Re-visiting Socially-Optimal Vaccine Subsidies: An Empirical Application in Kolkata, India

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Abstract

Although it is well-known that vaccines against many infectious diseases confer positive economic externalities via indirect protection, analysts have typically ignored possible herd protection effects in policy analyses of vaccination programs. Despite a growing literature on the economic theory of vaccine externalities and several innovative mathematical modeling approaches, there have been almost no empirical applications. Analysts often cite the existence of a herd protection effect of unspecified magnitude to justify universal provision of vaccines without user charges, even though public health budgets are severely limited in many poor countries and private vaccine demand could contribute substantial revenue. Recent research in epidemiology and economics offers the promise of more nuanced policy analysis using field data from locations where vaccination programs are under consideration.

The first objective of the paper is to develop a transparent, accessible economic framework for assessing the private and social economic benefits of vaccination. We also describe how stated preference studies (e.g., contingent valuation and choice modeling) can be useful sources of economic data for this framework. We next demonstrate socially-optimal policies using a graphical approach, starting with a standard textbook depiction of Pigouvian subsidies applied to herd protection from vaccination programs. We also describe non-standard depictions of marginal social benefits that highlight some counter-intuitive implications of herd protection that we feel are not commonly observed in the applied policy literature.

We then illustrate the approach using economic and epidemiological data from two neighborhoods in Kolkata, India. We use recently published epidemiological data on the indirect effects of cholera vaccination in Matlab, Bangladesh for fitting a simple mathematical model of how protection changes with vaccine coverage. We use new data on costs and private demand for cholera vaccines in Kolkata, India and approximate the optimal Pigouvian subsidy. Although the analysis is not meant to provide definitive policy advice for the specific neighborhoods in Kolkata, we find that, if the optimal subsidy is unknown, selling vaccines at full marginal cost may, under some circumstances, be a preferable second-best option to providing them for free.

Keywords: vaccine policy, private demand, Pigouvian subsidy, cholera, Kolkata, user charges, herd protection
I. INTRODUCTION

It is well-known that many vaccines provide indirect protection to the unvaccinated. These “herd immunity” or “herd protection” effects have long been recognized in economics and policy. Economists will be familiar with the implications of this positive externality: individual vaccine purchasing decisions do not consider community-level benefits and vaccines will be under-provided in a competitive private market. The textbook remedy is a Pigouvian subsidy, which equates the marginal cost of providing an additional vaccine with the marginal social rather than marginal private benefits of an additional vaccine (Pigou 1920).

The theoretical literature on vaccine pricing and policy is robust and growing. Economists starting with Francis (1997) began to examine vaccination policies with the standard models used in mathematical epidemiology (SIR, or Susceptible-Immune-Recovered, see Anderson and May 1991). Extending earlier work by Brito et al. (1992), Francis argued that in some cases there may be no vaccination externalities although Gersovitz (2003) showed that more plausible modeling assumptions guarantee some level of externality. Most of these mathematical economic-epidemiology models tend, however, to make fairly restrictive assumptions (e.g., the vaccine is 100% effective with unlimited duration and in Francis (1997) no one in the population ever dies). Another key theoretical insight is a call for standard mathematical models to account for agents’ reactions to rising (or falling) prevalence (Kremer 1996; Geoffard and Philipson 1996; Philipson 2000). The evidence for this “prevalence elasticity” is growing. Using panel data on flu vaccine demand among the elderly, Li et al. (2004) found that demand increases following years with increased flu mortality: a result paralleling earlier work on flu by Mullahy (1999), on AIDS and condoms by Ahituv et al. (1996), and on measles by Philipson (1996). Another focus of this theoretical literature is on whether it is feasible and socially optimal to (globally) eradicate a disease (Barrett and Hoel 2003; Barrett 2004).

Despite the theoretical appeal of this field of vaccine policy modeling, very few people besides economists use or cite this work. Epidemiologists have typically been concerned with finding the critical vaccination coverage rate that will drive a disease to eradication (Longini Jr. et al. 1978; Fine 1993; Becker and Starczak 1997; Patel et al. 2005). They have also used models to find the allocation of a fixed supply of vaccines that maximizes the number of cases avoided (Becker and Starczak 1997; Patel et al. 2005). Galvani et al. (2007) expand upon this theme by embedding an epidemiological model into a

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1 Many authors use the term “herd immunity” to refer specifically to the conferral of immunity to another person through the shedding of the live, attenuated virus. For example, the brother of a child who received a live attenuated polio vaccine may be exposed to the attenuated virus through normal contact with his sibling and indirectly receive the vaccine. We use “herd protection” in this paper to denote the population-level indirect protection that occurs when vaccination removes susceptible individuals from the population and impedes disease transmission.
game theoretic framework. They find that although the elderly receive a higher utility from receiving a flu vaccine than children, society would be better off by preferentially vaccinating children who have a lower utility of vaccination but a higher transmission rate than adults.

The most common types of economic evaluations of vaccination programs (cost effectiveness or cost utility analysis) typically omit herd protection effects (Beutels et al. 2002). The few existing analyses that do model herd protection assume a constant uptake rate per year in infants or very young children and estimate indirect effects in the population as coverage of young children gradually increases with time (Lloyd et al. 2007; Welte et al. 2004; Lee et al. 2007). Accounting for herd protection effects can make flu vaccination programs much more cost-effective, especially when incidence is indirectly reduced for elderly age groups (Reichert et al. 2001; Patel et al. 2005; Lee et al. 2007; Lloyd et al. 2007).2 We know of no applied economic evaluations that use a social cost-benefit framework to account for the full range of social benefits that arise from herd protection and no papers that explore the relationship between user fees and herd protection.

This paper seeks to bridge this gap and has three objectives. The first is to present a simple and accessible economic framework for thinking about private benefits, social benefits, and vaccination externalities (Section II). The second objective is to point out several implications of herd protection that are not commonly recognized in the applied vaccine policy literature using a graphical approach (Section III). The third objective is to demonstrate how epidemiological field data on the indirect protection of cholera vaccines might be combined with economic field data on private stated demand for cholera vaccines to approximate the socially-optimal user fee (Section IV). The intent is not to provide a detailed economic evaluation and policy prescription for the site we evaluate (two slums in Kolkata, India); rather, we point out several limitations and data gaps along the way and suggest ways in which our approach could be made more rigorous for just such a policy study.

We acknowledge from the outset what some may perceive as a weakness: our analysis is not grounded in the mathematical language of SIR models but instead takes a different approach. It is a one-period static model (i.e., vaccinate today and count benefits and costs that accrue during the subsequent periods that the vaccine is effective).3 We do this to avoid as many restrictive assumptions as possible and to begin with the most flexible possible model of observed behavior (economic demand functions for cholera vaccines). We prefer to use general functional forms more accessible to readers who are unfamiliar with SIR models to describe the epidemiology of indirect effects. As we will discuss in

2 However, herd protection effects can also be detrimental if vaccine protection wanes with age and if the disease is more serious for adults than children, such as the varicella vaccine (Edmunds et al. 2002).
3 Although a dynamic model would be of great interest, a credible model would need data on how demand changes with prevalence over time (data we do not currently have). Also, demand in the first period may in fact be more representative of the true private economic benefits because prospective purchasers might be less likely to take into account the potential for indirect protection when they make their decision to purchase the vaccine.
Section IV, however, our simple approach gives similar epidemiological predictions to those from a full SIR model of cholera transmission (Longini et al. 2007).

II. MODEL

We begin by developing a static (i.e., one-period) model of vaccine costs and benefits that incorporates both the direct and indirect effects of a one-time vaccination program against some infectious disease such as cholera. The vaccine thus protects recipients and non-recipients for a period corresponding to the duration of its effectiveness. For ease of exposition, we assume the program targets a homogenous population of size $N$ with an average incidence rate per year of $Inc$ (e.g., annual cases per 1,000 people). We assume that the government may ask users to share some or all of the cost of the program through a user fee $p$.

A. Private demand

Vaccines reduce a person’s risk of infection. As with other goods and services, people value the risk reductions obtained from vaccination differently. Some may place little value on the vaccine because they feel that the disease itself is not serious or dangerous. Some may place a very high value on the vaccine because they believe their risk of infection is high—either because the disease is very prevalent in their community and/or because their behavior puts them at higher risk. Others may have had a case or death in their families and know the pain and suffering first-hand. Some people may be more risk-averse than others (or less able to cope with the financial costs incurred if they fall ill). Others might be primarily concerned with reducing their risk of dying: in one stated preference study in Beira, Mozambique, 54% of respondents told researchers that reducing their risk of dying from cholera was the most important benefit of vaccination, 28% reported avoiding “pain and suffering,” and only 18% cited avoided treatment costs or lost wages (Lucas et al. 2007).

Individuals will maximize their utility subject to a budget constraint. The utility function might have arguments for any or all of the above considerations and the budget would constrain spending on the vaccine as well as all other non-vaccine expenditures (including other risk reduction strategies) to the individual’s income and assets. Unfortunately, there is little empirical data on how private demand for vaccines is affected by most of the factors in the preceding paragraph.

Rather than focus on the analytical details of this utility maximization framework, we assume that agents are rational decision-makers, perhaps using a health production function approach (Grossman 1972), and move straight to an observable Marshallian demand relationship. We restrict the arguments of

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4 Unlike an SIR framework, we assume that everyone who is infected with the contagion contracts the illness.
the function to only two parameters: the user fee \( p \) and incidence \((Inc)\) of the disease. The probability that an individual will choose to be vaccinated is:

\[
(1) \quad P(p, Inc) = \Pr(Vacc=1| p, Inc))
\]

In a population with homogenous preferences for vaccines, this will also correspond to the fraction of the population who choose to be vaccinated, or the “coverage rate.”

The demand function \( D(p, Inc) \) maps user fees and incidence levels to the total number of people vaccinated by multiplying this coverage rate with the population size \( N \):

\[
(2) \quad D(p, Inc) = N \times P(p, Inc)
\]

Where would one find these Marshallian demand functions? Let’s begin by focusing only on estimating \( D(p, \cdot) \), or the relationship between price and demand, holding incidence constant. Estimating \( D(p, \cdot) \) from revealed-preference market data would require that some non-zero price was charged for vaccines and that these prices varied over time or space. One could then map changes in the quantity of vaccines demanded (or the total coverage rate) to the exogenous price changes and, controlling for other confounders on demand, estimate a demand relationship. However, vaccine user fees are uncommon, especially in developing countries, and policy analysts are unlikely to find such price variation. The researcher will probably be able to observe at most one point on the demand function, e.g., the number of flu vaccines purchased in 2006 when the economic cost of the vaccine to recipients was \( \$X \).

A second approach for estimating \( D(p, \cdot) \) is a travel cost approach. Even where vaccines are provided free, users may incur financial travel costs (i.e., fuel or bus fare) as well as the economic costs of time spent traveling to the vaccination site and waiting to be seen. Jeuland et al. (2007) estimated demand and willingness-to-pay for cholera vaccines with a travel cost approach using data from a vaccine trial and in-person interviews in Beira, Mozambique.

A third option for estimating \( D(p, \cdot) \) is stated preference (contingent valuation or discrete choice) studies. Stated preference studies have been routinely used in environmental economics for non-marketed goods or services (see Venkatachalam 2004 for a useful literature review of the method and its strengths and weaknesses) and have more recently been used for vaccines that are either locally unavailable (e.g., a cholera vaccine in Kolkata, see Whittington et al. 2007; Cook et al. 2007; Islam et al. 2007; Lucas et al. 2007; Kim et al. 2007; Canh et al. 2006), or have not yet been invented (e.g., an HIV/AIDS vaccine—Suraratdecha et al. 2005; Cropper et al. 2004; Whittington et al. 2003).
In these SP studies, respondents are first asked a series of questions about their knowledge and perception of the disease and then informed about the properties of the hypothetical vaccines, including the vaccine’s effectiveness in protecting them from the disease. In contingent valuation (CV) surveys, respondents are asked how many vaccines they would purchase (for themselves and their household members) if the vaccine were available at a convenient location at a price of \( p \). By varying \( p \) randomly across respondents, CV allows researchers and policymakers to map \( D(p, \cdot) \). Choice model or stated choice studies map \( D(p, \cdot) \) by asking respondents to make repeated choices between two or more different vaccine alternatives that differ in terms of their attributes (see Cook et al. 2007 for an example).

There are fewer tools for identifying \( D(\cdot, \text{Inc}) \), or the effect of incidence rates on demand. Several studies have estimated this prevalence elasticity for flu and measles vaccines with panel data, observing the effect of lagged incidence on vaccine uptake (Li et al. 2004; Mullahy 1999; Philipson 1996) and for condoms and HIV (Ahituv et al. 1993; Ahituv et al. 1996). Longitudinal, rather than cross-sectional travel cost or stated preference studies could theoretically estimate \( D(\cdot, \text{Inc}) \) if incidence changed over time, although we know of no such studies. Furthermore, no SP studies of private vaccine demand have varied baseline incidence levels as part of the information treatment. It would be time-consuming and difficult to convey this information in a household questionnaire, and unethical to mislead respondents about their baseline risk of infection. For the remainder of the paper we will rely on demand functions estimated using data from stated preference studies where respondents were asked about a vaccine that was \( \text{Eff}\% \) effective in protecting them and were not told about the possibility of indirect protection. Because they provide no information on prevalence elasticity, we will restrict prevalence elasticity to zero and drop that argument from the coverage function and the demand function for notational simplicity.

B. Epidemiology and herd protection

In the absence of indirect (herd) protection, \( \text{Eff} \) represents the probability that a vaccinated individual will be immune to the disease if exposed. This “direct protection” is independent of coverage rates and unvaccinated persons experience no reduction in their chances of contracting the disease, regardless of coverage. The duration of the vaccine’s effectiveness (in years) is \( \text{Dur}.^5 \) Without indirect protection, the total number of cases avoided in the population is:

\[
\text{(3) Cases avoided } = \text{Dur} \cdot \text{Eff} \cdot \text{Inc} \cdot D(p)
\]

\[
^5 \text{Effectiveness may also wane over time, an extension we leave for future work.}
\]
Since $Dur$, $Eff$, and incidence ($Inc$) are constants, the number of cases avoided is strictly proportional to the number of people vaccinated $D(p)$. Since this is a monotonically decreasing function of price, the number of cases avoided decreases as the user fee increases.

When a disease is transmitted primarily from person to person, vaccines will provide indirect protection by reducing the number of susceptible individuals who can spread the disease among both vaccinated and unvaccinated persons. For the illustrative purposes of this paper, we choose to use a simple model of how disease incidence changes as a function of coverage for both the vaccinated and unvaccinated individuals. We split the population into two groups (the vaccinated and the unvaccinated) and redefine the vaccine’s “effectiveness” (probability of protection from infection) as a function of coverage rates. The function $U(P(p))$ maps coverage rates into the probability that an unvaccinated person will be protected. Reducing the number of susceptibles in the population may also increase a vaccine recipient’s effective protection (where the vaccine is not 100% effective); we call this protection to the vaccinated $V(P(p))$. In the presence of herd protection, we replace the term $Eff$ in Eq. (2) with these functions $V(\cdot)$ and $U(\cdot)$, and the number of cases avoided per year is:

$$\text{(4) Cases avoided per year } = \left[ \text{CA vac}_p + \text{CA unv}_p \right] = [V[P(p)] \cdot P(p) \cdot N \cdot Inc + U[P(p)] \cdot (1 - P(p)) \cdot N \cdot Inc]$$

C. Economic benefits

A policy analyst using an economic criterion to design a vaccination policy would seek to maximize the net present value of total social economic benefits net of social costs. The demand function $D(p)$—observed in a stated preference survey in our example—characterizes the marginal private benefits. That is, $D(p)$ evaluated at some price $p_i$ is equivalent to the private value of the vaccine to those people who would just choose to acquire it at a price $p_i$ or lower. The total private benefits (or willingness to pay) that accrue to all people who chose to be vaccinated at a price of $p_i$ are their expenditures on the vaccine (shown in brackets in Eq. 4) plus their consumer surplus, which is the area under the demand curve between $p_i$ and $\infty$ (or, alternatively, up to some maximum “choke” price $p^\circ$).

$$\text{(5) Private Benefits to Vacc. (WTP vac) } = \left[ p_i \cdot D(p_i) \right] + \int_{p_i}^{\infty} D(p)dp$$

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6 This is, of course, uncompensated demand; the correct welfare-theoretic measure of benefits would be the compensating variation, or the area under the Hicksian compensated demand function. Since expenditures on vaccines are likely to be a small part of the consumer’s budget, we use the common assumption that income effects are small and Marshallian CS is a good approximation for Hicksian CV.
This WTP measure is comprehensive and will include respondents’ expectations about reductions in mortality risk, privately-borne treatment costs, pain and suffering, cost of traveling to be vaccinated, etc. These benefits need not be discounted explicitly to obtain present values: we assume respondents discounted the benefits from the vaccine that would accrue over the $Dur$ years the vaccine is effective in their WTP responses.

The total social benefits that accrue when $D(p_i)$ individuals are vaccinated have several additional components. If the public sector provides free or subsidized treatment for cases of the disease, society will benefit from reducing these public expenditures for each case avoided in both the vaccinated ($CA_{\text{vacc}}$) and unvaccinated ($CA_{\text{unvacc}}$). We refer to these social benefits as public cost of illness avoided ($PubCOI$):

$$\text{(6) Public COI Avoided} = \sum_{t=0}^{Dur} \left[ \text{PubCOI} \cdot \frac{(CA_{\text{vacc}} + CA_{\text{unvacc}})}{(1 + r)^t} \right]$$

Because some of these social benefits accrue in the future, we discount them over the duration of the vaccine at a constant real rate of $r$ to get present values.

We know that individuals who choose not to purchase the vaccine at $p_i$ have marginal private benefits less than $p_i$. They may, however, still value the risk reduction that they receive through indirect protection, and these private benefits to the unvaccinated should be included in the total social benefits of the program. Because we cannot use their answers to the contingent valuation survey to estimate these benefits, we add two categories of private benefits as constant values per case avoided in the unvaccinated: privately-borne costs of illness and avoided mortality risk.

Private costs of illness might be both financial (i.e., drugs, doctor visits, lost wages) as well as economic (opportunity cost of time spent waiting or caretakers’ time). We assume this is a constant ($PrivCOI$) per case avoided. We value reductions in mortality risk using a value-of-statistical-life calculation ($VSL$). We assume an average VSL for the entire population, and multiply this by the case fatality rate ($CFR$), or the probability that a person who contracts the disease will die from it. The present value of the private benefits that accrue to the unvaccinated are therefore:

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7 Why not simply use the area under the demand curve between 0 and $p_i$ as the measure of private benefits to the unvaccinated? Suppose that respondents are told in a SP scenario that the vaccine will be 50% effective. Suppose at $p_i$, 40% of the population choose to be vaccinated, conferring effective protection to the unvaccinated ($U(D(p_i))$) of 22%. To use this information, we would need to scale WTP to account for the difference between the 50% coverage offered to respondents in the CV survey and the (say) 22% indirect protection the unvaccinated receive.

8 The average VSL may change, though, as one moves along the demand curve since those who place a higher value on reducing mortality risk will be more likely to purchase the vaccine (increasing the average VSL accruing to the unvaccinated as $p$ increases).
There is one further complication. Thus far our approach has been to measure private benefits to the vaccinated (at $p_i$) using the private demand relationship and to measure social benefits by assuming constant values per case avoided through indirect protection. Recall, however, that stated preference respondents typically ask respondents about their WTP for a vaccine with a given efficacy ($Eff\%$). At high coverage levels, their effective protection—$V[D(p_i)]$—may actually exceed $Eff$, and respondents’ answers will not reflect the value of this higher level of protection unless respondents know about herd protection effects or are explicitly told about them in the valuation scenario. We remedy this by applying the same private values per case avoided as described above ($PrivCOI + VSL \cdot CFR$) to the additional cases avoided from effective protection levels larger than $Eff$:

$$
\sum_{t=0}^{Dur} \left[ \left( PrivCOI + (VSL \cdot CFR) \right) \cdot \left( V[P(p_i)] - Eff \right) \cdot D(p_i) \cdot Inc \right] / (1 + r)^t
$$

Combining Eqs. 5–8 gives the total social benefits of the cholera vaccination program. The first line of equation 8 describes private benefits to the vaccinated based on Marshallian demand (from responses to the SP survey); the second describes the private benefits that accrue to the unvaccinated from indirect protection; the third line describes public sector cost-of-illness savings from avoiding all cases; and the fourth describes the private benefits that accrue to the vaccinated when the effective coverage is larger than individuals’ beliefs about vaccine effectiveness.

$$
Total Social Benefits = \left( p_i \cdot D(p_i) + \int_{p_i}^{\infty} D(p)dp \right)
+ \sum_{t=0}^{Dur} \left[ \left( PrivCOI + VSL \cdot CFR \right) \cdot CA_{unvacc} \right]
+ (PubCOI \cdot (CA_{vacc} + CA_{unvacc})
+ ((PrivCOI + VSL \cdot CFR) \cdot (V[P(p_i)] - Eff) \cdot D(p_i) \cdot Inc) / (1 + r)^t
$$

Finally, another potential source of social benefits that individuals do not account for in their private valuations may be larger macromconomic-scale benefits from vaccination including higher educational achievement (Miguel and Kremer 2004), increased labor productivity, or increased tourism. These effects are very hard to measure for any one additional vaccination program but may be quite large in aggregate (Bloom et al. 2005); we omit them in our model.
D. Costs

For simplicity, we assume here that the vaccination program has constant marginal costs. We assume that there are no fixed set-up costs, resulting in constant average costs and no economies or diseconomies of scale in vaccination. The total economic cost of manufacturing, transporting, storing, and administering the full course of the vaccination (for multiple-dose vaccines) is a constant $C$ per fully immunized person. These costs are present values; all costs are incurred in the first year.

\[ \text{(10) Social Costs} = C \cdot D(p_i) \]

E. Optimal policies

The economic efficiency criterion is to maximize net economic benefits (total social benefits, Eq. 9, less total social costs, Eq. 10). By taking the derivative of this expression with respect to price and setting it equal to zero, we can find the optimality conditions that provide $p^*$, or the socially optimal user fee. This will occur when marginal social benefits are set equal to marginal social costs (this expression is provided in Appendix A). The next section demonstrates both well-known and less-well-known policy implications of these types of optimality conditions.
III. OPTIMAL VACCINE SUBSIDIES: A GRAPHICAL APPROACH

Figure 1 depicts a demand curve $D(p)$, which also represents the marginal private benefits (the change in total private benefits of vaccinating one more person). In Figure 1, some percentage of the target population ($N - Q^o$) place no private value on the vaccine. They might be indifferent between taking or refusing a vaccine with zero price, or might in fact place negative value on the vaccine if they were concerned about side effects, time costs, or travel expenses to obtain the vaccine. In a competitive private market, vaccines would be sold at the price which equates the marginal cost ($MC$, assumed to be constant in Figure 1) with the marginal private benefits. This maximizes total private net benefits and occurs at point $X$; $Q^o$ people choose to be vaccinated at this market price $P^o$.

Figure 1. Subsidy $(P^o - P^*)$ is optimal; vaccines at zero cost may be a preferable second-best alternative

Because of indirect protection, however, each additional vaccinated person reduces the risk for the remaining unvaccinated population. The shape and location of the marginal social benefits (MSB) curve will depend on the epidemiology of the disease as well as the magnitude of the social benefits discussed in Section II. The marginal social benefits curve shown in Figure 1 is illustrative only, and is not based on empirical data.

The economically efficient solution from society’s standpoint occurs at point $Y$ where $MC$ is equated with marginal social benefits. To reach the optimal number of vaccines $Q^*$ in the private market, the government must offer a Pigouvian subsidy $s = P^0 - P^*$. The gain in social surplus (net economic benefits) from lowering the fee to $P^*$ is the shaded area $C$. 
Suppose, however, that the policymaker cannot measure or identify the marginal social benefits. The government (or donor) might then decide that rather than guessing at the optimal subsidy, it will provide vaccines at zero price as a second-best solution. The number of people who would choose to be vaccinated will be \( Q^m \). Because the MC of vaccination is larger than the MSB for every person vaccinated above \( Q^* \), society will lose welfare (relative to the optimum) in the amount equal to the shaded area D. Providing vaccines for free will be a better second-best solution than selling them at market price when area C is greater than area D (as depicted in Figure 1).

A related question is whether a program which provides vaccines at zero price will provide positive net economic benefits. This will be the case when the total social benefits (the entire area under MSB to the left of \( Q^m \), or the area bounded by the origin-\( Q^m \)-Z-Pc) exceeds the total social costs of providing the vaccines (the rectangular area equal to \( P^* \times Q^m \)). This is the case in Figure 1 (area A+B+C is greater than area D). If the MC curve were shifted upward, as in Figure 2, the total social benefits could be less than total social costs (area A+B+C is much smaller than area D). A zero-price vaccination program would fail a cost-benefit test and would be a wasteful use of health resources.

**Figure 2.** Vaccines at zero cost do not provide positive social net benefits

![Graph showing the comparison between zero-cost and market-price vaccination programs.](image)

If a second-best vaccination program with a zero vaccine price failed a benefit-cost test, a common reaction might then be to abandon the use of the vaccine, but this misses an important point. Some fraction (\( Q^o \) people) place a high value on the vaccine and are willing to purchase it at the market price. Although it is easy to assume that this is simply a high-income subset of the population, these individuals may in fact be poor but have more experience with the disease, have a high perceived risk of...
being infected, or have other sound reasons for wanting to be vaccinated. If health decision-makers were to prevent the vaccine from being sold at marginal cost (through either the public or private sector), $Q^o$ people would not have the opportunity to purchase the vaccine, resulting in foregone private benefits equal to area A and additional foregone social benefits equal to area B (Figure 2).

It is also possible that selling vaccines at marginal cost would be preferable to both (1) providing the vaccine for free or (2) not selling the vaccine at all. Suppose a large fraction of the population places a high value on the vaccine, but that private demand then drops off fairly quickly. In addition, suppose that the herd protection effect was large at modest coverage rates: once a relatively small number of people are vaccinated, the disease incidence drops quickly and the number of infected is very low (although the number of susceptibles may still be high). In this case, when vaccines are sold at marginal cost, there is sufficient private demand to reach some critical level of coverage that confers large indirect protection to the remainder of the population. This situation is represented in Figure 3, where the social loss from providing vaccines for free (area D) is much larger than the social gain (area C). In this case, if the correct subsidy cannot be identified, selling vaccines at the market price would be a better second-best solution than providing them for free.

**Figure 3.** Selling vaccines at full MC is the preferable second-best solution

![Diagram](image)

Figure 4 shows a different situation where the marginal herd protection benefits are large even at high coverage rates. Here there is no subsidy that can induce the socially optimal number of people $Q^*$ to be vaccinated ($P^*<0$). Selling vaccines at the market price is clearly not the preferable second-best solution because MSB are larger than MC even at $Q^m$ (area $C_1$). The question now is whether a program with free vaccines (with $Q^m$ vaccinated) is a preferable second-best to a program that would provide

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additional monetary or non-monetary incentives for people to be vaccinated (including compulsory programs). Inducing between \( Q^m \) and \( Q^* \) people to be vaccinated would result in social welfare gains equal to the area \( C_2 \), but inducing more than \( Q^* \) people to vaccinate would incur welfare losses equal to area \( D \). This type of program would be the preferable second best when \( C_2 > D \).

**Figure 4.** Inducing higher levels of vaccination with incentives or compulsion is the preferable second-best solution.

The universal assumption that free vaccines are always socially optimal (or a preferable second-best solution) is unwarranted on economic efficiency grounds and in some cases may lead to unwise use of scarce health resources. Knowing which of these situations apply for a given vaccine in a given location is an empirical question. The remainder of the paper is devoted towards demonstrating an empirical framework for determining which “state of the world” exists in a specific policy context.
IV. APPLICATION—CHOLERA VACCINATION IN TWO SLUMS IN KOLKATA, INDIA

A. Cholera

Cholera is a water-borne bacterial disease characterized by intense, watery diarrhea. It is easily treated by quickly re-hydrating the patient with intravenous fluids; antibiotics are generally unnecessary and ineffective (Schaecter et al. 1998, Todar 2006). Cholera can kill a patient within 24–48 hours, though in practice cases are rarely fatal as long as patients have access to IV rehydration (best CFR estimates are on the order of 1%). Since \textit{Vibrio cholerae} lives in estuarine waters and has hosts besides humans, it is impossible to completely eradicate cholera. Once the bacteria crosses from the aquatic environment into an index human case, it may spread rapidly only where water and sanitation conditions are poor. Large population centers near estuaries with poor sanitation often have cholera endemically with cases occurring nearly every year and where a large fraction of the population has acquired some immunity through prior infection (examples include Kolkata (Calcutta), India; Matlab, Bangladesh; and Beira, Mozambique). “Epidemic” numbers of cases can occur where the population has no acquired immunity (i.e., refugee camps or after natural disasters) and where an index case passes into very poor water and sanitation conditions. For the purposes of this paper, we will focus on endemic cholera, where cases occur nearly every year.

One approach to controlling endemic cholera is the use of newly-developed oral cholera vaccines (OCVs). These vaccines have mainly been used in trials of effectiveness and to limit the spread of large outbreaks (Clemens et al. 1986; Clemens and Sack 1990; Sanchez and Vasquez 1994; Naficy et al. 1998; Calain et al. 2004; Calain et al. 2004; Lucas et al. 2005; WHO 2006). A promising vaccine appears to be the two-dose oral recombinant B-subunit (WC/rBS) type evaluated in a series of case-control studies in Bangladesh, Peru and Mozambique. Field trials in Bangladesh and Peru indicated 85–90 percent protection for 6 months followed by declining effectiveness to about 50 percent over three years (Clemens et al. 1986; Clemens and Sack 1990; Sanchez and Vasquez 1994); in Mozambique, effectiveness over the first year was 78 percent (Lucas et al. 2005). A variant of the vaccine (WC) is now safely produced and routinely used in Vietnam (Jamison et al. 2006).

B. Evidence for herd protection from oral cholera vaccines

Placebo-control trials are the gold standard in epidemiology because they eliminate problems such as yearly variation in incidence and potential differences between those who choose to be vaccinated

---

9 According to the WHO’s monitoring of cholera cases (WHO 2006), there were 131,943 cholera cases worldwide and 2,272 deaths, for a gross worldwide case fatality rate of 1.7%. Worldwide CFR from same source is 2.3%. This average, however, reflects wide differences in access to treatment: Naficy et al. (1998) use a CFR of 1% for treated cases but 30% for untreated cases. CFRs may also differ by age: Murray et al. (1998) use 0.7% for children under five years old but a much lower CFR (0.14%) for children over five and adults.
and those who do not. However, by ignoring herd protection effects for placebo recipients, these studies may underestimate the vaccine program’s community-level risk reduction relative to results from non-placebo controlled campaigns (Trach et al. 1997; Lucas et al. 2005; Thiem 2006). There has therefore been interest recently in re-examining evidence from placebo-control trials based on new techniques for estimating direct as well as indirect effects (Haber 1999).

One such re-examination was performed on data from a 1985 cholera vaccine trial in Matlab, Bangladesh (Clemens et al. 1986; Ali et al. 2005). The trials targeted all children between the ages of 2 and 15 as well as women older than 15 years. Vaccine coverage varied significantly within neighborhoods, called baris, from 28% to over 51% of the target population (Table 1) or 15% to 37% of the overall population in the bari. This variation allowed the authors to test for herd protection effects. They found an inverse monotonic relationship between the coverage rate and the incidence rate in a bari, such that incidence among placebo recipients declined as coverage increased (leftmost column of Table 1). This inverse relationship was also observed for children less than two years of age who were not eligible for vaccination (Ali et al. 2007). Herd protection effects are especially important for children less than one year of age because the existing vaccine is not considered safe for that age group and because their cholera incidence and diarrhea mortality rates are especially high, ICDDR, B (2005). Ali et al. also found evidence of borderline significance that incidence declined among vaccinated individuals as vaccine coverage increased.

Table 1. Cholera incidence in Matlab, Bangladesh, by coverage rates (Ali et al. 2005)

<table>
<thead>
<tr>
<th>Level of coveragea</th>
<th>Target Population</th>
<th>Vaccine recipients</th>
<th>Placebo recipients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Cases</td>
<td>Incidence (per 1,000)</td>
</tr>
<tr>
<td>&lt;28%</td>
<td>24,954</td>
<td>5,627</td>
<td>15</td>
</tr>
<tr>
<td>28–35%</td>
<td>25,059</td>
<td>8,883</td>
<td>22</td>
</tr>
<tr>
<td>36–40%</td>
<td>24,583</td>
<td>10,772</td>
<td>17</td>
</tr>
<tr>
<td>41–50%</td>
<td>24,159</td>
<td>11,513</td>
<td>26</td>
</tr>
<tr>
<td>&gt;51%</td>
<td>22,394</td>
<td>12,541</td>
<td>16</td>
</tr>
<tr>
<td>Total</td>
<td>121,149</td>
<td>49,336</td>
<td>96</td>
</tr>
</tbody>
</table>

a Percent coverage is defined as the fraction of the target population (women and children) who were vaccinated, not the fraction of the entire population (which would include men). The 1986 trial targeted 124,000 people from a total population of 188,000 (i.e., 66%).

We use the 10 data points highlighted in bold in Table 1 (5 each for vaccinated and unvaccinated subgroups) to fit relationships for disease reduction as a function of coverage. More details on the estimation approach are provided in Appendix B. To summarize, we first assume that the incidences for vaccinated and unvaccinated populations can be modeled with a set of two differential equations. We estimate the parameters for these differential equations by fitting them to the data in Table 1 using
ordinary least squares and non-linear least squares regression techniques. Using these exponential functions of incidence as a function of coverage, we can calculate the percentage reduction in incidence for both the vaccinated and the unvaccinated compared to a baseline of zero coverage. We call these percentage reduction functions “effective protection” functions (Figure 5); they correspond to the $V(\cdot)$ and $U(\cdot)$ functions discussed in Section II.

Figure 5. Effective protection for vaccinated and unvaccinated individuals based on Ali et al. (2005) data with SIR predictions from Longini et al. (2007)

We believe this functional relationship between coverage and protection levels is a useful approximation until more robust epidemiological models of disease spread and vaccine protection can be integrated with economic models. Indeed, a recent paper by Ira Longini and colleagues (2007) arrived at very similar predictions by applying a state-of-the-art SIR mathematical model to the same Matlab dataset (their predictions are plotted on Figure 5). Ideally, more sophisticated epidemiological models, given sufficient data, could also incorporate how herd protection effects differ within and between age groups.

C. Private demand, economic benefits and costs

We selected two urban slums in Kolkata, India as the site for the illustration of our cost-benefit calculations because of the wealth of new economic data on cholera collected there. With a combined population of 185,000 people, the Tiljala and Narkeldanga slums are both impoverished, densely-crowded
cholera-endemic neighborhoods with some of the world’s highest prevalence rates. We use data that has been recently collected in Kolkata on (1) the private economic benefits of cholera vaccines (Whittington et al. 2007), (2) baseline prevalence and vaccine cost data from a recent cholera vaccine trial which involved pre-vaccination surveillance (Deen et al. 2006; Sur et al. 2005; Lauria and Stewart 2007), and (3) public and private cost of illness collected as part of the surveillance activities (Poulos et al. 2007).

Private benefits

Our data on private demand and private economic benefits come from a contingent valuation (CV) survey that several of the authors carried out in 2004 in Tiljala and Beliaghata, a middle-class neighborhood (Whittington et al. 2007). We asked respondents about their willingness-to-pay for a cholera vaccine that was 50% effective and would protect them for three years. Specifically, we asked them how many cholera vaccines they would purchase for themselves and their household members if the price were $x$, with one of four randomly-assigned prices. We analyzed these count data as a function of price, income, and other socioeconomic characteristics using a negative binomial regression model (see Whittington et al. (2007) for a more complete description of the econometric approach). We gave respondents in Beliaghata overnight to think about their answers to reduce any interviewer bias or yea-saying. Like previous studies, we found that giving respondents time to think reduced average WTP (Whittington et al. 1992; Lauria et al. 1999; Cook et al. 2007).

We model private demand from this study as an exponential function with two parameters: a constant ($\alpha = 0.65$) representing the fraction of the population that would be covered if the vaccine were provided free, and a slope parameter ($\beta = -0.28$) representing the response to price.

\[
\begin{align*}
\text{(11) Coverage levels} & \quad = P(p) = \alpha \cdot \exp(\beta \cdot p) \\
\text{(12) Total number vaccinated} & \quad = D(p) = N \cdot \alpha \cdot \exp(\beta \cdot p)
\end{align*}
\]

Vaccination Costs

The social cost of a cholera vaccination program is composed of three main components: (1) the cost of acquiring vaccines from the manufacturer, (2) the cost of delivering and administering the vaccine to the target population, and (3) the time and pecuniary costs incurred by household members to travel to the vaccination outpost and to wait to receive the vaccine. For acquisition cost, we assume vaccines can be purchased from manufacturers for US$0.45 per dose. Preliminary estimates from Vietnam suggest that production costs could be as low as US$0.40 per dose (Thiem 2006), and the International Vaccine Institute has received quotes of US$0.40–US$0.45 per dose for typhoid vaccine, which is made using a
similar manufacturing process (DeRoeck 2007). We add 15% for customs, shipping, and insurance, and assume 10% wastage of vaccines, making the total vaccine acquisition cost ~US$0.57 per dose.

Because there are no published estimates of the costs of administering cholera vaccines, we base our estimates on Lauria and Stewart’s 2007 literature review of 22 vaccine cost studies in low and middle income countries. Their best estimate for “delivery cost” in a low income country like India is US$0.5 per dose (see Jeuland et al. (2007) for a more detailed discussion of cholera vaccine delivery costs). There may be economies (or diseconomies) of scale in vaccination such that average delivery costs fall (rise) as the number of people vaccinated increase. Because there is very little data to attempt to identify this relationship, however, we prefer the simplicity of a constant marginal delivery cost measure.

To capture the time and pecuniary costs of traveling and waiting, we assume that every vaccine recipient walks 10 minutes to a nearby clinic (no financial transportation costs), where he or she spends 20 minutes waiting to be vaccinated. We value this time equally for adults and children at one-half the median hourly wage among our respondents in Tiljala (US$0.15). The economic costs of traveling and waiting to be vaccinated is therefore US$0.04 per dose (0.5hrs * US$0.075/hr).

The total social cost of providing the cholera vaccine is ~ US$1.11 per dose ($0.57 acquisition + US$0.5 delivery + US$0.04 traveling/waiting). Because immunization against cholera requires two doses, the total cost per vaccinated person is ~US$2.2. None of the three components of vaccine cost are known with a great degree of certainty; this estimate is our best approximation for the purposes of this paper.

Costs of illness

Before the cholera vaccine trial began in Narkeldanga, NICED and IVI conducted an extensive passive surveillance study in the neighborhood. Patients who presented with cholera symptoms at program health clinics provided stool samples for laboratory confirmation (Deen et al. 2006; Sur et al. 2005). Lab-confirmed cases were then asked to participate in a study examining the privately-borne costs of illness associated with their illness with cholera (Poulos et al. 2007). These household surveys covered direct financial costs (transportation, medicines, doctor fees, overnight stays, under-the-table payments, etc.) as well as direct and indirect economic costs (lost wages for patient and caretaker, value of time away from school for children). Poulos et al. (2007) found private COI to be US$5.3 for cases in children and US$6.5 for adult cases. Because our model does not distinguish between adult and child cases, we use a weighted average of US$5.5 because incidence is six times higher in children (Deen et al. 2006).

The publicly-borne cost-of-illness was estimated based on reported expenditures for treating 102 cholera cases at two Kolkata public hospitals: Kolkata’s Infectious Diseases and Beliaghata General
Hospital. Poulos et al. (2007) found public COI to be approximately US$15 for child cases and US$16 for adult cases. We use US$15 for our analysis.

Value-of-statistical life

Estimates of the value of a statistical life (VSL) are now available for a number of less developed countries. We extrapolate data primarily from two recent studies in Delhi, India (Bhattacharya et al. 2007) and Matlab, Bangladesh (Maskery et al. 2007). Both studies estimated VSLs in the range of US$30,000 to US$100,000. The Bangladeshi study examined parents WTP to reduce their child’s risk of death from disease. The Indian study examined commuters’ WTP to reduce risk of death from traffic accidents. Two other studies in India used a labor hedonic approach (Shanmugam 2001; Simon et al. 1999) and found much higher VSLs (US$370K–US$1.4M). Given that average incomes are very low in the two Kolkata slums, we prefer a conservative estimate of US$50,000.

Other parameters

Table 2 summarizes the parameters used for the illustration. We use a (real) financial discount rate of 8%. We assume that the information campaign would be sufficiently large that everyone in the two targeted slums would have heard about the availability of vaccines. We use an overall population incidence of 1.64 cases per 1000 per year based on the pre-trial surveillance study done in Narkeldanga (Deen et al. 2006).
### Table 2. Parameter values for two neighborhoods in Kolkata, India

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population</td>
<td>185,000</td>
</tr>
<tr>
<td>$\alpha$: coverage (%) at zero price</td>
<td>65%</td>
</tr>
<tr>
<td>$\beta$: response to price</td>
<td>-0.28</td>
</tr>
<tr>
<td>Incidence (per 1000)</td>
<td>1.64</td>
</tr>
<tr>
<td>Case fatality rate</td>
<td>1%</td>
</tr>
<tr>
<td>VSL</td>
<td>US$50,000</td>
</tr>
<tr>
<td>Discount rate</td>
<td>8%</td>
</tr>
<tr>
<td>Marginal cost per person</td>
<td>US$2.2</td>
</tr>
<tr>
<td>Private COI per case</td>
<td>US$5.5</td>
</tr>
<tr>
<td>Public COI per case</td>
<td>US$15</td>
</tr>
</tbody>
</table>
D. Results

Total private net benefits are maximized when the user fee is set to the full marginal cost of US$2.2 per person immunized (not per dose). At this fee, a relatively small percent of the population (35%, or 65,000 people) would be covered. This can be seen in Figure 6 as the intersection of MC and MPB, or in Figure 8 as the maximum of total net private benefits (solid black lines in both graphs). Because of herd protection, however, we estimate that this level of vaccination would avoid 242 of the 303 annual cholera cases (73%) in the two slums. Of these 242 cases avoided per year, 148 are among the unvaccinated.

Total social net benefits of the vaccination program are maximized at a price of US$1.7 per fully immunized person. The implied subsidy of US$0.5 increases coverage to 40%, preventing an additional 13 cases per year. At this optimal fee, the total social benefits of the program are US$677,000. Most of the total social benefits come from private benefits to the vaccinated (WTP\textsubscript{vacc}) and from reducing mortality risk in the unvaccinated (Table 3). Because both public and private costs-of-illness per case are not large, these categories of benefits do not contribute much to the overall total, and the conclusions are not sensitive to different parameter estimates (i.e., optimal subsidy barely changes when public and private cost of illness per case are doubled). If we use a VSL estimate of $25,000 (half our base case estimate), however, the optimal subsidy falls to US$0.35 (coverage = 39%). With a VSL estimate of $100,000, the optimal subsidy would be US$0.65 (coverage = 42%).

<table>
<thead>
<tr>
<th>Benefits</th>
<th>(‘000US$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Private benefits for the vaccinated (WTP\textsubscript{vacc}, Eq. 4)</td>
<td>$394</td>
</tr>
<tr>
<td>Public COI avoided (vacc. and unvacc., Eq. 5)</td>
<td>$11</td>
</tr>
<tr>
<td>Private COI avoided (unvacc., Eq. 6)</td>
<td>$2.2</td>
</tr>
<tr>
<td>Value of mortality risk reduction (unvacc., Eq. 6)</td>
<td>$201</td>
</tr>
<tr>
<td>Private COI + VSL (vacc. for Eff&gt;50%, Eq. 7)</td>
<td>$69</td>
</tr>
<tr>
<td><strong>Total Social Benefits</strong></td>
<td><strong>$677</strong></td>
</tr>
</tbody>
</table>
Figure 6. Marginal social benefits vs. marginal social costs of cholera vaccines in two slums in Kolkata, India.

Figure 7. Cases avoided with increasing coverage

Figure 8. Total social benefits
What if the government or a donor did not have access to these estimates of optimal \( p^* \) and coverage rates? What if they decided to provide the vaccine for free? First, such a program would probably produce net economic benefits. If vaccines are provided free of charge, we expect that 65% of the population would be vaccinated (the right-most point on the x-axis of Figures 6–8, which corresponds to \( Q^m \) in the graphs in Section III) at a cost to the government US$265,000. The program would prevent 286 cholera cases per year, or 94% of the cases expected to occur without vaccination.

How would the welfare loss associated with providing the vaccine for free compare to the social gain associated with increasing coverage above the market outcome of 35%? Put differently, can we compare the size of area D with area C in the graphs in Section III to determine whether selling at market price or providing vaccines for free is the preferable second-best? The total net social benefits at the market outcome (\( p=2.2, \text{cov}=35\% \)) are US$508,000 (area A+B). At the socially optimal price of \( p^*=1.70 \) per person and coverage of 40%, total social net benefits are US$512,000(area A+B+C). This makes area C equal to US$4,000, or the additional private and social net benefits of increasing coverage from 35% to 40%. For each person over 40% vaccinated, however, social costs now exceed the social benefits. With no user fee, 65% of the population is vaccinated, and the total social net benefits are $440,000. Area D is therefore $72,000 (US$512,000–US$440,000), much larger than area C. In this example, with this specific set of parameter values and with our assumed herd protection relationship, the preferable second best is to sell vaccines at market price rather than provide them free. This analysis also does not take into account the large difference in the financial requirements of funding a US$265,000 program in two neighborhoods when resources for health in India are very limited.

V. DISCUSSION

We begin with the limitations of our approach. First, most of the parameters involved are not known with certainty and a careful policy analysis would examine how sensitive our conclusions are to that uncertainty. Second, although we believe our epidemiological framework is a useful approximation, an agent-based SIR model would be preferable for policy analysis of indirect effects. Third, we extrapolate epidemiological effects observed in rural Bangladesh to urban Kolkata. On the one hand, one might that think indirect protection effects would be much higher in a densely-crowded urban area with more possibilities for interaction with infected patients. On the other hand, the control groups in Matlab lived in patrilinearly-related clusters (baris) where contact may actually be higher. Again, one would like to compare policy results using different specifications of the herd protection function to account for this uncertainty.

Finally, a dynamic model would have cholera vaccinations occur every three years or continuously through time where each member of the population would need to renew protection every three years. If we could identify prevalence elasticity, we could model how demand changes over time as...
direct and indirect protection lowers incidence. One might expect to see a cyclical pattern where demand is high initially but falls as cases disappear. This might continue until a point where a sufficient number of people are neither vaccinated nor have acquired immunity from previous infection and an outbreak occurs. This would drive demand back up in subsequent periods and repeat the cycle. In this respect, future research might incorporate perceptions of prevalence rather than assuming that the population accurately knows actual prevalence in the community.

Some in the health sector may not find this approach compelling. “Cholera affects the poor,” they might argue, “and we simply shouldn’t be charging people user fees for vaccines, regardless of what is the ‘social optimum.’” We understand that society may view vaccines as a special class of merit goods, one that everyone should have a right to, regardless of ability or willingness to pay for them. Donors may well view vaccines against a disease that afflicts people living in unhygienic conditions beyond their control as a moral obligation—or simply as a good gift. Some donors, though, will still be concerned that their resources are used most effectively for both health and non-health projects. They might also view their role as catalyzing health improvements in the short run while expecting that local governments will eventually take over financial responsibility for programs (GAVI 2004).

In this light, our analysis of costs and benefits of these two slum neighborhoods in Kolkata illustrate some important points. These neighborhoods are both very impoverished and have some of the highest cholera incidence rates in the world. Using the private benefit estimates arising from our stated preference work, a free program would pass a social cost-benefit test. Stated preference remains controversial, however, and many health policy analysts prefer to use either a cost-effectiveness approach or a cost-benefit approach that limits benefits to avoided treatment costs. Using standard techniques in cost-effectiveness analysis, we estimate that a free cholera vaccination program in Kolkata would cost ~US$3,200 per DALY avoided without herd protection, or $1030 per DALY avoided with herd protection (Jeuland et al. 2007). These are among the worst half of interventions listed in the Disease Control Priorities Project (see Figure 1 in Laxminarayan et al. 2006). This is driven largely by the relatively high cost (US$2.2 per person), the incidence of cholera (1.64/1000), and the low case fatality rate and cost of illness (because cholera cases do not last long and are easily treatable). Using a measure of economic benefits that includes only avoided public and private treatment costs, the social costs ($265,000) would greatly exceed social benefits even with indirect protection—roughly $17,700 without discounting, or 864 cases avoided over 3 years * ($15 + $5.5). We suspect that many donors or policymakers might find these economic indicators unattractive. A common reaction among health policy analysts might be to abandon cholera vaccination for Kolkata slums and focus on ensuring adequate treatment capacity when cases occur during the rainy season.

There is, however, middle ground between providing vaccines for free and not providing them at all. From an economic perspective, making vaccines available at full marginal cost (perhaps through government clinics or hospitals or during a mass campaign) would seem to be the preferable second best
option to not making them available at all. A policy of “market closure” would forego several hundred thousand dollars of potential economic benefits in Kolkata; and it is a common policy response by governments in many developing countries. It is worth emphasizing again that these potential benefits need not accrue only to “rich” households. Our stated preference studies show that income is only one of several determinants of private vaccine demand. Many non-rich households value protection from cholera for themselves and their families very highly and are prepared to pay for such protection.

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APPENDIX A: Optimal conditions for social benefits

No indirect protection

For the case in which there is no herd protection, without loss of generality, we rewrite \( q = N - P(p) = N \cdot \alpha \cdot \exp(\beta \cdot p) \), and the optimization problem is simply:

\[
\text{Maximize} \quad NB = p \cdot q - c \cdot q
\]

The first order condition (B2) which gives maximum net benefits can then be written and solved:

\[
\frac{dNB}{dp} = 0 = p^* - c \quad \Rightarrow p^* = c
\]

In this case, net benefits are maximized when the price (or marginal private benefit WTP) is set equal to the marginal cost of vaccination. This is the familiar market equilibrium.

Social Net Benefits with indirect protection

We next add the various components of social benefits (see Eq. 5–8 in main text) for the vaccinated and the unvaccinated due to herd protection effects. As above we write \( q = N \cdot P(p) \), and redefine \( V(q/N) = V[P(p)] \):

\[
\begin{align*}
\text{Maximize} \quad NB &= p \cdot q + \sum_{t=1}^{\text{Dur}} \left( \text{PubCOI} \cdot \left[ \left( CA_{\text{vacc}} + CA_{\text{unvacc}} \right) \right] \right. \\
&+ \Pr_{iv\text{COI}} \cdot \left[ \left( CA_{\text{vacc,herd}} + CA_{\text{unvacc}} \right) \right] \\
&+ VSL \cdot CFR \cdot \left[ \left( CA_{\text{vacc,herd}} + CA_{\text{unvacc}} \right) \right] / (1 + r)^{t-1} - c \cdot q
\end{align*}
\]

\[
\begin{align*}
&= p \cdot q + \sum_{t=1}^{\text{Dur}} \left( \text{Inc} \cdot \text{PubCOI} \cdot \left[ \left( V(q/N) - U(q/N) \right) \cdot q + U(q/N) \right] \right. \\
&+ \sum_{t=1}^{\text{Dur}} \left( \text{Inc} \cdot \left[ \Pr_{iv\text{COI}} \cdot \left[ U(q/N) - U(q/N) \cdot q \right] \right] \right. \\
&+ \sum_{t=1}^{\text{Dur}} \left( \text{Inc} \cdot \left[ VSL \cdot CFR \cdot \left[ U(q/N) - U(q/N) \cdot q \right] \right] \right. \\
&+ \sum_{t=1}^{\text{Dur}} \left( \text{Inc} \cdot \left[ \left( \Pr_{iv\text{COI}} + VSL \cdot CFR \right) \cdot \left[ \left( V(q/N) - Eff \right) \cdot q \right] \right] \right. \\
&\frac{(1 + r)^{t-1}}{(1 + r)^{t-1}} - c \cdot q.
\end{align*}
\]
The optimal solution is now:

\[
p^* = c - \sum_{t=1}^{Dur} \left[ \left( \frac{\text{Inc} \cdot \{\text{PubCOI} \cdot \{V(q/N) + V'(q/N) \cdot (q/N)\} \}}{(1 + r)^t} \right) \\
- \left( \frac{\text{Inc} \cdot \{Pr\cdot VSL\cdot CFR\} \cdot \{(V(q/N) - Eff) + V'(q/N) \cdot (q/N)\} \}}{(1 + r)^t} \right) \right] \\
\]

(A4) \[
= c - \sum_{t=1}^{Dur} \left( m_{\text{pubCOI},\text{unvacc}} + m_{\text{privCOI},\text{vacc, herd}} + m_{\text{VSL},\text{vacc, herd}} + m_{\text{pubCOI},\text{unvacc}} + m_{\text{privCOI},\text{unvacc}} + m_{\text{VSL,unvacc}} \right)/(1 + r)^t \]
APPENDIX B: ESTIMATING INDIRECT HERD PROTECTION EFFECTS

We assume that the incidences for vaccinated and unvaccinated populations can be modeled with a set of two differential equations. The first equation predicts incidence among the vaccinated subgroup \( v \) as a function only of coverage \( x \). We define coverage here over the entire population of the study area, not only the target population (which was 66% of the whole population). The second equation (for the incidence among the unvaccinated, \( u \)) is similar but modified so that incidence can never be higher in the vaccinated subgroup than the unvaccinated. The two equations are shown below, where \( kv \) and \( ku \) are rate constants.

\[
\begin{align*}
\text{(B1) Incidence among vaccinated:} & \quad v = v_o \cdot \exp(-kv \cdot x) \\
\text{(B2) Incidence among unvaccinated:} & \quad u = u_o \cdot \exp(-kv \cdot x) + (U_o - V_o) \cdot \exp(-ku \cdot x)
\end{align*}
\]

The parameters for Equation (B1) can be estimated with a simple OLS regression of each quintile’s percent coverage of the entire population\(^{10} \) on the log of incidence rates among the vaccinated. The intercept in this regression model \( v_o \) is 4.5 cases per 1000 \( (p = 0.03) \) and the rate constant \( (kv) \) is -0.029 \( (p = 0.10) \). The \( R^2 \) for the regression is 0.65. With the estimated parameters for Eq. (B1) in hand, we then estimate the parameters of equation (B2) with a simple non-linear least squares model. The \( R^2 \) for this model is 0.97 and the intercept \( (u_o) \) is significant at the 10% level \( (p = 0.07) \), but the rate constant \( (ku) \) has a p-value of 0.15. Rewriting Eqs. (B1) and (B2) with these estimated parameters gives:

\[
\begin{align*}
\text{(B3) } v(x) & = 4.5 \cdot \exp(-0.03 \cdot x) \\
\text{(B4) } u(x) & = 4.5 \cdot \exp(-0.03 \cdot x) + (13.6 - 4.5) \cdot \exp(-0.047 \cdot x)
\end{align*}
\]

Figure B1 plots the observed Matlab data against these exponential fits. As coverage increases, the incidence for unvaccinated individuals approaches that for the vaccinated subgroup. As coverage increases from 0 to 100%, the expected annual incidence for the vaccinated subgroup decreases from 4.5 cases per 1,000 persons to near zero cases, while the expected incidence for the unvaccinated subgroup similarly declines from 13.6 cases per 1,000 persons to near zero.

\(^{10}\) We take the average number of vaccinated people in each quintile by dividing the total number of vaccinees by the total number of eligible people (Table 1). We then adjust this to reflect the percent coverage for the entire population, assuming that the target population is 66% of the entire population. For example, in the first quintile in Table 4.5, 5,627 people were vaccinated from the eligible population of 24,494 (23%). This represents a total population coverage rate of 15% (23% * 0.66). We also fit a model using midpoints of the coverage quintiles but we preferred this approach because it fit the results from Longini et al (2007) better.
Using these exponential functions of incidence as a function of coverage, we can calculate the percentage reduction in incidence for vaccine recipients compared to a baseline of zero coverage (i.e. $u(0) = u_o = 10$ cases per 1,000 persons) with eq. (B3). The percentage reduction in incidence among the unvaccinated is calculated similarly, in eq. (B4).

\begin{align}
V(x) = \frac{U_0 - V(x)}{U_0} &= 1 - \frac{V_0}{U_0} \exp(kv \cdot x) \\
U(x) = \frac{U_0 - U(x)}{U_0} &= \left[1 - \frac{V_0}{U_0} \exp(kv \cdot x)\right] - \left[1 - \frac{V_0}{U_0} \exp(ku \cdot x)\right]
\end{align}

Figure B2 plots percent reduction in incidence (i.e. the probability of protection) for both vaccinated and unvaccinated individuals in the population using Eqs (B5) and (B6). Note that when coverage is near zero, the vaccine reduces incidence by about 67% (13.6 to 4.5). Thus, the inferred vaccine protection in the absence of herd protection would be about 65%, somewhat higher than the 50% protection level originally reported for the Matlab trial (Clemens et al. 1990).

As shown in Figure B2, the marginal change in effectiveness (or probability of protection) resulting from taking the vaccine is dependent on coverage. At low coverage, there is a greater private incentive to be vaccinated because the marginal increase in protection is large. At high coverage rates, though, more of the total protection derives from the indirect effects of herd protection, and the additional
protection from taking a vaccine is small. Thus, from a social perspective, the marginal benefit per vaccine distributed decreases monotonically based on our functional forms in equations (B1)–(B6) (this is shown in Figure B2 as dashed vertical lines showing the marginal benefits of distributing more vaccines at coverage rates of 10%, 30%, and 60%). Intuitively, the socially efficient outcome will equate this marginal benefit with the marginal cost of producing the vaccine, which may occur at some coverage rate between 0 and 100%.

**Figure B2.** Effective protection for vaccinated and unvaccinated individuals

![Graph showing effective protection for vaccinated and unvaccinated individuals](image-url)