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Socio-Demographic and Spatial Patterns of Autism and Vaccine Exemptions

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Abstract

The number of U.S. children entering schools without mandated vaccinations has increased over the past two decades, forming pockets of low immunization. This study examines mechanisms underlying spatial clusters of non-medical exemptions in California. Although the current wave of vaccine hesitancy began with the controversy around vaccines and autism, we find that the locations of children with autism, as well as that of alternative medicine practices, are not associated with the broad spatial patterns of exemptions. The role of sorting into different neighborhoods according to maternal education is also limited. However, a series of tests show that the diffusion of vaccine safety concerns among non-Hispanic white parents is likely to have contributed to the spatial clustering. Self-selection into private and charter schools has a strong impact as well as potential spillover effects. Our findings suggest that the concentration of exempted children in a few schools is partly an unintended consequence of the charter school movement. Network interventions may be useful to reduce clusters of low immunization.

Keywords

Socioeconomic status; race and ethnicity; spatial clustering; autism; vaccination exemptions; diffusion

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1. Introduction

Widespread immunization can potentially eradicate diseases such as measles, hepatitis B, rubella and mumps (Hinman 1999). The global public health efforts, however, are being undermined by the decrease in immunization coverage in some high-income countries (Falagas and Zarkadoulia 2008). The number of children entering U.S. schools without mandated immunizations has increased over the past two decades (Omer et al. 2006; Wang et al. 2014). Large exemption clusters create pockets of low immunity and can have substantial public health consequences (Eames 2009; Salathe and Bonhoeffer 2008).

The socio-demographic patterns of exemptions go against what we understood about immunization. One of the most robust findings in demographic research is that maternal education has a positive effect on child's immunization status (e.g., Desai and Alva 1998). However, the increases of exemptions are in neighborhoods that are predominately white and high socioeconomic status (SES) (Atwell et al. 2013; Birnbaum et al. 2013; Carrel and Bitterman 2015; Imdad et al. 2013; Lieu et al. 2015; Omer et al. 2008; Safi et al. 2012).

How can we explain the increasing rates of non-medical exemptions, their spatial clustering, and the reversed socioeconomic gradient? This study makes two contributions toward addressing these questions. First, we evaluate the role of the autism epidemic by examining the spatial relations between autism prevalence and non-medical exemptions in California. It has been suggested that concerns over vaccine safety have overtaken the lack of access to healthcare as the primary obstacle to high immunization coverage (Salathe and Bonhoeffer 2008). The current wave of vaccine safety concerns began after Wakefield et al. made the now-discredited claim in 1998 that the Measles, Mumps, and Rubella (MMR) vaccine causes autism (Bearman 2010). To our knowledge, our study is the first attempt to use population-wide data to examine the association between the epidemiological patterns of autism and non-medical vaccine exemptions.

Second, we provide a methodological approach to separate school-level mechanisms from those generating broad spatial clusters of exemptions. Although studies have documented the concentration of exemptions in predominately white and affluent neighborhoods, it is unclear what drives these associations. It is often assumed that spatial clusters are merely caused by a concentration of high-risk individuals (or in this case, schools) in certain areas. However, demographic studies of contraceptive use and other fertility decisions have demonstrated that neighborhood networks can be as crucial (Behrman, Kohler and Watkins 2002; Entwisle et al. 1996; Kohler 1997). In the same vein, our results show that the diffusion of vaccine safety concerns over racially homophilous social networks is likely to have contributed to the broad spatial clustering of exemptions.

The rest of this paper is organized as follows: The next section describes the increase in personal belief exemptions in California and discusses mechanisms that may have generated the spatial patterns. Using population-wide data from California between 1992 and 2014, we then examine the roles of autism prevalence and other factors. We then use a series of tests to examine potential effects of social diffusion. Lastly, we discuss our findings' implications on intervention policies.

2. The Rise of Personal Belief Exemptions

U.S. children are required to meet state-mandated vaccination requirements to attend private and public schools. Most states allow exceptions based on medical, religious and philosophical reasons; the latter two are referred as personal belief exemptions (PBEs) in California. Figure 1 shows the average PBE rates among public, charter and private kindergartens between 1992 and 2014. Herd immunity requires immunization levels of about 90% (higher for extremely infectious diseases, e.g., pertussis, and slightly lower for others, e.g., measles and Ebola). In 2014, average PBE rates were still below 10%. However, the PBEs were unevenly distributed. The top 5% of public, private and charter schools with the highest PBE rates have greater than 10%, 20% and 45% of students exempted, respectively. Why are more parents seeking PBEs and how do we explain the uneven distribution?

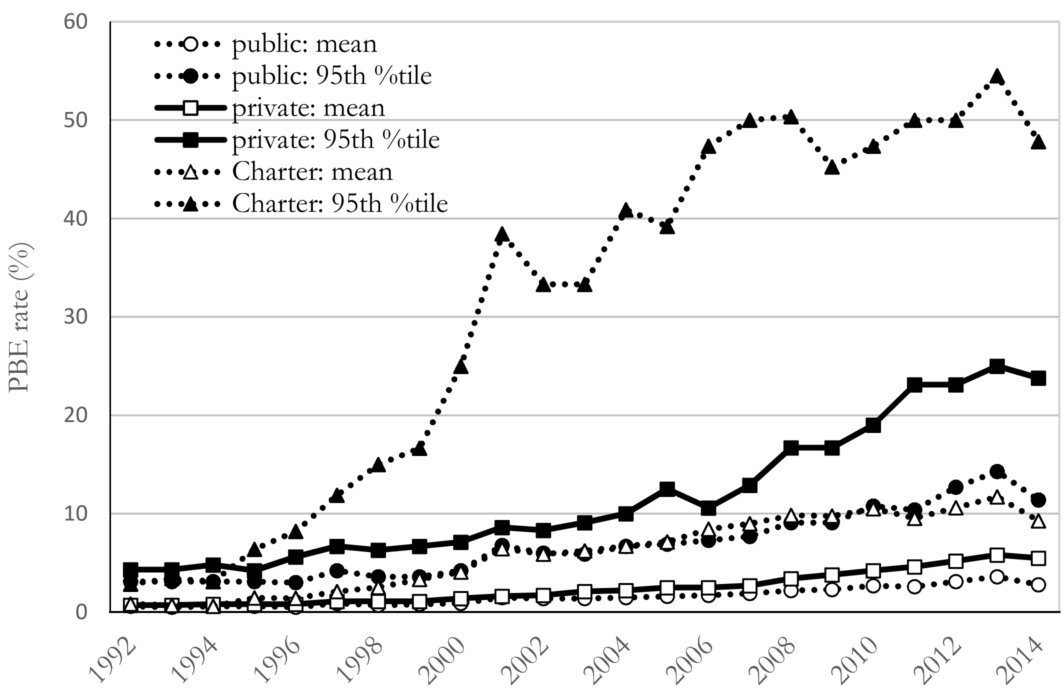

Figure 1. PBE rates in California kindergartens, 1992-2014

2.1 Access to Health Care

Lack of health care access is associated with under-immunization even in high-income countries (Falagas and Zarkadoulia 2008). Every child in the U.S. should have access to free vaccination, either through private or public programs (CDC 2014). However, other costs associated with office visits can make it difficult for less affluent parents to adhere to the recommended schedule. Low SES indicators such as low maternal education, low maternal age, low-income, unmarried parents, ethnic minority status, and lack of/insufficient health insurance are still associated with substandard immunization level (Bobo et al. 1993; Ehresmann et al. 1998; Lieu et al. 2015; Luman et al. 2003; Smith, Chu and Barker 2004; Williams et al. 1995). Lack of access to physicians contributes to the low immunization rates in rural areas (Richards et al. 2013).

More importantly, lack of access to a physician can generate PBEs if parents file them as "convenience" measures by parents who cannot keep up with the required schedule or the paperwork (Jones and Buttenheim 2014). These exemptions would be generated by a different mechanism than those filed by parents who are intentionally not vaccinating their children. If access to health care remains an important factor in the U.S., we should expect:

Hypothesis 1. Lack of access to physicians generates PBE clusters across schools, particularly in rural areas.

2.2 The Vaccine-Autism Controversy

The seemingly unexplained increase in autism diagnoses (but see Eyal et al. 2010; King and Bearman 2009; Liu, King and Bearman 2010) has fueled the popularity of the vaccine-autism link. Distrust of pharmaceutical companies and other for-profit health organizations, as well as potential conflict of interests in the science community, is a major site of contention in the autism-vaccine debate (Gross 2009). Despite many studies demonstrating that vaccines do not cause autism (Taylor, Swerdfeger and Eslick 2014), a survey in 2009 still found that 1 in 4 parents believe that some autism cases are caused by vaccines (Freed et al. 2010). The popularity of hypotheses on how vaccination may cause autism (or other health issues) is constantly shifting (Gerber and Offit 2009). A current theory asserts that vaccinations overload an infant's immune system. The hypothesis lacks scientific evidence like its predecessors (Offit et al. 2002). Nonetheless, "selective" and "alternative" vaccination schedules are getting popular (Offit and Moser 2009). Not surprisingly, parents who request PBEs are more likely to have concerns about vaccine safety than parents who do not (Gaudino and Robison 2012; Prislin et al. 1998).

Parents who intentionally choose not to vaccinate their children are sometimes depicted as acting out of ignorance. However, this portrayal is inconsistent with the positive association between education and PBEs at both the individual (Freed et al. 2010; Gust et al. 2004; Smith et al. 2004) and neighborhood levels (e.g., Lieu et al. 2015). Under a game theoretic framework, it will be individually rational[1] not to vaccinate when a substantial proportion of the population

[1] Certainly, these decisions are irrational from the public good and community health perspectives. However, there is often tension between individual and collective interests, such as in the "tragedy of the commons".

is vaccinated, and the risk associated with vaccination is non-zero (Bauch and Bhattacharyya 2012; Bauch and Earn 2004; Manfredi et al. 2009). If we assume that parents are acting according to their self-interests, vaccination decisions are a weighing of costs and benefits. Behavioral economics have shown that human decisions are bounded by cognitive and psychological biases (e.g., Kahneman and Tversky 1979). We argue that social factors are as important: vaccination decisions are malleable to local information and vulnerable to social influence.

How do income and education factor in? It may be that high-SES parents be more aware of the actual costs than parents with fewer resources, or they have a higher perceived cost of vaccination due to exposures to anti-vaccine materials online (Jones et al. 2012). Access to the Internet alone should not be sufficient to explain the positive education gradient—there are also ample resources online about the scientific evidence on vaccine safety. However, research has shown that direct approach to debunking vaccine myths can backfire (Horne et al. 2015). The conflicting nature of the information (Zimmerman et al. 2005) may have contributed to the hesitancy (Wang, Baras and Buttenheim 2015).

It is important to point out that it is not necessary for more educated parents, on average, to be more likely to have anti-vaccine beliefs than less educated parents to create a positive SES gradient. First, a higher PBE rate among children of high SES parents will result if their parents feel more ready to *act on* their distrust of professionals than parents with less education (see Mechanic 1996). In fact, a study finds that although low SES and black parents have *more* vaccine safety concerns than their counterparts, they still vaccinate their children (Shui, Weintraub and Gust 2006). Second, high SES parents only need to be more *varied* in their beliefs for some of them to be skeptical enough to go against the strong normative pressure to vaccinate. Hence, we expect:

Hypothesis 2: Sorting of parents by SES into different neighborhoods generates broad clusters of PBEs across schools.

Perceived costs and benefits of immunizations may be sensitive to local information. On the one hand, knowing a child with autism can make concerns about the disorder particularly salient, and increase the probability of a vaccine refusal. Figure 2 shows the spatial clusters of autism diagnoses in California in 2010 (see Mazumdar et al. 2013). Did these clusters have any roles in shaping the patterns of PBEs?

Figure 2. Spatial clusters of autism diagnoses in California, 2010

On the other hand, outbreaks of vaccine-preventable disease could have the opposite effect. Historical data show that vaccination rates increase after an outbreak (Bauch and Bhattacharyya 2012). Exposure to consequences of infectious diseases leads to more pro-vaccine attitude (Horne et al. 2015). The local incidence of vaccine preventable disease, therefore, should increase the perceived level of risk of an infectious disease and decrease the likelihood of PBEs:

Hypothesis 3: Proximity to children with autism increases the probability of seeking a PBE, while proximity to incidences of vaccine-preventable diseases decreases it.

Other factors may intensify the spatial clustering of PBEs by making certain neighborhoods or schools more attractive to parents who are skeptical about vaccines. The availability of alternative medicine practitioners could be a factor (Salmon et al. 2005): previous studies have shown that a vocal minority of chiropractors continue to be skeptical of the necessity and effectiveness of vaccines, choosing instead to believe the disease is caused by misalignments within the body (Campbell, Busse, and Injeyan 2000; Colley and Haas 1994).

At the school level, the high rates of exemptions in private schools (Birnbaum et al. 2013; Carrel and Bitterman 2015) may be partly due to a positive association between alternative pedagogical orientations and alternative health beliefs. Although they are publicly funded, charter schools are independently run and can have alternative pedagogical orientations. Parents choose to which charter schools to apply. Admission is not determined by where the student lives but by random lottery. Thus, selection of parents with vaccine hesitancy into certain neighborhoods and charter/private schools will affect PBE rates:

Hypothesis 4: The density of alternative medicine practices (e.g., chiropractors, acupuncturists) increases PBE rates across schools, while selection into charter and private schools increase school-level PBE rates.

2.3 Social Diffusion of Vaccine Safety Concerns

Sorting into neighborhoods by SES may not be sufficient for the manifold differences in PBE rates among non-charter public schools. The difference in exposures to anti-vaccine messages also cannot explain why, after controlling for the effects of education and income, unvaccinated children tend to have white parents (Smith et al. 2004). Of course, race/ethnicity can have independent effects on health via pathways such as discrimination and behavioral factors. However, differences in vaccine-related beliefs seem to be more relevant in the case of PBEs.

We argue that the diffusion of vaccine-related beliefs though spatially embedded, racially homophilous networks explains why PBEs are more common in white neighborhoods. First, although SES may not be associated with risk aversion (Halek and Eisenhauer 2001), risk perception has been shown to correlate among network neighbors (Scherer and Cho 2003). Second, race/ethnicity creates the strongest divides in social networks in the U.S., more so than education, age or religion (McPherson, Smith-Lovin and Cook 2001). Third, the adoption of high-risk or unproven behaviors (such as PBE) tends to require multiple affirmations (Centola and Macy 2007; Kohler, Behrman and Watkins 2001; see also May and Silverman 2003). Knowing many parents who had refused or delayed vaccines can lend credibility and legitimacy to refusals. Moreover, adoptions requiring a high threshold (i.e., many friends already adopted) will intensify the spatial clustering of exemptions (Salathe and Bonhoeffer 2008). It is because social relations tend to cluster spatially, and only dense networks can allow the high adoption thresholds to be met (Centola and Macy 2007).

Such social diffusion processes are endogenous and stochastic. As Granovetter (1978) points out, a cascade of adoptions can take place in one neighborhood, but fail to happen in a similar neighborhood, due to a small difference in the distributions of adoption thresholds. Therefore, we predict:

Hypothesis 5: The percentage of non-Hispanic white residents is positively associated with broad clusters of PBEs net of SES effects. However, its effect varies across space.

We perform additional tests to examine the effect of race/ethnicity separate from that of SES. First, we study the effect of percent non-Hispanic white among a homogenous population with regard to SES: Head Start participants. Head Start is a government-funded program that provides education, nutrition and health services to young children from low-income families. In general, families must earn less than or equal to the federal poverty level line to be eligible. If the effect of percent non-Hispanic white is due to unmeasured SES effects, we should expect to find no effect among Head Starts. Second, we use the correlations of PBE rates across school types (i.e., public schools and childcare centers) to help rule out school or school-district specific factors. Lastly, we consider the effect of racial segregation. If diffusion within homophilous networks at least partially drives the high prevalence of vaccine concerns among white parents, we should expect children living in more segregated areas to have higher PBE rates while controlling for the effects of other SES variables.

3. Data and Methods

3.1 Data

Our outcome measure is the number of PBEs reported yearly by school. All covariates are lagged three years and six years for childcare centers and kindergartens, respectively. This lag is appropriate because the majority of vaccination decisions take place long before a child goes to school, i.e., typically when the child is 0-12 months old. Using a 5-year lag does not change the results (Table S1 in the Supplementary Materials). Most of the covariates are measured for "school neighborhood", defined as a 500-child radius drawn around the school (or childcare center), representing a school's "catchment" area. The radius is calculated based on block-level census data on 3-9 year-olds from 1990, 2000 and 2010 and supplemented by Esri Sourcebook (Liu and Bearman 2015). Our measurements allow us to compare areas of different population densities.

PBEs. Students in California are required to provide proof of meeting immunization requirements when entering childcare, kindergarten, and the seventh grade. The California Department of Public Health (CDPH) provides exemption data from 1992 to 2014 for kindergartens in public and private schools with more than 10 students. Data for licensed childcare centers with more than 10 students are from 2010-2014. We match the PBE data to enrollment records available from the California Department of Education (CDE).

Proximity to physicians. Access to physicians is measured by the count of general, family, and pediatric physicians within a school's radius. Addresses of physicians are taken from the annual American Medical Association Directory of Physicians. Counts of alternative health practitioners, specifically chiropractors and acupuncturists, are from licensing records from the California Department of Consumer Affairs. To ensure that proximity to alternative healthcare practitioners is not due to a spurious effect of proximity to business areas, we measure local densities of randomly selected licensed professionals, as well as the density of veterinarians, which should not be associated with beliefs about vaccination.

Autism. We use point-level data from the California Department of Developmental Services (DDS) data between 1992 and 2011 to count children with an autism diagnosis within a school's radius. The DDS provides service to a vast majority of individuals with a full syndrome autism disorder in California (Croen, Grether and Selvin 2002). The DDS does not provide services to people with Asperger Syndrome or Pervasive Developmental Disorder-Not Otherwise Specified (PDD-NOS). Further details of the data are described elsewhere (Liu et al. 2010). Count of autism advocacy organizations is collected from records of tax-exempt organizations kept by the Internal Revenue Service and are recorded at the county-level.

Pertussis. Reported numbers of pertussis cases in California for 2000 to 2010 are obtained from the Immunization Branch of the CDPH. Incidences are aggregated at the level of county and used in the analysis as rates per 1000 population.

SES measures. School-neighborhood level SES is measured by average education and logged property values in the 500-child radius. Education is measured as the highest year of schooling completed by the mother at the time of birth. This information is obtained from the California Birth Statistical Master File (BSMF) for 1992 to 2007. Median property values and population densities for the full study period are interpolated using Censuses' block-group level data. They are then averaged across the school neighborhood and logged to adjust for skew.

Race/ethnicity. Racial composition is represented as the percentage non-Hispanic white among children within the school's radius. The CDE provides school enrollment breakdowns by race/ethnicity. White isolation index at the school district level measures the extent to which non-Hispanic white students are exposed only to one another. Isolation index at the school board level is used for the eight school boards of the Los Angeles Unified School District due to its large size.

3.2 Analytic Methods

We conduct analyses at two different levels. At the school level, we use negative binomial regression models. It is because information on PBEs is only available at the school level. The results should not be used to make inference at the individual level. Spatial scan statistic is then used to examine broader clusters of PBEs across schools. We compare the unadjusted clusters with a series of maps after adjusting for the school-level covariates. It allows us to identify the relative contributions of the covariates in generating the broad clusters.

School-level models. Effects of the covariates on the number of PBEs are estimated using negative binomial regression with random effects clustering at the school level. Expected count of PBEs (u_{ij}) is calculated as $\log(u_{ij}) = \log(t_{ij}) + \alpha + \beta x_{ij} + \gamma z_j + \upsilon_{ij}$, where schools are indexed by *i* and year by *j*, $\log(t_{ij})$ is the logged number of enrolled students (exposure), α is the constant, x_{ij} is a vector of independent covariates measured by school and year while β is estimated covariate effects, z is a set of indicator variables for year with γ estimated effects, and υ_{ij} is the error term, composed of $\nu_i \sim N(0,\sigma_v^2)$ and $\varepsilon_{ij} \sim N(0,\sigma^2)$. These models are appropriate for the school-level count of PBEs due to over-dispersion. Caution is needed in interpreting statistical significance, as the errors may not be independently distributed due to spatial autocorrelation. We choose not to include spatial errors or lags (see Anselin 2013) in our models because the locations of unexplained PBE clusters are our key interest. Instead, we examine the pattern of autocorrelation in the errors by spatial scan statistic described below. We use three-level models with random effects at the school and county levels to estimate the effects of county-level predictors.

Unadjusted and adjusted clusters. We use Kulldorff Spatial Scan Statistic (Kulldorff 1999) to identify statistically significant spatial clusters of high PBE rates across public schools in 2014. Maximum likelihood estimation is used to identify circular areas that encompass schools with an increased probability of PBEs compared to the overall risk in California. Likelihood ratios are calculated by comparing observed numbers of PBEs with expected numbers of PBEs based on enrollments and the overall count of PBEs, and statistical significance is assessed through 9999 Monte Carlo randomizations. Only statically significant (using p=0.05) clusters of increased PBE likelihood ratios are presented.

We adjust for the effects of covariates, including: demographic characteristics (logged median property values, logged population density, mother's highest level of education, and percent non-Hispanic white), access to health care resources (count of physicians), prevalence of alternative health practitioners (counts of chiropractors and acupuncturists), and incidence of autism (count of autism).

We use a geographically weighted Poisson regression to explore spatial non-stationarity of local regression coefficients (Nakaya et al. 2005). It uses distance-weighted sub-samples to produce local estimates, with the weights determined by model fit. Model comparison using Akaike information criterion (AIC) assesses the local variability of coefficients. The model is fitted using the GWR4 software (Tomoki et al. 2014).

4. Results

4.1 School-Level Correlates

Table 1 shows associations of covariates with PBEs at the school-level. Socio-demographic variables have the expected effect. A one-year increase in average mother's educational attainment is associated with a 19% increase in PBEs, net of other covariates. A 10% rise in percent non-Hispanic white a school neighborhood is associated with a 21% increase in PBEs. While logged property values have a statistically significant positive association with PBEs on its own, the effect becomes insignificant in the full model. Areas with higher population densities have lower PBE rates than less populated areas. This result implicates the importance of access to health care resources, yet the effect of population density remains to be statistically significant after controlling for physician count.

Table 1. Correlates of PBEs among public school kindergartens, 1998-2014[1]

	IRR adjusted only for years[2]	Sig.	95% C.I.		Fully adjusted IRR	Sig.	95% C.I.	
Average mother's years of education	1.532***	0.000	1.505	1.560	1.190***	0.000	1.163	1.218
Logged property values	1.651***	0.000	1.575	1.730	0.974	0.317	0.926	1.025
Logged block group density	0.683***	0.000	0.669	0.698	0.782***	0.000	0.766	0.799
% white (decile)[3]	1.339***	0.000	1.329	1.348	1.217***	0.000	1.205	1.230
Count of physicians	1.010***	0.000	1.008	1.012	1.004***	0.000	1.002	1.006
Count of acupuncturists	1.038***	0.000	1.030	1.045	0.996	0.249	0.988	1.003
Count of chiropractors	1.043***	0.000	1.038	1.048	1.029***	0.000	1.023	1.034
Count of children with autism diagnosis	1.013***	0.000	1.007	1.019	1.006*	0.039	1.000	1.012

Note:

[1] 2-level random intercept negative binomial regression model with yearly observations nested in schools using 1998-2014 public school data; N= 89,550 school-years. Year indicator variables included but coefficients not shown. All independent variables lagged 6 years. †p ‹ .10; *p ‹ .05; **p ‹ .01; ***p ‹ .001

[2] Adjusted for the effects of dummy indicators for year.

[3] Measured in 10% increments

Count of autism diagnoses has the expected positive effect on PBEs. As did the count of alternative health practitioners, although only the effect of chiropractors retains significance once the other covariates are included. Proximity to business areas cannot explain this result: a variable created to measure proximity to the same number of random business addresses does not have a statistically significant effect on PBEs (not shown). However, the causal mechanisms underlying such patterns remain unclear. Another robustness check indicates that count of veterinarians also has a significant, positive effect on PBEs net of the effects of other variables (IRR=1.02, p>0.0001). Like veterinarians, chiropractors could have been associated with unmeasured neighborhood-level characteristics and PBEs.

4.2. Clustering of PBEs across Schools

We now evaluate the relative contributions of the covariates identified by the school-level analysis in generating clusters of PBEs across schools. Figure 3A shows the spatial clustering of PBEs among public kindergartens before adjustments. The area in the shaded regions has a statistically significant higher relative risk of PBEs than the state overall. Clusters of PBEs are found in the sparsely populated area in the north; coastal urban centers (e.g., San Francisco, Santa Clara, Santa Barbara, Los Angeles, and San Diego); and areas in the Central Valley. Figures 3B-H show the spatial clusters after each adjustment. If the distribution of a covariate is responsible for broader patterns of spatial clustering, the shaded circles should disappear (i.e. the increased relative risk of PBE should be reduced).

Figure 3. Adjusted spatial clusters of PBEs across public schools by covariates, 2014

Hypothesis 1: access to physicians in rural areas. Because physician count increases rather than decreases PBEs at the school-level, they could not have generated the rural PBE clusters. Figure 3B shows that adjusting for the *positive* effect of physician count has the most impact around Santa Maria and Santa Barbara. Using distance to the nearest physician instead of physician count yield similar results. Although the causal mechanism is unclear, controlling for logged population density largely explains away the cluster of high PBEs in the rural areas near the Oregon border (Figure 3C).

Certainly, there are factors other than proximity that can limit access to health care. However, the PBE rates after a law change in 2014 provide other support that the effect of access to health care is limited. In 2014, California mandated a physician consultation before filing a PBE. There were slight declines in the PBE rates of kindergarteners for the 2014-15 and 2015-16 school years, as they fell to 2.54% and 2.38% respectively, from the 3.15% reported for the 2013-14 school year (California Department of Public Health, Immunization Branch 2016). It provides some evidence that the majority of PBEs are not merely convenience measures.

Hypothesis 2: sorting by SES. Our results suggest that sorting of parents by SES into neighborhoods does not have much of a role in generating broad PBE clusters. Figure 3D shows that controlling for maternal education has almost no effect, despite its strong effect on PBEs at the school level. It demonstrates that the mechanism generating broad spatial clusters of PBEs can be different from mechanisms at the school level. Figure 3E shows the effects of logged property values on clustering of PBEs. While logged property values do not appear to have a consistently strong impact at the school level, adjusting for its spatial distribution has some effect on the clusters in the coastal urban areas, closely resembling the effects of physician count.

Hypothesis 3: autism and pertussis. We expect exemption decisions to be sensitive to exposures to autism and vaccine-preventable diseases. Although proximity to children with autism has a statistically significant effect in the school model, it has little effect on spatial clustering across schools (Figure 3F). While the major spatial cluster of autism was in Los Angeles (Figure 2), high PBE rates are found in other places such as San Francisco, Santa Barbara, and San Diego.

As only county-level information was available, we use a three-level mixed-effects Poisson model instead of spatial scan statistics to examine the effect of incidence rates of pertussis on PBEs (Table S2 in the Supplementary Materials). We find that incidence rates of pertussis per 1000 among children aged 0-6 decrease PBE rates by 3.8%, net of other factors. However, this result is not significant at $\alpha=0.05$ ($p=0.086$).

Because social interactions are unlikely to span large geographical areas, it is not surprising that proximity to children with autism has a very local effect. We also test the effect of proximity to autism advocacy organizations in the 3-level model. It serves as an indirect test of the effect general awareness about autism, which may span a greater distance. However, the county-level count of autism advocacy organizations does not have a statistically significant effect on PBEs.

In short, while it is associated with increased PBE rates at a very local level, proximity to children with autism does not have a broad impact on the spatial patterns of PBEs. County-level incidence rates of pertussis and proximity to autism advocacy organizations also have little impact.

Hypothesis 4: other selection. While sorting of parents by SES may not have a substantial impact on the broad pattern of clustering, selection of parents by other factors, such as attitudes towards alternative medicine, into certain neighborhoods may have a more direct effect. Figure 3G shows that adjusting for the locations of chiropractors and acupuncturists, however, has little overall effect on PBE clustering patterns across schools. In contrast, the effects of selection of parents into certain private or charter schools are to be substantial. After adjusting for SES indicators, the incidences of PBEs are still 217% and 335% higher in private and charter schools, respectively, than non-charter public schools (Table S3 in the Supplementary Materials). School type appears to partially mediate the effect of logged property values (The IRR of logged property values decreases to 1.015 from 1.081 and is no longer statistically significant). Interestingly, the effect of mother's years of education remains approximately the same after controlling for school type.

Private and charter schools vary widely in their instruction styles and other characteristics, which makes some of them more attractive to parents hesitant about vaccinations than others. As Figure 1 has already indicated, PBE rates vary within charter and private schools. Figure 4 plots the Lorenz curves of PBEs by school type. They show the cumulative shares of the student population against the cumulative shares of PBEs in 2014. Lorenz curve is a standard measure of inequality. If the number of PBEs in a school is simply proportional to the size of the student population, the curves should fall on the diagonal. Instead, Figure 4 shows that about 70% of PBEs came from schools constituting only to 20% of the student population regardless of school type.

Hence, even though private and charter schools have higher exemption rates than public schools in general, their high PBE rates are driven by a small fraction of schools. This finding is consistent with a selection of parents with a high level of hesitancy about vaccines into certain private or charter schools.

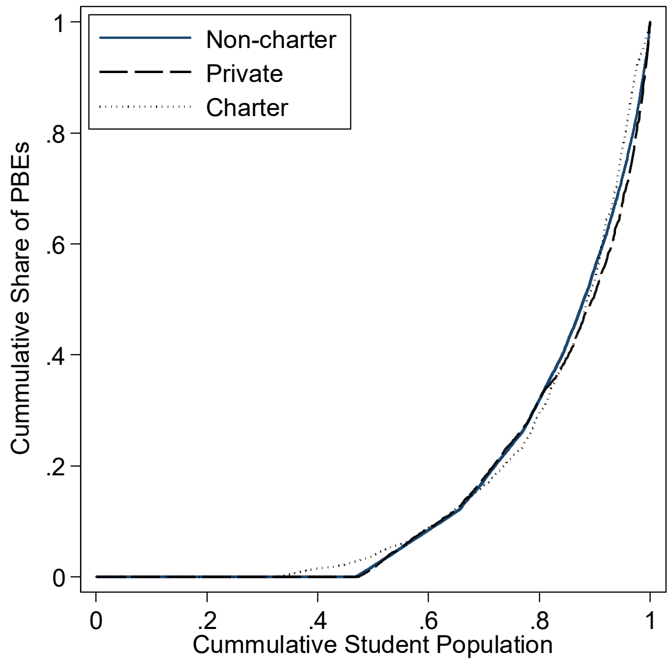

Figure 4. Lorenz curves of PBE distributions in 2014 by School Type

To summarize, we find partial support for Hypothesis 4. At the school level, PBEs are more frequent in private and charter schools, potentially indicating a selection process. Such selection can generate very high PBE rates in certain schools but unlikely to create broad PBE clusters. At the same time, alternative health practices do not seem to explain broader patterns of PBEs.

Hypothesis 5: Percent non-Hispanic white and social diffusion. So far, we have not identified any key factors that can explain PBE clusters. Our last hypothesis is about race/ethnicity. Compared to other factors, adjusting for the percentage of non-Hispanic white has a substantial effect and reduces both the number and sizes of clusters in urban centers and rural areas alike (Figure 3H). The diffusion of vaccine skepticism/hesitancy through racially homophilous social networks is consistent with this result.

First, we need to rule out that percentage white is merely picking up unmeasured SES effects. A stringent test is to examine its effect on PBEs among a population that should be homogeneous regarding SES, i.e., children in a Head Start program. Figure 5 shows that percentage of non-Hispanic white residents is positively associated with PBE rates across school types, and has the *strongest* effect among Head Starts Centers. A 10% increase in percent non-Hispanic white in the area around a Head Start is associated with a 37% increase in PBEs, controlling for other covariates. Unmeasured SES effects should not have driven this result.

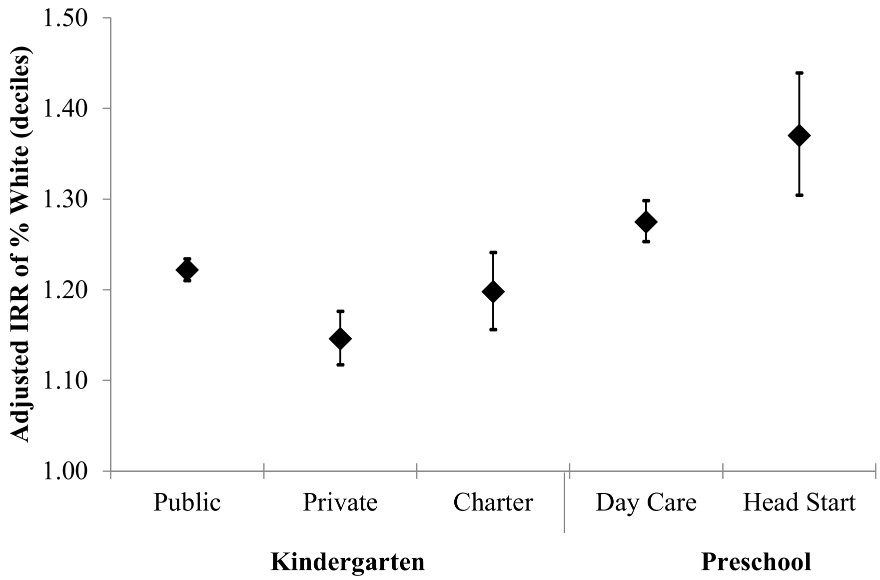

Figure 5. Effect of percent non-Hispanic white (measured in 10% increments) by school type, across kindergartners (1998-2014) and childcare centers (2010-2014).

Note: All IRRs estimated via negative binomial regression and adjusted for average mother's years of education, logged property values, logged block group densities, counts of physicians, chiropractors, acupuncturists, and children with an autism diagnosis, and yearly indicator variables. Public schools: N=84,303; private schools: N=27,378; charter schools: N=5,247; day care centers: N=30,801; Head Start centers: N=6,049.

Second, it is puzzling why adjusting for percentage non-Hispanic white would have a larger effect than mother's years of education, which has a comparable effect on PBEs in the school-level model. We need to rule out it is due to different patterns of racial and educational segregation. For instance, if people are more segregated by race/ethnicity than education, and that some white neighborhoods coincide with the PBE clusters, we will see the results in Figure 3H even if the two variables are both unrelated to PBEs. To rule this out, we compare their Moran's I spatial correlation statistics at the Census block group level in 2010. We find that percent non-Hispanic white (observed = 0.170, expected < 0.001, $p< 0.001$) and mother's education (observed= 0.174, expected < 0.001, $p< 0.001$) have similar levels of spatial autocorrelation. Hence, spatial autocorrelation in the covariates cannot explain why percent non-Hispanic white has a stronger effect than maternal education.

It remains possible that some other unmeasured characteristics associated with both non-Hispanic white and PBE. While we cannot completely this rule out, findings from three additional tests are consistent with our diffusion hypothesis. First, because diffusion is an endogenous process, neighborhoods of similar racial/ethnic compositions can have different PBE rates. In contrast, if some unmeasured confounders at the individual level are responsible for the percent non-Hispanic white effect, local regression coefficients should be uniform across space. We use a geographically weighted Poisson regression model to compare the spatial variations of the local regression coefficients of mother's years of education and percent non-Hispanic white. Allowing the parameter of percent non-Hispanic white to vary spatially improves the model fit (AIC drops by 606.7; a lower AIC value indicates a better model fit). Allowing the effect of mother's years of education is to vary does not lead to as much of an improvement (AIC drops by 541.4). The result is consistent with a diffusion process causing race's effect to vary across neighborhoods.

Second, we use the correlation of PBE rates across school types to test whether school- or district-specific factors are driving the spatial patterns. School- or district-specific factors should not affect different school types. Moreover, districts do not bound childcare centers. Figure 6 shows that high PBE rates among kindergarteners in a public school are associated with an increase in PBEs in nearby childcare centers. This result is consistent with the diffusion hypothesis. Unfortunately, we cannot test how much of this effect is driven by unvaccinated siblings attending different types of schools.

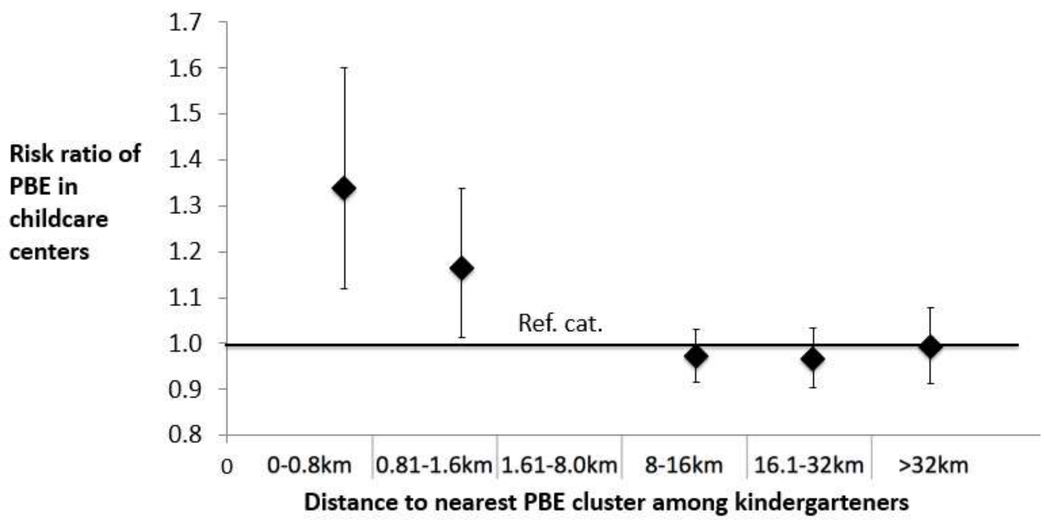

Figure 6. The effect of proximity to nearest PBE cluster across school types

Note: All IRRs estimated via negative binomial regression and adjusted for average mother's years of education, logged property values, logged block group densities, counts of physicians, chiropractors, acupuncturists, children with an autism diagnosis, and yearly indicator variables.

Third, results presented in Table S4 in the Supplementary Materials confirm our expectation for the effect of racial segregation. School PBE rates are higher in school districts where whites are more isolated than in districts with more opportunities of inter-group mixing. The effect is statistically significant even after controlling for percent non-Hispanic white, SES, and other covariates.

Figure 3I shows the 57 PBE clusters after adjusting for all covariates. The clusters comprise 80 charter and 316 non-charter public schools. 30 of the 35 single-school clusters consist of only one charter school, with an average PBE rate 17 times higher than the state overall. The other clusters consist of 2 to 171 schools. While less than 4% of non-charter schools have more than 10% of the children exempted in 2014, 14% of the non-charter schools in the multiple-school clusters have such high PBE rates. While it remains possible that some unmeasured local factors are driving the results, the presence of multiple-school clusters, as well as the high percentage (88%) of clusters with at least one charter school, indicates a potential spillover effect.

5. Discussion

The rise of non-medical exemptions means vaccinated children are increasingly exposed to non-vaccinated children (Buttenheim, Jones and Baras 2012). Outbreaks have started among exempted children and spread to others (CDC 1997; Parker et al. 2006; Sugerman et al. 2010). Although California banned PBEs in 2016 following a measles outbreak at Disneyland, many parents still oppose the law, and compliance can be an issue[2]. Parental decisions against vaccination and their effects continue to play out in many other states (Yang and Silverman 2015) and countries (Falagas and Zarkadoulia 2008).

This study aims to contribute to the existing literature on the relationships between demographic factors, social networks, and immunization. Specifically, we seek to explain the increase in PBEs, their spatial clustering, and the positive socioeconomic gradient by evaluating mechanisms underlying their spatial clustering. First, confirming previous findings (Jones and Buttenheim 2014), we find that traditional explanations focusing on health care access cannot explain current patterns of PBEs. Second, while the average level of SES in a school's vicinity has a positive effect on PBEs, it has limited effect on the broad spatial clusters. Despite the vaccine-autism hypothesis has a key role in starting the current anti-vaccine movement, there is not much of an overlap between the clusters of autism and PBEs. The effects of proximity to alternative medicine locations are similarly limited. Nonetheless, selection into charter schools and private schools has a substantial effect. Lastly, the percentage of non-Hispanic white has an unexpectedly large effect on the broad spatial clustering.

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[2] Some parents claimed to have falsified their children's immunization records, which led to heated debates in online forums. See https://www.theguardian.com/us-news/2015/jan/25/disneyland-measles-outbreak-anti-vaccination-parents, while vaccine-skeptical parents interviewed in a recent California newspaper article mentioned the possibility of obtaining a medical exemption for their child from an "underground" network of physicians

The last finding indicates that race/ethnicity is more than a mere indicator of SES. We find other evidence that is consistent with a diffusion process over racially homophilous social networks: (1) the effect of the percentage of non-Hispanic white varies more across space than maternal education's, consistent with the stochastic nature of complex diffusion; (2) the percentage of non-Hispanic white in a school's vicinity increases the PBE rate of children from low-income families enrolled in Head Start programs; (3) segregated white communities have higher PBE rates than mixed communities; (4) proximity to a PBE cluster increases PBE rates across institutional boundaries. Certainly, these are all indirect tests of diffusion. Nonetheless, alternative explanations, such as those focusing on compliance among ethnic minorities (e.g., Hispanics), may not be able to simultaneously explain the increasing trend, spatial variations, and socio-demographic profiles of PBEs.

To our knowledge, our study is the first attempt to separate the effects of residential sorting and diffusion of vaccine concerns in generating broad spatial clusters of PBEs. Understanding the causes of the spatial clustering of PBEs can help us form policies relevant to the social contexts. First, our results suggest that policy makers should be reminded that an unintended consequence of the charter school movement is the concentrations of exempted children in certain schools, which may have potential spillover effects to nearby schools. Second, a growing literature shows that social networks have a substantial influence on health-related decisions (see Smith and Christakis 2008; Valente 2010); our results indicate that vaccine decisions are not an exception. Anti-vaccine beliefs can be resilient to corrective information (Horne et al. 2015). However, network interventions (Valente 2012) that (i) target whole communities instead of individuals may facilitate norm changes and discourage spatial PBE clusters. (ii) Interventions utilizing existing social ties can be cost-effective in creating cascades of changes in behavioral changes, as demonstrated by the large "I voted" experiment on Facebook (Bond et al. 2012).

That said, the difficulties of identifying how much of a spatial pattern is caused by social influence versus other factors have been well discussed (e.g., Manski 1993). A limitation of this study is that we do not have access to individual immunization records, which would have allowed us to examine mechanisms at the different levels better. Even with individual-level data, it is not straightforward to isolate the effects of demographic factors in the presence of network autocorrelations—correlations in both behaviors and socio-demographic characteristics among network neighbors (DellaPosta, Shi and Macy 2015). However, given that PBEs are still relatively rare, administrative data can highlight the broad social patterns over time and space. Without direct measures of the social networks and vaccine beliefs, we cannot directly ascertain the social diffusion effects. Future studies combining epidemiological and individual-level data could shed light on the diffusion mechanisms.

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Supplementary Materials

Table S1. Correlates of PBEs among public school kindergartens, 5 year lag, 1998-2014[1]

	IRR adjusted only for years[2]	Sig.	95% C.I.		Fully adjusted IRR	Sig.	95% C.I.	
Average mother's years of education	1.535***	0.000	1.508	1.563	1.186***	0.000	1.159	1.214
Logged property values	1.673***	0.000	1.596	1.753	0.989	0.670	0.940	1.040
Logged block group density	0.669***	0.000	0.655	0.684	0.776***	0.000	0.759	0.792
% white (decile)[3]	1.344***	0.000	1.334	1.354	1.221***	0.000	1.208	1.233
Count of physicians	1.009***	0.000	1.007	1.011	1.004***	0.001	1.002	1.006
Count of acupuncturists	1.036***	0.000	1.029	1.043	0.998	0.509	0.991	1.005
Count of chiropractors	1.040***	0.000	1.035	1.045	1.026***	0.000	1.021	1.032
Count of children with autism diagnosis	1.010***	0.000	1.004	1.016	1.004	0.184	0.998	1.010

Note:

[1] 2-level random intercept negative binomial regression model with yearly observations nested in schools using 1998-2014 public school data; N= 89,550 school-years. Year indicator variables included but coefficients not shown. All independent variables lagged 5 years.†p ‹ .10; *p ‹ .05; **p ‹ .01; ***p ‹ .001.

[2] Adjusted for the effects of dummy indicators for year.

[3] Measured in 10% increments

Table S2. Three-level model for correlates of PBEs among public school kindergartens, 2006-2014[1]

	IRR	Sig.	95% C.I.	
Average mother's years of education	1.257***	0.000	1.222	1.293
Logged property values	1.294***	0.000	1.186	1.411
Logged block group density	0.910***	0.000	0.884	0.937
% white (decile)[2]	1.158***	0.000	1.143	1.174
Count of physicians	0.999	0.166	0.997	1.001
Count of acupuncturists	0.970***	0.000	0.962	0.978
Count of chiropractors	1.030***	0.000	1.025	1.036
Count of children with autism diagnosis	1.007*	0.025	1.001	1.012
Count of autism advocacy orgs (county)	0.996	0.105	0.992	1.001
Pertussis rate, ages 0-6, per 1000 (county)	0.962†	0.086	0.921	1.006

Note:

[1] 3-level random intercept Poisson model with yearly observations nested in schools within counties using 2006-2014 public school data; N= 49,153 school-years. Year indicator variables included but coefficients not shown. All independent variables lagged 6 years. †p ‹ .10; *p ‹ .05; **p ‹ .01; ***p ‹ .001

[2] Measured in 10% increments

Table S3. Effects of school type on PBEs among kindergartens, 1998-2014[1]

	IRR	Sig.	95% C.I.		IRR	Sig.	95% C.I.	
School type[2]								
Private schools					2.174***	0.000	2.074	2.279
Charter schools					3.347***	0.000	3.109	3.604
Average mother's years of education	1.144***	0.000	1.119	1.170	1.145***	0.000	1.121	1.170
Logged property values	1.081**	0.002	1.030	1.136	1.015	0.534	0.969	1.063
Logged block group density	0.829***	0.000	0.812	0.846	0.807***	0.000	0.791	0.823
% White (decile)[3]	1.211***	0.000	1.200	1.223	1.204***	0.000	1.193	1.216

Note:
[1] 2-level random intercept negative binomial regression model with yearly observations nested in schools using 1998-2014 public and private school data; N= 116,928 school-years. Year indicator variables included but coefficients not shown. Demographic variables lagged 6 years. †p ‹ .10; *p ‹ .05; **p ‹ .01; ***p ‹ .001.
[2] Reference category: public, non-charter schools.
[3] Measured in 10% increments

Table S4. Effect of racial isolation on PBEs, rates among public kindergartens[1]

	Adjusted IRR[2]	Sig.	95% C.I.	
Average mother's years of education	1.190***	0.000	1.163	1.218
Logged property values	0.986	0.592	0.937	1.038
Logged block group density	0.803***	0.000	0.786	0.821
% white[3]	1.135***	0.000	1.121	1.149
Count of physicians	1.005***	0.000	1.003	1.007
Count of acupuncturists	0.999	0.737	0.991	1.006
Count of chiropractors	1.024***	0.000	1.019	1.030
Count of children with autism diagnosis	1.005†	0.082	0.999	1.011
White isolation Index*100	1.013	0.000	1.012	1.014

Note:
[1] 2-level random intercept negative binomial regression model with yearly observations nested in schools using 1999-2014 public school data; N= 83,825 school-years. Demographic variables lagged 6 years. †p ‹ .10; *p ‹ .05; **p ‹ .01; ***p ‹ .001.
[2] Yearly indicator variables included, but coefficients not shown
[3] Measured in 10% increments