is that measles outbreaks alter perceptions regarding disease susceptibility. First, they raise de facto exposure to the illness during the time of the outbreak. Second, they may raise awareness in those who have not paid much attention to possible disease risks prior to the outbreak.

Although the reasons for suboptimal vaccine uptake despite their general availability in most developed countries have been much studied, they still have not been fully understood. A frequent misinterpretation of the underlying causes for non-vaccination is considered one of the reasons why many interventions to increase vaccine uptake fail to show the desired effects (Thomson et al., 2016; Dubé et al., 2015; Sadaf et al., 2013). Besides the social context and established behavioral patterns, individual risk perception is identified as key factor for vaccine uptake in models of health behavior (Smith et al., 2017; Thomson et al., 2016; Brewer et al., 2017). Risk perception includes both a deliberative and an affective component. Deliberative risk perception refers to a rational judgement of the probability of contracting a disease and the benefits of vaccination. Affective risk perception, in turn, is not driven by logical reasoning but rather reflects an emotional response to health threats (Ferrer et al., 2016). Emotions are considered to be critically relevant in risk judgements and to be even stronger predictors of health behavior than assessments based on deliberation (Renner and Reuter, 2012; Ferrer et al., 2013).

An important aspect in individual risk judgements is a lack of concern regarding vaccine-preventable diseases (Larson et al., 2014). Aside from the fear of possible side-effects of vaccinations, a low perceived susceptibility to the respective illness is one of the most frequently self-reported reasons for not vaccinating one's child (Smith et al., 2017). This can be attributed to the fact that vaccination programs in the second half of the 20th century have led to a massive decline in many vaccine-preventable diseases. Personal experiences thus no longer unveil the benefits of vaccinations. This lack of experience impacts perceived disease risk, though it is not clear whether this is mainly through altering probability judgements or through inhibiting affective reactions (Brewer et al., 2017).

In my empirical strategy, I exploit the variation in timing and location of regional disease outbreaks and estimate a two-way fixed effects model with birth cohort and region fixed effects. To this end, I combine data of reported measles cases from 2008 to 2019 with individual-level vaccination data of one major sickness fund of the statutory health insurance in Germany. To examine whether the key assumptions for the applied estimation approach hold, a series of pre-estimation and sensitivity checks is performed. First, parallel pre-treatment trends in the outcome of interest are established by means of event studies that account for both pre- and post-event trends and further tested through placebo regressions. Second, to assess a possible bias due to heterogenous treatment effects under staggered treatment, an alternative estimator that is robust to differential treatment timing is applied. All sensitivity checks bolster confidence in the applied two-way fixed effects approach.

My results show that vaccination activity, measured by the share of children aged 9 to 15 months who receive their first measles vaccination, increases significantly in the 6 months following a local measles outbreak. Accordingly, the share of children with on-time vaccination, that is within the recommended age range, increases by 0.8 percentage points for both the first and second vaccination dose. This corresponds to reduction in the share of not timely vaccinated children of about 4.1 % and 2.6 % for the first and second dose, respectively. The effect is observed only for children who are in the recommended age for vaccination during the outbreak, however not for those slightly younger (0 to 8 months). This indicates that changes in the perceived disease risk due to a local measles outbreak are short-lived and fade away quickly once the disease outbreak is stopped.

Besides vaccination of children, I also examine the effect of measles outbreaks on catch-up immunizations in adults aged 20 to 50 years. My results show that demand for catch-up vaccinations in these age groups significantly increases as a consequence of local outbreaks. However, also here, demand drops back to pre-outbreak levels few months later.

This study is related to recent research on vaccination responses to disease outbreaks by Oster (2018), Schaller et al. (2019) and Schober (2020). Both Oster (2018) and Schaller et al. (2019) analyze the effect of pertussis outbreaks on child vaccinations in the US. Oster (2018) combines county-year data on vaccination among kindergarten children with county-year data on pertussis outbreaks. Applying a fixed-effects model, she finds that pertussis outbreaks between birth and the time of entering kindergarten decrease the share of unvaccinated children entering kindergarten. Similarly, Schaller et al. (2019), using state-level data on infant immunizations in the US, find that the rate of on-time receipt of the pertussis vaccine at two months of age increases with pertussis outbreaks within a child's state while they were in utero or during their first two months of life.

Further, this paper complements a recent study by Schober (2020), where the author explores the effects of one major measles outbreak in Austria in 2008 on subsequent vaccination uptake. Using administrative data on child immunization, he finds that the vaccination rate of children who are at the recommended age for immunization during or after the outbreak significantly increases compared to a control group of children born one year earlier. My study adds to the findings in Schober (2020) in different ways: First, the analysis is extended in that it covers not only one specific measles outbreak, but several both smaller and bigger outbreaks in different regions over a time span of 10 years. This variation allows to identify causal effects of disease outbreaks on the vaccination response in a two-way fixed effects design. Further, I not only assess child immunization but also look at adult vaccination behavior. Given that about 25 % of those affected in recent years were adolescents and adults, in whom measles more likely lead to severe complications such as encephalitis (RKI, 2017), closing immunity gaps in adults poses an additional public health challenge.

The next section provides a description and summary statistics of the data I use for the analysis. In section 2.1, I describe the data on reported measles cases in Germany and how I define a measles outbreak. Section 2.2 describes the health insurance claims data which provide detailed information on measles vaccinations. The estimation strategy is outlined in Section 3. Section 4 presents the main results along with different robustness checks in Section 5. Finally, I discuss the results and conclude in Section 6.

2 Data

To examine the vaccination response to measles outbreaks, I combine two different data sets. One data set with weekly measles incidences by county, out of which I derive the dates and regions of measles outbreaks, and a second data set with individual level vaccination data, constructed out of claims data of a major sickness fund.

2.1 Measles outbreaks

Data on measles cases come from the Robert Koch-Institute (RKI), the German public health agency. Since measles is a notifiable disease, reporting of incidences is mandated according to the German Act on the Prevention and Control of Infectious Diseases in Men (*Infektionsschutzgesetz, IfSG*). The online database reports weekly measles cases per county[1] since 2001 (RKI, 2020b). While the yearly number of infections has decreased considerably in the last decades, reported cases have been fairly stable and

[1] *Landkreise & kreisfreie Staedte*.

above the defined target incidence of <1/1,000,000 for the last 15 years (RKI, 2020a). Measles typically occur in regional and temporary waves of few to several weeks.

A behavioral reaction to a measles outbreak presupposes that individuals are aware of that outbreak. Therefore, in a first step I define what establishes a perceptible disease outbreak. To assess whether measles outbreaks generate public attention, I draw on data of internet search activity for measles. I assume that if people learn about local measles outbreaks (e.g. through media or their personal environment), it increases their online search activity for the disease. Conversely, a significant increase in search activity following a disease outbreak indicates that people have notice of the outbreak. Using internet searches as an indicator for public attention has been shown to be a valid method and is common practice in social sciences (Ripberger, 2011; Stiles and Grogan-Myers, 2018; Mellon, 2011; Scheitle, 2011).

Data on internet search activity come from *Google Trends*, an application that allows to extract data on the volume of *Google* search queries over time and geographical regions (Google, 2020). Reported data represent relative volumes that display the search interest in a specific term relative to overall search activity and relative to the interest in that term over time. Search interest is normalized and displayed as a value on a scale between 0 and 100, with 100 designating the highest relative interest in that term over the selected period. For all other points in time, search interest is expressed relative to that time with the highest interest. This allows to identify periods in which interest was particularly high without running the risk of bias due to a general increase in internet search activity over time. For Germany, information on search volumes is available on the federal state level. I therefore aggregate the measles data to a federal state level, too, before merging them with the search volume data.

Figure A-1 in the Appendix depicts monthly measles cases and internet search activity by federal state. It shows that relative search interest in all federal states was at a peak in early 2015 due to a massive outbreak in Berlin accompanied by nation-wide media coverage. All other increases in search activity were less intensive compared to the one in 2015. They still clearly stand out from an otherwise evenly low level of search intensity and seem to coincide with disease outbreaks.[2]

To define what constitutes a relevant measles outbreak, I assess at what disease intensity in terms of incidence level people typically become aware of the outbreak in the sense that they increase their internet search activity. To this end, I estimate the following equation:

$$Search_{ts} = \beta\, m_{ts}^{50\text{-}75^{th}p} + \gamma\, m_{ts}^{75\text{-}90^{th}p} + \delta\, m_{ts}^{90\text{-}95^{th}p} + \eta\, m_{ts}^{>95^{th}p} + \lambda_t + \mu_s + \epsilon_{ts} \tag{1}$$

where $Search_{ts}$ is a dummy variable indicating if the search activity within one year-month and federal state is above the 95 % percentile in search intensity for that federal state. $m_{ts}^{50\text{-}75^{th}p}$ to $m_{ts}^{>95^{th}p}$

[2]A notable exception is the increase in search intensity in most states in 2019 which can be attributed to the nationwide discussion about and introduction of the mandatory immunization.

are dummy variables that indicate if measles cases in any one county within that federal state are in the respective percentile range. Using these categories of measles outbreak intensity allows to identify the threshold above which an outbreak receives attention. λ_t and μ_s are time (year-month) and federal state fixed effects, respectively.

I further assess whether the search volume in one federal state considerably increases with measles outbreaks in other states. One central assumption of the identification strategy is that a regional outbreak leads to increased attention only in the affected region but not in other regions. This assumption is clearly violated with respect to the Berlin outbreak in 2015. Awareness increased in all federal states irrespective of the local outbreak situation. I will later make use of this fact to disentangle the effect of increased awareness combined with an actual disease outbreak and awareness generated by media coverage of an outbreak in a remote region. To make sure that the association between search activity and measles cases is not explained only by the massive outbreak in 2015, I further run the same analysis excluding the year 2015.

Table 1: Effect of measles outbreak on internet search activity

Google search activity $> 95^{th}$ percentile			
	[all years]		[excl. 2015]
Measles cases in own federal state			
50-75th percentile	-0.003	-0.003	-0.005
	(0.011)	(0.011)	(0.011)
75-90th percentile	0.018	0.016	0.016
	(0.015)	(0.016)	(0.017)
90-95th percentile	0.071 **	0.086 ***	0.086 ***
	(0.022)	(0.023)	(0.025)
>95th percentile	0.189 ***	0.194 ***	0.236 ***
	(0.023)	(0.030)	(0.035)
Measles cases in other federal state			
50-75th percentile		-0.008	-0.013
		(0.095)	(0.096)
75-90th percentile		-0.029	-0.033
		(0.103)	(0.105)
90-95th percentile		0.081	0.082
		(0.111)	(0.113)
>95th percentile		0.053	0.091
		(0.115)	(0.119)
N	$2,320$	$2,320$	$2,128$

Note: Based on data from Robert Koch Institute (measles cases) and Google Trends (internet search activity). All estimations include federal state and month-year fixed effects. Period of observation: 2008 to 2019. * p<0.1, ** p<0.05, *** p<0.001.

Table 1 shows the results of the above estimation. Monthly measles cases that exceed the 90th percentile are associated with a significant increase in the probability of internet search activity increasing to above the 95^{th} percentile. The fact that this applies only to the federal state in which the county is located, however not to other federal states, supports the assumption of no spillover effects to other regions in terms of attention. These results also hold if the year 2015 is excluded from the analysis.

Based on this result, I use the 90th percentile as cutoff for a relevant disease outbreak. For the main analysis, outbreak data from the county level are aggregated to two-digit post code regions. I assume that if one county within a region experiences a measles outbreak above the 90th percentile, the whole region is affected. Other regions, even within the same federal state, may serve as control regions.

Table A-2 in the Appendix depicts monthly measles cases by 2-digit post code region (the level used in the main analysis) over time and identifies all outbreaks above the 90th, 95th, and 99th percentile cutoff, respectively.

2.2 Vaccination data

National vaccination recommendations are developed by the Standing Committee on Vaccinations (STIKO), which is part of the Robert-Koch Institute (RKI), the public health agency of the Germany ministry of health. Generally, federal health authorities adopt recommendations by STIKO into their health and prevention guidelines and advise practitioners to act accordingly. As for the measles vaccination, all federal states except Saxony have adopted the STIKO recommendations. According to those, a first vaccination dose should be given at the age of 11-14 months, with 9 months being the minimum age, and a second dose at the age of 15-23 months. Since 2010, STIKO also recommends a measles immunization for adults born after 1970 if they only received one dose of vaccination or if their immunity status in not clear (RKI, 2010). For all vaccinations recommended by STIKO, patients or families do generally not have to pay for, since these are part of the health plans of both the statutory and private sickness funds.[3]

For information on vaccinations, I use claims data of the *BARMER* sickness fund, one major sickness fund of the statutory health insurance in Germany. *BARMER* offers researchers remote access to their anonymized claims dataset upon request. Claims data are collected by health care providers for billing purposes with the sickness funds. They document the utilization of all billable health care services, which include vaccinations, of all insured persons with the exact date of administration. Longitudinal linkage of individual data allows to follow persons over time. With about 9.3 million insured persons in 2017, *BARMER* is the second biggest sickness fund in Germany and covers about 11 % of the German population, though with regional differences that range from about 18 % of the population in the federal state of Brandenburg to about 6 % in the city state of Bremen (Grobe and Szecsenyi, 2021). Analyses have shown that the *BARMER* data can generally be considered a representative sample of the German popu-

[3]In response to insufficient vaccination numbers and to recurring measles outbreaks, Germany recently passed a law that mandates measles vaccinations for children and particular staff in health care and community facilities. The law, which took effect in March 2020, requires all children who seek to attend a school or preschool facility to prove that they have been immunized.[4] With compulsory schooling in place, this basically equals a compulsory vaccination for all children aged 6 and older. Parents who refuse to vaccinate their children face fines up to € 2,500 (Federal Ministry of Health, 2019).

lation (Schreyögg and Krämer, 2015). While there is no official vaccination registry in Germany, health insurance claims data have been shown to provide a valid and comprehensive source of information about vaccinations (Rieck et al., 2014).

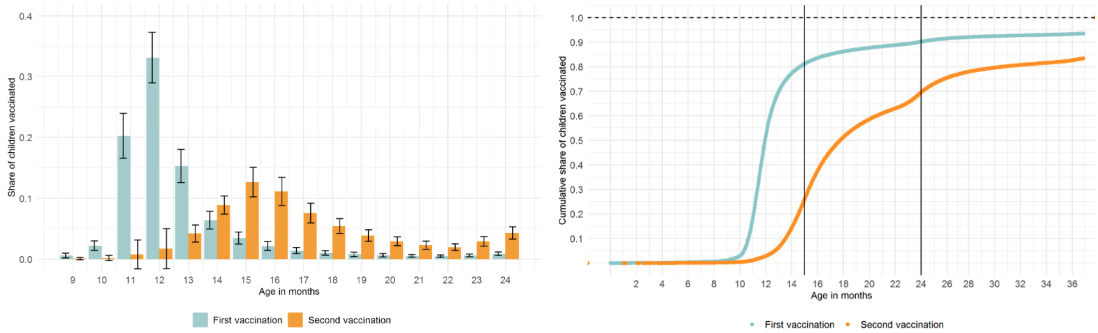
Information on demographic and socio-economic background is generally limited in health insurance claims data. Still, next to data on utilization of health care services, they comprise some basic characteristics including gender, date of birth, and place of residence. These information allow to identify whether a measles outbreak occurred in the child's region during their first months of life. Further, for those who are insured as principal members (not co-insured family members), the data also provide information on employment status and, given they are employees, on profession and highest educational degree. I made use of the possibility to link children to the principal member they are co-insured with (typically a parent) to obtain information on the parents' socio-economic background, following the approach by Grobe (2017).

The final sample for the main analysis consists of 581,123 children who are born between 2008 and 2017 and are insured with the *BARMER* without interruption from birth until at least their second birthday, which is the date until when the second measles vaccination should be administered. For some analyses, only those who are observed until their third birthday are included ($N = 490,129$). Information on the urbanization degree of the place of residence was available for 97.6 % while information on parents' socio-economic background was available for 49.3 % of individuals in the sample. Birth cohorts are defined based on the birth month.

A descriptive analysis of the vaccination data is presented in Figure 1. The left-hand graph shows the average monthly share of children in each age group who receive a measles vaccination. The right-hand graph represents the corresponding cumulative shares of children with first and second vaccination dose by age up to 36 months. In the sample, around 80 % of children receive their first measles vaccination between the age of 9 to 15 months, another 10 % up to the age of 24 months. As for the second vaccination, around 70 % of children receive it until their second birthday, with most of them getting vaccinated between the age of 13 to 20 months.[5]

[5]Overall vaccination rates in my sample are somewhat lower than the vaccination rates reported by the RKI based on the national vaccination surveillance program. RKI determines vaccination rates for several recommended childhood vaccinations per birth cohort and age group based on claims data from the statutory health insurance, provided by each federal state's association of statutory health insurance physicians (ASHIP). While the RKI data cover the whole statutory health insurance, vaccination rates are reported for yearly birth cohorts and therefore do not allow for differentiation by exposure to measles outbreaks. Differences in the overall vaccination rates between the *BARMER* data and data from the vaccination surveillance program can be attributed to slightly different methods of computation and to the different population of insured persons.

Figure 1: Age at first and second measles vaccination



Note: Based on 581,132 (left graph) and 490,192 (right graph) observations from the *BARMER* data. The sample includes all children born between 2008 and 2017 who are observed until at least their second/third birthday. Observations from Saxony excluded, as Saxony does not follow STIKO recommendations regarding the age of vaccination.

I use two main outcome measures for the analysis: The first measure is the monthly share of children in the target population of children aged 9 to 24 months who are administered a first or second vaccine dose. For this purpose, the data are arranged in long format with each observation referring to a one-month period – within an individual's age range of 9 to 24 months – and contains the information whether the individual has received a vaccination during that month. While this measure informs about general vaccination activity, it does not provide information about whether an acute change in vaccination rates reflects a temporal shift in vaccination or a change in the overall share of people who get vaccinated. Therefore, as a second measure, I use the share of children at a particular age who have received a first or second vaccination dose. To this end, using the data in wide format, I construct dummy variables that indicate for each individual if the respective vaccine has been administered until a specific age. With regard to on-time vaccination, this is not later than at the age of 15 months for the first vaccination and not later than at the age of 24 months for the second vaccination, according to recommendations by the RKI.

Table 2 displays summary statistics for vaccination behavior, exposure to measles outbreaks, and demographic variables in the combined data sample.

Table 2: Summary statistics

Variable	Observations	Mean	SD
Measles vaccinations			
Monthly vaccination rate, 1^{st} dose, age 9 to 15 mos.	$4,067,924$	0.116	0.321
Monthly vaccination rate, 1^{st} dose, age 16 to 24 mos.	$5,230,188$	0.010	0.097
Monthly vaccination rate, 2^{nd} dose, age 9 to 24 mos.	$9,298,112$	0.044	0.206
1st vaccination by age of 15 mos.	$581,132$	0.806	0.396
1st vaccination by age of 24 mos.	$581,132$	0.902	0.297
1st vaccination by age of 36 mos.	$490,129$	0.936	0.245
2nd vaccination by age of 24 mos.	$581,132$	0.691	0.462
2nd vaccination by age of 36 mos.	$490,129$	0.833	0.373
Demographic variables			
Female	$581,132$	0.488	0.500
Urban	$567,102$	0.687	0.464
East	$567,102$	0.190	0.392
University degree (main insured person)	$286,610$	0.166	0.372
Exposure to measles outbreak (treatment)			
Birth to age of 15 mos.	$581,132$	0.197	0.398
Birth to age of 8 mos.	$581,132$	0.125	0.331
Between age of 9 to 12 mos.	$581,132$	0.045	0.207
Between age of 13 to 15 mos.	$581,132$	0.027	0.162

Note: Summary statistics based on *BARMER* data. The sample includes all children born between 2008 and 2017 who are observed until at least their second birthday. Observations from Saxony excluded, as Saxony does not follow STIKO recommendations regarding the age of vaccination.

3 Estimation strategy

In my empirical strategy for examining whether vaccination rates in children increase as a response to a local measles outbreak I exploit the variation in timing and location of disease outbreaks. This means that the identification of causal effects is based on the idea that regions without measles outbreaks in a particular time constitute a valid counterfactual for regions that do experience an outbreak, after accounting for general differences between regions and for common time effects. To this end, I apply a two-way fixed effects model which includes both birth cohort and region fixed effects.

The basic estimation equation is as follows:

$$Vac_{icr} = \alpha + \beta\, Outbreak_{cr} + \delta\, X_{icr} + \gamma_c + \mu_{region} + \tau_{region} + \epsilon_{ist} \tag{2}$$

Vac_{icr} represents the vaccination outcome of child i in birth cohort c and region r. The two outcome measures used in the analysis are discussed above in Section 2.1.

$Outbreak_{cr}$ is a dummy variable that indicates whether a cohort c in region r was exposed to a measles outbreak during the first 15 months of their life. Accordingly, β is the regression coefficient of interest, representing the effect of a measles outbreak during the first months of life on the probability of a child receiving (on-time) vaccination.

X_{icr} is a vector of individual characteristics as described above. γ_c are month-year birth cohort fixed effects that account for aggregate, non-region-specific, differences over birth cohorts. μ_{region} are region fixed effects that capture any variation in vaccination rates over regions (due to, for example, different population characteristics, regional policy efforts, or different pediatricians' attitude towards vaccination). Finally, I control for general trends in vaccination within regions by including region-specific linear time trends, τ_{region}. Standard errors are clustered at the region level.

The key assumption for my identification strategy is strict exogeneity, that is the timing of a disease outbreak must be as good as random with respect to other time-variant factors related to vaccination behavior. To verify this assumption, I start by adopting an event-study design that expands the above estimation by non-parametrically accounting for pre-event trends through dummies for monthly leads of the measles outbreaks. If outbreaks were non-random, regions with an event might exhibit diverging trends even before the event, resulting in significant non-zero coefficients for these leads.

For events like disease outbreaks, like other shocks, we can generally expect that they have an effect that goes beyond the acute event but still wanes over time. Therefore, I also include dummies for monthly lags of the measles outbreaks in the event-study estimation. This allows to assess the overall pattern of the effects as these lags allow to identify the presumably gradually unfolding and again waning effects of the events. The event-study model is estimated by the following equation:

$$Vac_{icr} = \sum_{lead=2}^{lead^{max}} \delta^{lead} \left(Outbreak_r^* - lead\right) + \sum_{lag=0}^{lag^{max}} \beta^{lag} \left(Outbreak_r^* + lag\right) + \gamma_c + \mu_r + \epsilon_{icr} \tag{3}$$

$Outbreak_r^*$ denotes the starting month of a measles outbreak in region r. Thus, δ^{lead} are the coefficients for each month leading to the outbreak. $(Outbreak^* - 1)$ is omitted from the regression as the baseline period. Equivalently, β^{lag} are the coefficients for the months following the outbreak. Both the leads and lags cover 9 months each (i.e. $lead^{max}$ and lag^{max} are set to 10 and 9, respectively). When estimating equation 3, outbreak leads and lags are combined into two-month bins to increase power. Only the baseline month, which is the month prior to an outbreak, is not combined with any other month for symmetry and because it includes all control observations. The estimated coefficients can be interpreted as the change relative to the month before a measles outbreak.

Recent literature has shown that in scenarios with differential treatment timing, as is the case in this study, no or parallel pre-treatment trends are not sufficient evidence of strict exogeneity (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; de Chaisemartin and D'Haultfoeuille, 2020). There must also be homogeneity of treatment effects for the standard two-way fixed effects estimator to identify an unbiased measure of the overall average treatment effect (Goodman-Bacon, 2021;

Gardner, 2021). This is because the estimates of the relative period coefficients may be biased due to the mechanics of ordinary least squares estimation, where effects from other relative periods do not cancel out (Goodman-Bacon, 2021; Sun and Abraham, 2021). Or, as Gardner (2021) puts it, the composite error term is correlated with the treatment variable and group fixed effects. That is, the two-way fixed-effects estimator identifies the overall average treatment effect only if strong assumptions regarding treatment effect homogeneity hold. One possible way to work around this when heterogeneity is suspected is to estimate separate treatment effects for each cohort and period and then aggregate these to obtain the overall average treatment effect (Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; Gardner, 2021). I will apply this approach as a sensitivity check using the estimator suggested by Sun and Abraham (2021).

4 Results

4.1 Main results

Figure 2 presents the results of the event-study analysis. The graphs show the coefficients and corresponding 95 % confidence intervals of the event-study regression as set out in equation 3. Outcome is the share of children in the respective age group who receive their first or second measles vaccination dose within one month. Each coefficient refers to a two-month time bin.[6] The panel data are normalized such that the reference period is the one month before a measles outbreak occurs. All leading months more than 5 and up to 10 months ahead of the outbreak are binned at -5.

The graph depicts the difference in the monthly vaccination rates relative to the average rate measured in the month before a measles outbreak occurs. In the analysis of first vaccination doses, I differentiale between two age groups. Monthly vaccination rates among the 9 to 15 months old children increase by around 0.25 to 0.4 percentage points in the first six months after a measles outbreak in relation to a mean of 11.6 % (relative increase of 2.2 to 3.4 %). The increase spikes in the first two months and then gradually drops back to pre-outbreak levels seven to eight months after the outbreak. For children aged 16 to 24 months, there seems to be no or, if at all, only a minimal increase in first dose vaccination rates in the four months following a measles outbreak.

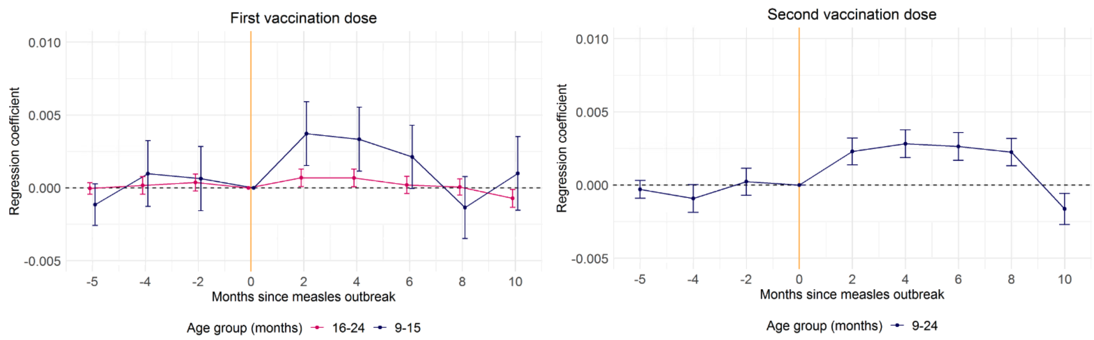
Also for second dose vaccinations, results indicate a significant increase in vaccination rates of about 0.25 percentage points in the eight months following a measles outbreak. Since second dose vaccinations are more evenly distributed over age, I do not differentiate between age groups here. The drop below pre-outbreak levels after nine to ten months seems plausible insofar as some vaccinations may have

[6]Results using month-by-month indicators are similar, however somewhat noisier.

been preponed to the preceding months. Below, I will look in more detail at the question whether excess vaccinations after outbreaks are caused by an increase in the overall share of children who get vaccinated or rather by a shift in the timing of vaccinations.

Coefficients for all pre-outbreak periods are close to zero and insignificant, supporting the key assumption of no significant pre-trends in the outbreak regions.

Figure 2: Event study



Note: OLS estimations based on 4,481,600 observations from 2008 to 2019. All estimations include birth cohort and region fixed effects. Standard errors are clustered on the regional level. * p<0.1, ** p<0.05, *** p<0.001.

Columns (I) and (II) of Table 3 present the corresponding estimates from the DiD model as set out above in equation 2.[7] The outbreak indicator here refers to the first six months following a measles outbreak. The coefficients present the effect of a measles outbreak on the share of children at the age of 9 to 24 months who receive their first or second vaccination dose within one month. During the six months after a measles outbreak, this share in first dose vaccinations significantly increases by 0.1 percentage points (1.8 % relative increase).

Table 3: Effect of exposure to measles outbreak on vaccination

	Monthly vaccination rate		1^{st} dose completed			2^{nd} dose completed	
	1^{st} dose	2^{nd} dose	at 15 m.	at 24 m.	at 36 m.	at 24 m.	at 36 m.
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Measles outbreak	0.001 **	0.003 ***	0.008 ***	0.004 **	-0.000	0.008 ***	0.004 *
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)	(0.004)
Y mean	0.056	0.044	0.806	0.902	0.936	0.691	0.833
% change in non-vaccinated	1.8 % [a]	6.8 % [a]	4.1 %	4.1 %	0.0 %	2.6 %	0.6 %
N	4,481,600	4,481,600	280,100	280,100	241,752	280,100	241,752
Individuals [b]	280,100	280,100			*– same as N –*		

Note: OLS estimations based on data from 2008 to 2019. All estimations include individual controls, birth cohort and region fixed effects, as well as region-specific time trends. Standard errors are clustered on the regional level. * p<0.1, ** p<0.05, *** p<0.001.
[a] Percentage change in the share of children vaccinated per months. [b] For estimations based on data in long format, the number of individuals in the data sample is reported separately from the number of observations (N).

[7] In Table A-1 in the Appendix, I examine the sensitivity of the results to different specifications that include only a reduced set of control variables.

The estimated coefficients in columns (III) to (V) refer to the effect of a measles outbreak at any time during a child's first 15 months of life on the probability of receiving a first measles vaccination at the age of 15/24/36 months. Children have a 0.8 percentage points higher probability of receiving their first measles vaccination on time if they experience a prior measles outbreak. This corresponds to a 4.1% reduction in the size of the group of children who are not vaccinated against measles by the age of 15 months (19.4% of all children, see Table 2).

While this indicates that there is an effect of measles outbreaks on the likelihood that a child receives the first vaccination dose by the age of 15 months, it does not reveal if this effect can be attributed to more children getting vaccinated or to a temporal shifting, i.e. children getting vaccinated earlier such that some who would have received the vaccination later otherwise are instead vaccinated on-time before they reach the age of 15 months instead. To assess if this effect occurs at the intensive or the extensive margin (or both), I further estimate if a measles outbreak in the first months has an effect of the probability that children have received their first vaccination by the age of 24/36 months. In case of an effect merely on the time of vaccination, there would be no effect on the probability of having received the vaccination at age 2. Whereas in case of an effect on the overall share of children who get vaccinated, this would be reflected in an increase in children vaccinated at an older age.

The coefficient on the probability of receiving their first vaccination by the age of 36 months is close to zero and insignificant. This result indicates that the effect is rather a shift in the timing of vaccination than an increase in the overall share of children receiving vaccination.

In Table A-1 in the Appendix, I further show the results of different specifications in terms of the inclusion of control variables. Specification (I) represents the basic two-way fixed effects estimation, where I control for both month-year birth cohort and region fixed effects. In specifications (II)-(IV), I gradually add region-specific time trends and individual control variables. Information on educational attainment of the main insured person is added separately, as it is available only for a subset of observations and therefore reduces the sample size considerably. Generally, the coefficients are fairly stable over all specifications. I mainly refer to specification (IV), which includes region-specific time trends and all available control variables, when interpreting the estimation results.

4.2 Heterogenous effects

Table 4 presents heterogenous effects by gender, socio-economic background, and age of the children. I focus on the two main outcomes of monthly first dose vaccination rate and the probability of receiving on-time vaccination by the age of 15 months. The results indicate that the effect is fairly stable over the child's gender, area of residence, and educational level of the principal insured person.

However, the vaccination response crucially depend on the children's age. The vaccination activity increases significantly for children aged 9 to 15 months and seems to decrease the share of children who receive a vaccination in the group of those aged 16 to 24 months (Column V in panel A). This points to a shifting effect, i.e. children get vaccinated earlier, which results in a negative coefficient for those at older ages.

Table 4: Effect of measles outbreaks on vaccination; heterogenous effects.

	Female (I)	Urban (II)	East (III)	Academic (IV)	Age (V)
Panel A: Monthly vaccination rate (1^{st} dose)					
Measles outbreak	0.001	0.001	0.001 *	0.001 *	
	(0.001)	(0.001)	(0.000)	(0.001)	
#Interaction	0.001	0.001	0.002	0.001	
	(0.001)	(0.001)	(0.001)	(0.001)	
Age 9-12 months					0.090 ***
					(0.002)
Age 13-15 months					0.026 ***
					(0.002)
Age > 15 months					-0.044 ***
					(0.001)
N	4,481,600	4,481,600	4,481,600	4,481,600	4,481,600
Individuals [a]	280,100	280,100	280,100	280,100	280,100
Panel B: First dose at age of 15 months					
Measles outbreak	0.008 **	0.005	0.004	0.006 **	
	(0.003)	(0.006)	(0.003)	(0.002)	
#Interaction	-0.002	0.003	0.010	0.003	
	(0.005)	(0.008)	(0.007)	(0.003)	
Age 0-8 months					0.003
					(0.003)
Age 9-12 months					0.015 **
					(0.006)
Age 13-15 months					0.012 ***
					(0.003)
N	280,100	280,100	280,100	280,100	280,100

Note: OLS estimations based on data from 2008 to 2019. All estimations include individual controls, birth cohort and region fixed effects, as well as region-specific time trends. Standard errors are clustered on the regional level. * p<0.1, ** p<0.05, *** p<0.001.
[a] For estimations based on data in long format, the number of individuals in the data sample is reported separately from the number of observations (*N*).

This is reflected by results regarding the on-time vaccination (Panel B). I show the results for a given exposure at different age spans within the range between birth and the age of 15 months. Since vaccinations against measles are administered not before the age of 9 months, this allows to draw inferences regarding the sustainability of a possible outbreak effect. Children at ages younger than 9 months at the time of the outbreak can only get vaccinated several months later, when the outbreak has again waned.

I differentiate between an outbreak during the first 8 months, that is before an immunization is at all possible, an outbreak when the child is 9 to 12 months old, that is shortly before or during the first two months when an immunization is recommended, and an outbreak when the child is 13 to 15 months old. The coefficients are bigger and consistently significant for outbreaks during the later months of life (9 to 15 months). The probability of receiving the first measles vaccination on time increases by 1.5 (1.2) percentage points if the measles outbreak occurs while a child is 9 to 12 months (13 to 15 months) old. In contrast, an outbreak during the first 8 months increases the probability of on-time vaccination by only 0.3 percentage points, with this result further being insignificant. This result points to a strongly waning effect of measles outbreaks once they have ebbed away. An outbreak before children have reached the age range where a vaccination is recommended (and possible) has only a minor effect on the likelihood of receiving the vaccination once they enter that age range. To further assess this waning effect, I estimated the same equation but added a dummy variable for experiencing a measles outbreak during the three months pre birth. Coefficients for this additional treatment are close to zero and insignificant, supporting the result of a quickly waning effect of measles outbreaks on vaccination behavior (results not presented here, available upon request).

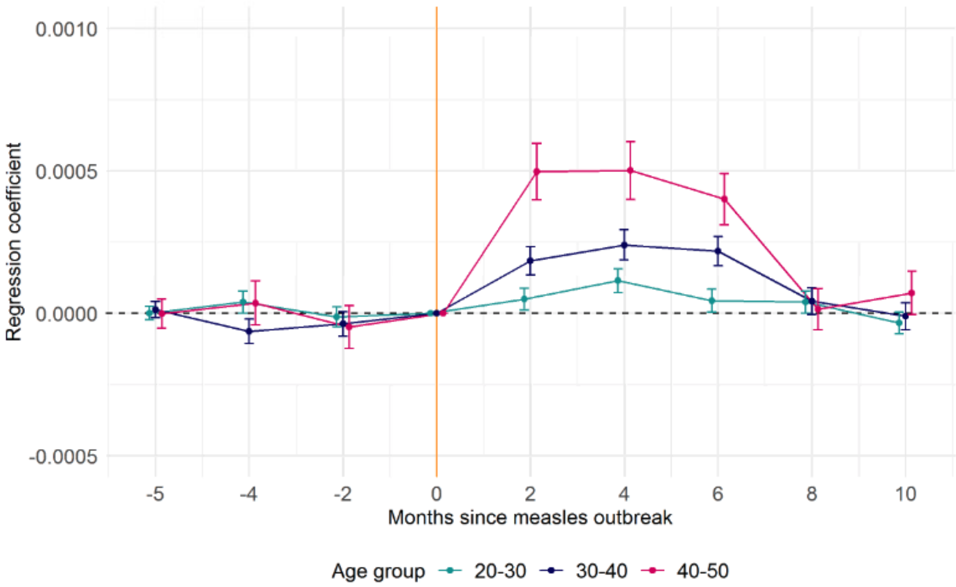
4.3 Effect on catch-up vaccinations in adults

An increasing share of measles infections does not fall upon children but upon adolescents and adults. In 2016, about 33 % of those infected were above the age of 20 (RKI, 2017). Therefore, closing immunity gaps in adults poses an additional public health challenge. Since available vaccination data cover only the most recent years, it is not possible to reliably determine the vaccination status of the adult insured population.[8] It is still possible, though, to assess the current uptake of measles vaccines relative to the population in the respective age groups (vaccination rate) and to examine if demand for vaccines increases as a consequence of a measles outbreak.

To this end, I constructed an additional sample, covering the years 2008 to 2019, with monthly vaccination data for all individuals between the age of 20 to 50 within this time period. On average, about 0.09% of individuals in the sample receive a measles vaccination each month. I apply the same estimation approach as for the main analysis. The outcome of interest is the monthly vaccination rate. The event study graph shows that, similar to the vaccinations in children, monthly vaccination rates significantly increase in the six months after the onset of a measles outbreak but drop back to pre-outbreak levels by around the seventh or eighth month. The effect is most pronounced for the age group of 40 to 50 years old.

[8]Data based on a nationwide survey indicate that in the group of people born in the 1970s and 1980s measles vaccination coverage is about 46.7 % (95 % CI 42.2 - 51.2) and 79.8 % (95 % CI 76.3 - 82.9), respectively (Poethko-Müller and Schmitz, 2013).

Figure 3: Monthly measles vaccinations; share in adults aged 20 to 50 years



Note: OLS estimations based on data from 2008 - 2019. The estimations include birth cohort and region fixed effects. Standard errors are clustered on the regional level. * p<0.1, ** p<0.05, *** p<0.001.

The corresponding DiD estimates in Table 5 match the results of the event study. Coefficients for the indicator of a measles outbreak are significant for all age groups and range from 0.0001 for the 20 to 30 years old to 0.0004 for the 40 to 50 years old. While from an absolute perspective these may seem like of insignificant magnitude, they represent a relative increase of 14.7%, 21.2% and 45.9% (for the three age groups, respectively).

Table 5: Effect of measles outbreaks on vaccination; adults

	Basic	Female	Urban	East	Academic
Panel A: Age 20 - 30					
Measles outbreak	0.0001 ***	0.0000	-0.0000	0.0001 ***	0.0001 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
#Interaction		0.0001 ***	0.0001 ***	-0.0001	0.0000
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Y mean	0.00068				
% change	14.7 %				
N	$1,549,708$	$1,549,708$	$1,549,708$	$1,549,708$	$1,549,708$
Panel B: Age 30 - 40					
Measles outbreak	0.0002 ***	0.0001 **	0.0000	0.0002 ***	0.0002 ***
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
#Interaction		0.0002 ***	0.0002 **	0.0000	0.0000
		(0.0000)	(0.0001)	(0.0001)	(0.0001)
Y mean	0.001				
% change	21.2 %				
N	$1,144,806$	$1,144,806$	$1,144,806$	$1,144,806$	$1,144,806$
Panel C: Age 40 - 50					
Measles outbreak	0.0004 ***	0.0003 ***	0.0003 ***	0.0004 ***	0.0004 ***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
#Interaction		0.0003 ***	0.0001	0.0001	0.0004 ***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Y mean	0.001				
% change	45.9 %				
N	$479,495$	$479,495$	$479,495$	$479,495$	$479,495$

Note: OLS estimations based on data from 2008 - 2019. All estimations include individual controls, birth cohort and region fixed effects, as well as region-specific time trends. Standard errors are clustered on the regional level. * p<0.1, ** p<0.05, *** p<0.001.
^{a} For estimations based on data in long format, the number of individuals in the data sample is reported separately from the number of observations (*N*).

5 Sensitivity analysis

5.1 Placebo outbreaks

Although the region-specific time trends account for general trends in vaccination behavior, there is the possibility of other unobservable developments affecting the likelihood of on-time vaccination. To test this, I conduct a falsification test, where I assume placebo outbreaks to take place in the month before the first affected cohort is born and in the months after the last affected cohort turns 15 months, respectively. (= 15 months before/after the actual outbreak).

As expected, the results in Table 6 show no significant effect of a placebo outbreak 15 months later on vaccination outcomes of children at age 0 to 15 months during that hypothetical outbreak. For an earlier placebo outbreak, I find significant effects on the probability of a child having completed the second dose at the age of 24 and 36 months, respectively. This result is plausible insofar as it displays the effect of the real outbreak on children at older ages during that time. Coefficients on the placebo outbreaks for monthly vaccination rates and for receiving the first dose on time, however, are again consistently close to zero and insignificant, supporting confidence in the general identification strategy.

Table 6: Placebo outbreak - Effect of exposure to measles outbreak on vaccination

	Monthly vaccination rate		1^{st} dose completed			2^{nd} dose completed	
	1^{st} dose	2^{nd} dose	at 15 m.	at 24 m.	at 36 m.	at 24 m.	at 36 m.
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Placebo outbreak: 15 months later							
Measles outbreak	0.000	0.000	0.000	0.002	0.002	-0.000	0.002
	(0.000)	(0.001)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Placebo outbreak: 15 months earlier							
Measles outbreak	0.000	0.000	0.001	0.004	0.004 *	0.007 **	0.008 **
	(0.000)	(0.001)	(0.003)	(0.003)	(0.002)	(0.004)	(0.003)
N	4,481,600	4,481,600	280,100	280,100	241,752	280,100	241,752
Individuals [a]	280,100	280,100		*– same as N –*			

Note: OLS estimations based on data from 2008 - 2019. All estimations include individual controls, birth cohort and region fixed effects, as well as region-specific time trends. Standard errors are clustered on the regional level. * p<0.1, ** p<0.05, *** p<0.001.
[a] For estimations based on data in long format, the number of individuals in the data sample is reported separately from the number of observations (*N*).

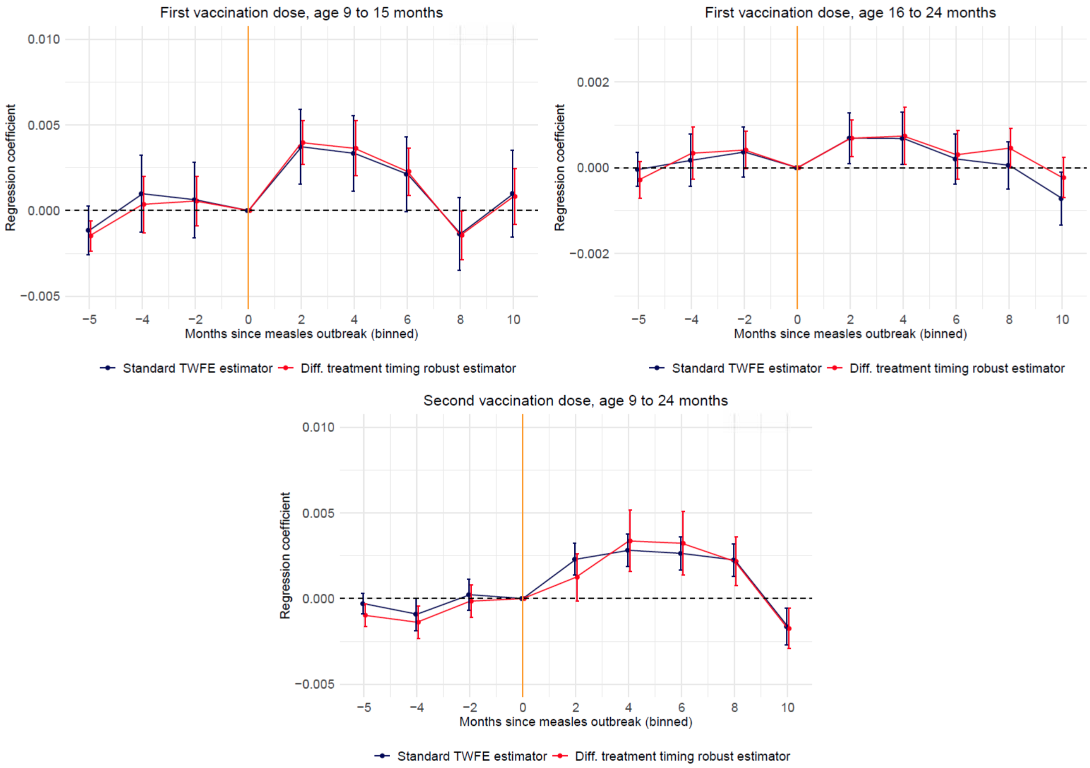
5.2 Alternative estimator to account for possible treatment heterogeneity

To test for the sensitivity of the results with regard to alternative estimation strategies that explicitly take into account possible treatment heterogeneity in a setting with differential treatment timing, I apply the estimator proposed by Sun and Abraham (2021).[9] Their approach is to estimate separate average treatment effects for each group and period, which are then aggregated to measure the overall effect of the treatment. The single treatment effects are thereby weighted according to the shares of the cohorts that experience at least the respective number of periods relative to the treatment timing. Also here, never-treated units are included as controls when estimating the treatment effects for the relative time periods. Estimations based on the approach by Sun and Abraham (2021) are implemented with the user-level *sunab* method incorporated in the R package *fixest* (Bergé, 2018).

Figure 4 shows the coefficients and corresponding 95 % confidence intervals of the event-study regression using the standard two-way fixed-effects estimation on the one hand and the estimation approach proposed by Sun and Abraham (2021) on the other hand.

[9] The estimator based on Sun and Abraham (2021) is implemented using the sunab command within the R package fixest.

Figure 4: Comparison of event studies based on different estimators



Note: OLS estimations based on data from 2008 - 2019. All estimations include birth cohort and region fixed effects. Standard errors are clustered on the regional level. * p<0.1, ** p<0.05, *** p<0.001.

Although the estimated coefficients for the pre- and post-outbreak periods differ slightly, the interpretation of the graphs remains the same. Monthly vaccination rates both for the first and second dose significantly increase in the first six months after the outbreak. Similarly, the corresponding estimates of average treatment effects based on the Sun and Abraham method are close to those based on the naive two-way fixed effects estimation (see Table 7). This is not surprising insofar as, although treatment effects may be heterogenous across regions, the measles outbreaks take place spread over a long period and overlap only partially. This circumstance gives only limited rise to biased estimates as a consequence of differential treatment timing combined with heterogenous effects.

Table 7: Effect of exposure to measles outbreak on monthly vaccination rates - Comparison of estimators

	1^{st} dose monthly vaccination rate		2^{nd} dose monthly vaccination rate	
	Standard TWFE estimator	Diff. treatment timing robust estimator	Standard TWFE estimator	Diff. treatment timing robust estimator
	(I)	(II)	(III)	(IV)
Measles outbreak	0.001 **	0.002 ***	0.003 ***	0.003 ***
	(0.001)	(0.001)	(0.001)	(0.000)
Y mean	0.056	0.056	0.044	0.044
% change in vaccinated p. month	1.8 %	2.7 %	6.8 %	6.0 %
N	4,481,600	4,481,600	4,481,600	4,481,600
Individuals [a]	280,100	280,100	280,100	280,100

Note: OLS estimations based on data from 2008 to 2019. All estimations include individual controls, birth cohort (monthly) and region fixed effects, as well as region-specific time trends. Standard errors are clustered on the regional level. * p<0.1, ** p<0.05, *** p<0.001.
[a] For estimations based on data in long format, the number of individuals in the data sample is reported separately from the number of observations (*N*).

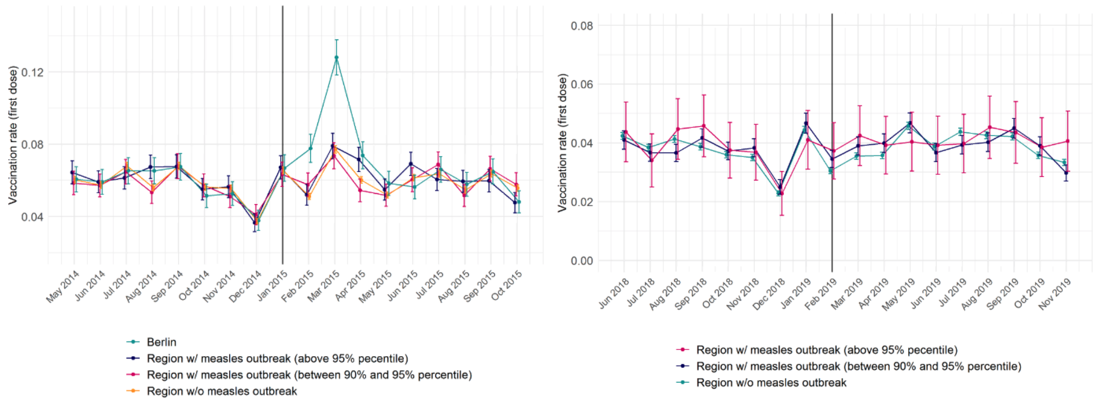
5.3 Spillover effects to other regions

As stated above, one of the key assumptions of the identification strategy is that there are no spillover effects, i.e. that local measles outbreaks increase awareness and risk perception in the affected region, however not in other regions. The Google search analysis indicates that awareness generally tends to increase in the federal states where the outbreak takes place but not so in other federal states. Still, since the Google search data are available only on a federal state level, I cannot fully rule out an increase in awareness in one region as a consequence to an outbreak in a neighboring region (across or within federal states). If this awareness further leads to changes in risk perception and accordingly to behavioral changes, it would lead to downward biased estimates.

To look into this in more detail, I start with a descriptive analysis of two occasions related to measles that incontrovertibly attracted nationwide public attention. The first occasion is a massive measles outbreak that occurred in Berlin at the beginning of 2015 and involved nationwide media coverage. The outbreak counted a total of 1,359 measles cases in the Berlin area, the highest number since reporting of measles had become obligatory in 2001 (Robert Koch-Institut, 2015). While first cases were already reported in October 2014, the outbreak reached its peak in terms of attention in February 2015 after the death of a 2-year old child. Public interest (measured by Google search activity) in 2015 was by far the highest in all federal states, irrespective of actual measles cases within the states at that time (see Figure A-1 in the Appendix). A second peak in nationwide interest can be observed at the beginning of 2019. This time, however, public attention cannot be attributed to a specific measles outbreak – although there were some minor regional outbreaks – but rather to the public debate about the introduction of a mandatory measles vaccine.

Figure 5 displays monthly first dose vaccination rates before and after the two events. The vertical lines mark the last month before the increase in search activity. Although there seem to be some temporal variations over the year, vaccination rates obviously increase strongly in Berlin in February and March 2015. In all other regions, vaccination rates increase only slightly, although public attention in February 2015 increases likewise. Notably, vaccination rates in 2019 seem to remain unchanged altogether despite the strong increase in public attention, even in regions with reported measles cases.

Figure 5: Monthly vaccination rates in times of high public awareness of measles



Note: Monthly vaccination rates among children aged 9 to 24 months; based on data from May 2014 to October 2015 (left graph) and June 2018 to November 2019 (right graph).

This suggests that spillover effects in terms of public attention due to a measles outbreak elsewhere do not trigger a strong behavioral response. To further confirm this result, I rerun the main estimation as set out in equation 2 but add a dummy variable that indicates a high search intensity (> 95th percentile>) in region r in year-month c without a simultaneous measles outbreak.[10] The results are shown in Table 8. All coefficients on the additional high search intensity variable are insignificant, indicating that public attention alone does not lead to a response in vaccination behavior. While this rules out strong spillover effects on vaccination behavior and thus bolsters confidence in the identification strategy, it also provides important insight into the mechanism behind the vaccination response to measles outbreaks. It suggests that rather changes in affective risk perception, induced by disease outbreaks in one's own region, drive the behavioral response.

[10] Since Google search activity is observed at the federal state level, I assign the search intensity to all regions within that federal state.

Table 8: Effect of exposure to measles outbreak and high search volume on vaccination

	Monthly vaccination rate		1^{st} dose completed			2^{nd} dose completed	
	1^{st} dose	2^{nd} dose	at 15 m.	at 24 m.	at 36 m.	at 24 m.	at 36 m.
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Measles outbreak	0.001 **	0.003 ***	0.007 **	0.003	-0.002	0.009 ***	0.003
	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
High search intensity	-0.000	-0.001	-0.001	-0.003	-0.002	-0.001	0.000
	(0.001)	(0.001)	(0.004)	(0.002)	(0.002)	(0.004)	(0.003)
N	4,481,600	4,481,600	280,100	280,100	241,752	280,100	241,752
Individuals [a]	280,100	280,100			*– same as N –*		

Note: OLS estimations based on data from 2008 - 2019. All estimations include individual controls, birth cohort and region fixed effects, as well as region-specific time trends. Standard errors are clustered on the regional level. * p<0.1, ** p<0.05, *** p<0.001.
[a] For estimations based on data in long format, the number of individuals in the data sample is reported separately from the number of observations (*N*).

6 Discussion and conclusion

The goal of this paper was to assess the role of disease awareness and risk perception for vaccination behavior by examining the vaccination response to local measles outbreaks in Germany. My results show that both child vaccinations as well as catch-up vaccinations in adults increase subsequent to a measles outbreak, where an outbreak is defined as a rise in monthly disease cases to above the 90th percentile of monthly cases over the years 2008 to 2019.

The probability of a child receiving their first or second measles vaccination within one month increases significantly in the first six months after the onset of the outbreak. This results in a reduction in the share of children who have not yet received their first (second) vaccination at the age of 15 (24) months by 4.1 % and 2.6 %, respectively, in those cohorts affected by an outbreak in their region. Notably, the results indicate that the effect is temporary, i.e. that vaccination rates increase shortly after an outbreak but drop back to pre-outbreak levels after about 8 to 10 months. Further, assessing heterogenous effects by children's age reveals an effect primarily at the intensive margin. Vaccinations are preponed as a response to a measles outbreak, resulting in a higher share of children vaccinated on-time. However, I do not find a significant effect on the share of children vaccinated at older ages. This indicates that measles outbreaks affect the timing, though not the overall long-term vaccination coverage. Accordingly, even after a local outbreak, none of the regions reached a vaccination rate of 95 % or higher in the cohorts who were at the recommended age for vaccination at that time (see Figure A-3 in the Appendix).

As for adults, local measles outbreaks lead to an increase in monthly vaccination rates by 14.7 % for the age group 20-30, by 21.2 % for the age group 30-40, and by 45.9 % for those ages 40-50 in the first six months after an outbreak. Also here, effects seem to be of temporary nature. After seven to eight months, vaccination rates do not significantly differ from pre-outbreak levels. It further needs to be taken into account that vaccination rates among adults are low in the first place. On average, only 0.07 % of adults get vaccinated every months, which corresponds to about 1 % per year. Given that an estimated 53.3 % of those born in the 1970s and 20.2 % of those born in the 1980s (age 40-50 and 30-40, respectively, during the period of observation) are unvaccinated (Poethko-Müller and Schmitz, 2013), a temporary increase of even 50 % does little to close the immunity gap.

This study is limited in that it examines the average effects of measles outbreaks without a further distinction between different regional circumstances and without investigating the role of doctors, schools, or public policy institutions in the vaccination response. Oster (2018) suggests that the public response to disease outbreaks plays an important role in incentivizing vaccination behavior. Assessing the interaction of different players with the disease outbreaks thus leaves an interesting topic for further research.

While the results of this study confirm that disease perception is a relevant factor for vaccination decisions, they still suggest that even a change in disease perception may have only a limited impact on raising vaccination rates to the level needed for herd immunity. Understanding the reasons for non-vaccination against serious but vaccine-preventable diseases remains a central topic in current health economic research. In order to find the right policy answers and to derive effective measures it is crucial to understand the channels through which vaccination behavior is influenced. While the findings of this study cannot be directly translated into policy measures, they may help in the further elaboration and shaping of vaccine campaigns and communication in public health.

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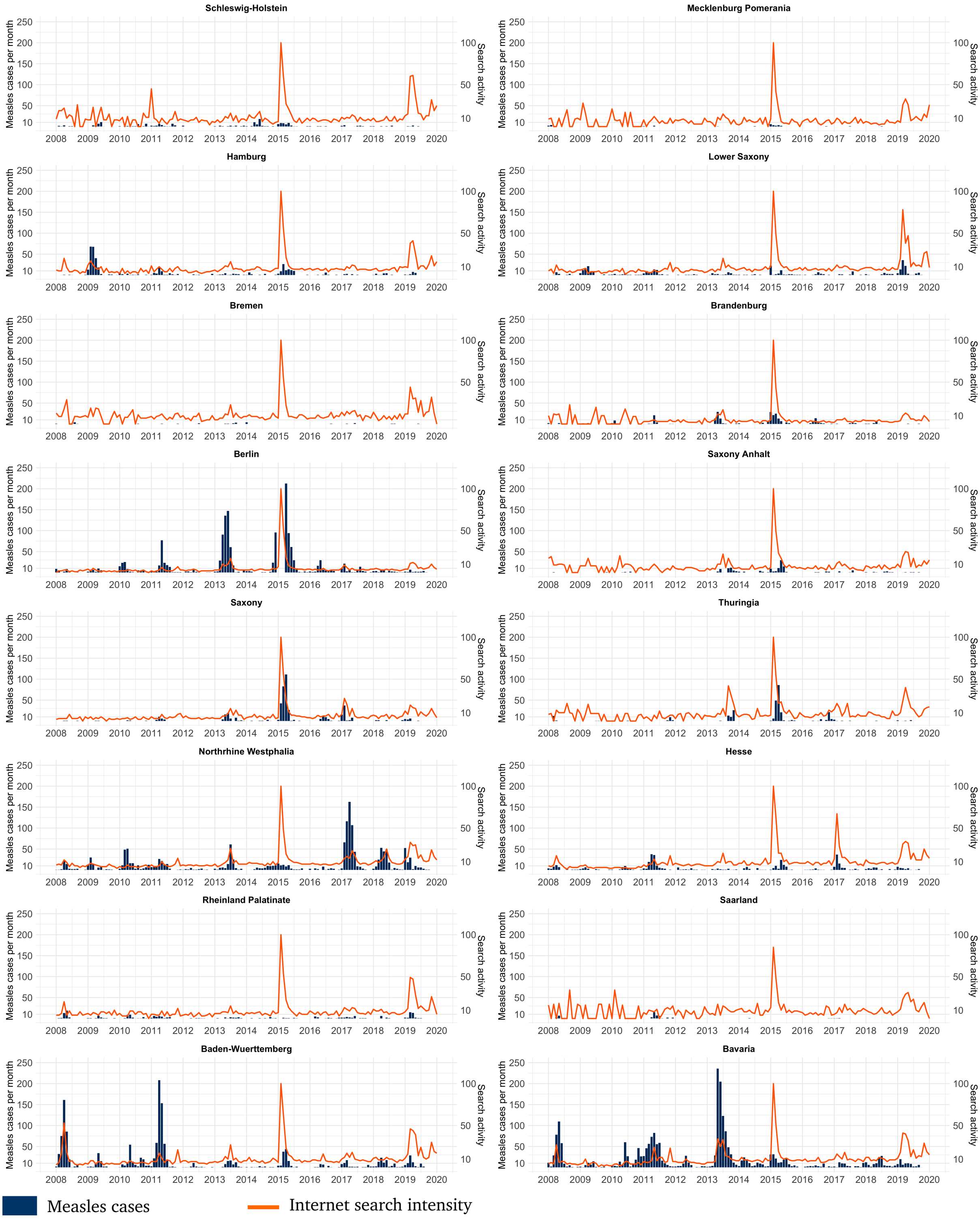
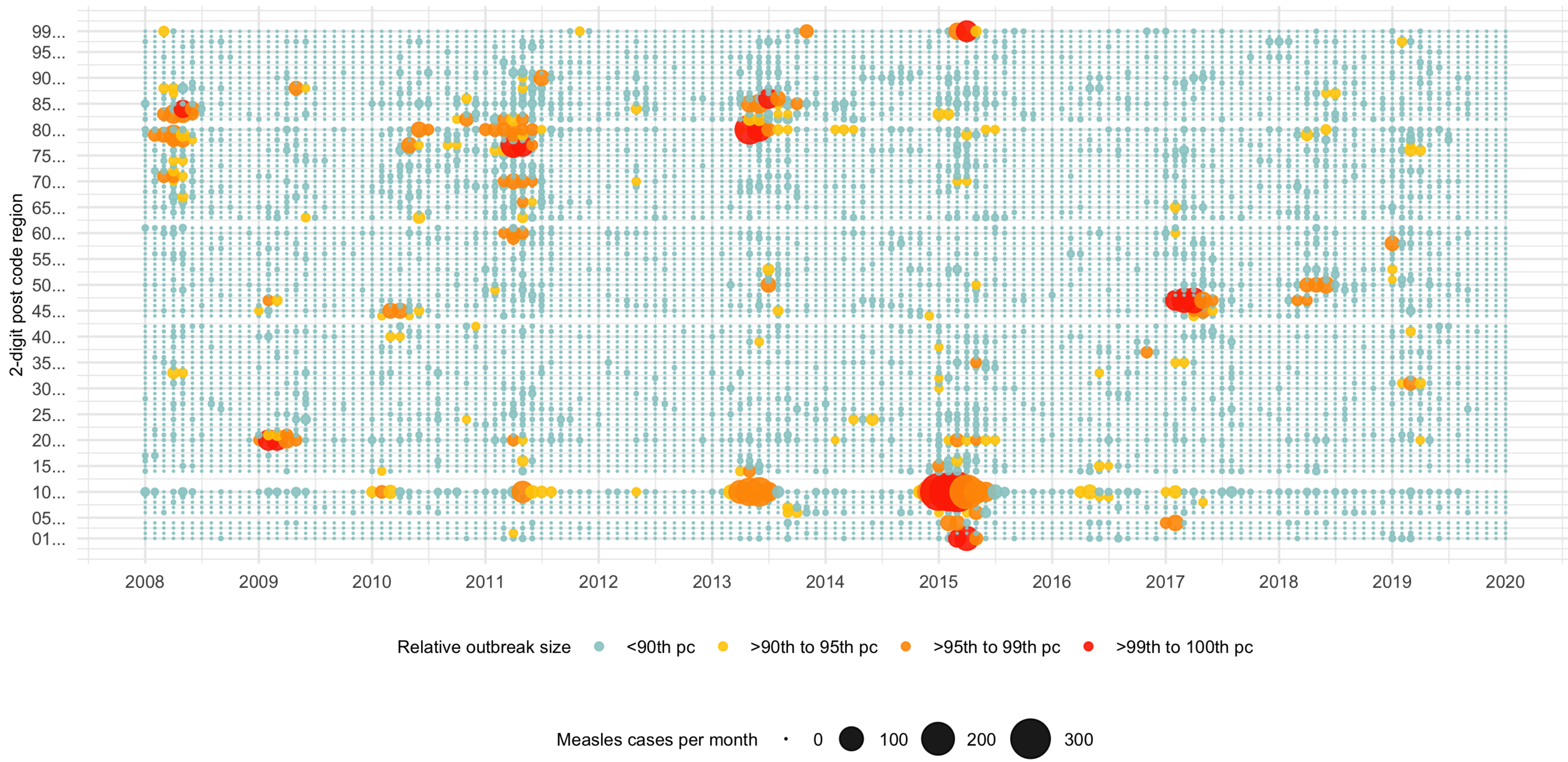
Appendix

Figure A-1: Monthly measles cases and internet search activity by federal state, 2008 - 2019



Note: Internet search activity measured as *relative* interest over time. Search interest is normalized and displayed as a value on scale between 0 and 100, with 100 representing the highest relative interest in the term over the selected period.
Data source: Data on measles cases come from the Robert Koch Institute; data retrieved on 07 November 2019 at https://survstat.rki.de. Data on internet search activity come from Google Trends; data retrieved on 08 January 2020 at https://trends.google.de.

Figure A-2: Monthly measles cases by 2-digit post code region, 2008 - 2019



Note: Monthly measles cases aggregated at the 2-digit post code region. Color coding indicates whether measles cases exceed the 90th, 95th, or 99th percentile (of monthly cases over the whole time period 2008 to 2019) in at least one of the counties in each region. Blank rows occur if digits are not assigned as leading digits in post codes.
Data source: Robert Koch-Institute; data retrieved on 07 November 2019 at https://survstat.rki.de.

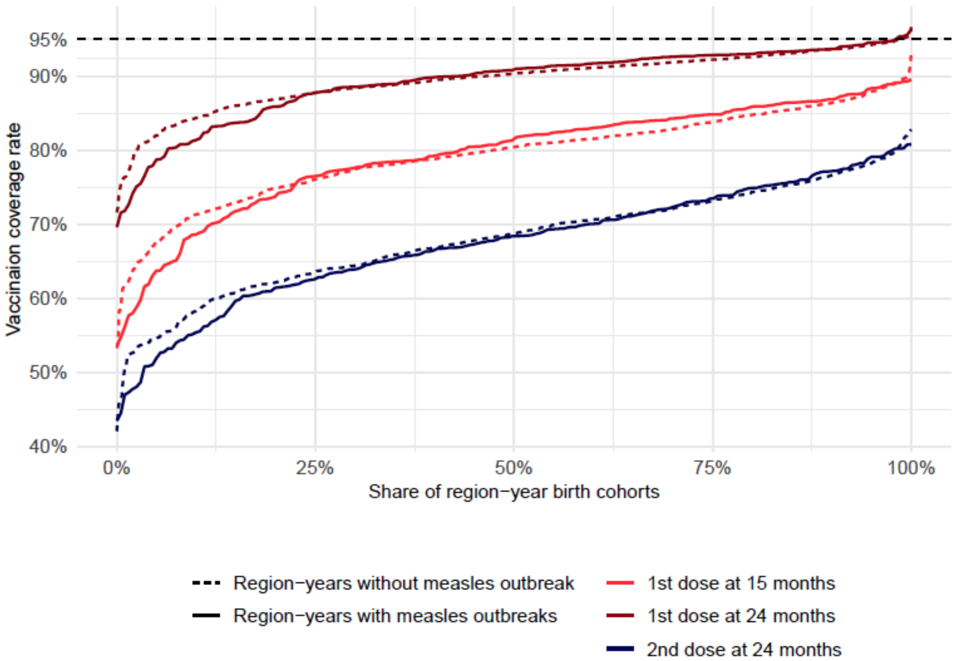
Table A-1: Effect of measles outbreaks on vaccination; comparison of specifications.

	Coefficients on measles outbreak			
	(I)	(II)	(III)	(IV)
Monthly vaccination rate, 1^{st} dose				
Measles outbreak	0.002 ***	0.002 ***	0.002 ***	0.001 **
	(0.001)	(0.001)	(0.001)	(0.001)
N	9,298,112	9,298,112	9,073,632	4,481,600
Individuals [a]	581,132	581,132	567,102	280,100
Monthly vaccination rate, 2^{nd} dose				
Measles outbreak	0.003 ***	0.004 ***	0.003 ***	0.003 ***
	(0.001)	(0.001)	(0.001)	(0.001)
N	9,298,112	9,298,112	9,073,632	4,481,600
Individuals [a]	581,132	581,132	567,102	280,100
1^{st} dose at 15 months				
Measles outbreak	0.004 **	0.008 ***	0.007 **	0.008 ***
	(0.002)	(0.002)	(0.002)	(0.002)
N	581,132	581,132	567,102	280,100
1^{st} dose at 24 months				
Measles outbreak	0.002	0.004 **	0.003	0.004 **
	(0.001)	(0.002)	(0.002)	(0.002)
N	581,132	581,132	567,102	280,100
1^{st} dose at 36 months				
Measles outbreak	-0.001	-0.000	-0.002	-0.000
	(0.002)	(0.001	(0.002)	(0.001)
N	490,129	490,129	478,901	241,752
2^{nd} dose at 24 months				
Measles outbreak	0.004 *	0.008 ***	0.009 ***	0.008 ***
	(0.002)	(0.003)	(0.003)	(0.003)
N	581,132	581,132	567,102	280,100
2^{nd} dose at 36 months				
Measles outbreak	0.003	0.004 *	0.003	0.004 *
	(0.002)	(0.002)	(0.003)	(0.004)
N	490,129	490,129	478,901	241,752
Year-month FE	x	x	x	x
Region FE	x	x	x	x
Region time trends	–	x	x	x
Individual controls (1)	–	–	x	x
Individual controls (2)	–	–	–	x

Note: OLS estimations based on data from 2008 - 2019; standard errors are clustered on the regional level; * p<0.1, ** p<0.05, *** p<0.001.

[a] For estimations based on data in long format, the number of individuals in the data sample is reported separately from the number of observations (*N*).

Figure A-3: Vaccination coverage rates per region-year cohort



Note: Birth cohorts are aggregated at a region-year level. Region-years with measles outbreaks are defined as regions where at least one monthly birth cohort within a year was affected by a measles outbreak during the first 15 months of their life.

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