

**Strategy for Determining Vaccination User Fees and Locations:  
A Case Study in Rural China**

Dohyeong Kim

A dissertation submitted to the faculty of the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of City and Regional Planning.

Chapel Hill  
2007

Approved by:

Dr. Dale Whittington

Dr. Donald Lauria

Dr. David Moreau

Dr. Harvey Goldstein

Dr. Yan Song

Dr. Marc Serre

©2007  
Dohyeong Kim  
ALL RIGHTS RESERVED

## **ABSTRACT**

DOHYEONG KIM: Strategy for Determining Vaccination User Fees and Locations:  
A Case Study in Rural China  
(Under the direction of Professor Dale Whittington)

Despite the enormous success of vaccinations in decreasing disease burden, there are still millions of deaths from vaccine-preventable diseases worldwide, especially in the developing world. The literature reports that people living in rural areas in China often fail to be immunized not only because of inability to pay user fee but also due to poor geographical accessibility to vaccination sites. However, the level of user fees and the locations of vaccination sites have not been systematically determined in vaccination planning practices, and little research effort has been dedicated to develop a scientific tool to design optimal vaccination strategies. This dissertation addresses important policy questions of how many vaccination sites are needed, where they should be located, and how much users should be charged, so as to maximize the outcomes of vaccination programs under budget constraints.

This research develops a decision-analytic tool to address these policy questions based on optimization models integrated with various quantitative techniques. The data were collected from a case study conducted in a rural area of southern China in 2004 with contingent valuation (CV) surveys to assess households' willingness to pay for typhoid vaccinations and using geographical information systems (GIS) to obtain location and road information. The data were used to estimate a household demand function for vaccinations which depends on user travel distance as well as the user fee. Using the demand information

in location models and simulations, this research demonstrates how the outcomes of vaccination programs change based upon the outpost locations and user fees, along with evidence of substantial private benefits brought about by locating outposts closer to users. It also estimates a cost function to show how much of the costs of delivering vaccinations are associated with the number of outposts and the range of vaccination coverage. All these results are integrated into an optimization tool to seek out the user fee and locations of vaccination outposts that meets specific policy objectives. Upon successful adoption and implementation in actual planning processes, this tool could play a critical role in determining user fees and locations for market-based public health vaccination services in developing countries.

## TABLE OF CONTENTS

LIST OF TABLES.....	viii
LIST OF FIGURES.....	x
Chapter	
1. Introduction.....	1
2. Literature review.....	10
2.1 Stated preference methods for vaccinations: contingent valuation (CM) vs. choice modeling (CM).....	11
2.2 Effect of travel distance on demand.....	14
2.3 Optimal location of vaccination sites.....	17
2.4 Cost of vaccination programs.....	22
2.5 Conclusions.....	26
3. Stated preference demand study for typhoid vaccinations in Daxu Township.....	27
3.1 Background.....	28
3.2 Study site: Daxu Township, Lingchuan County, Guangxi Province, China...32	
3.3 Research Design.....	36
3.4 Econometric models.....	42
3.5 Results.....	44
3.5.1 Characteristics of the sample.....	44
3.5.2 Knowledge and perceptions about typhoid .....	47

3.5.3	Demand for Vi Vaccines.....	47
3.5.4	Private benefits of vaccination.....	55
3.5.5	Comparison with the results of Poulos et al. (2006b)'s household CV study.....	58
4.	Simulation analysis examining the effects of user fees and vaccination locations on the vaccination program.....	61
4.1	Cell-based analytic framework.....	62
4.2	Extreme cases: vaccination in each cell vs. a mega-site at CDC.....	71
4.3	Set covering model.....	74
4.4	p-median model.....	79
4.5	Comparison of set covering and p-median models.....	83
4.6	Conclusion.....	86
5.	Estimation of vaccination delivery costs.....	88
5.1	Background.....	88
5.2	Cost estimation approach.....	90
5.3	Illustrative example.....	93
5.4	Cost summary.....	98
6.	Models for determining optimal user fee and locations.....	103
6.1	Optimization model for maximizing vaccination coverage.....	104
6.2	Parameter values.....	107
6.3	Solutions.....	108
6.4	Sensitivity analysis.....	112
6.4.1	Number of outposts.....	112
6.4.2	Parameters in cost and demand functions.....	119

6.4.3	Non-zero vaccine purchase cost.....	123
6.5	Maximizing cases avoided.....	125
7.	Use of optimization tools in vaccination planning processes.....	135
7.1	Use of optimization tools in planning contexts: Obstacles and resolutions...136	
7.1.1	Unawareness or distrust of the benefits of optimization tools.....	139
7.1.2	Complexity of political aspects with competing objectives.....	140
7.1.3	Lack of adequate communication and interaction.....	141
7.1.4	Shortage of expertise and resources.....	143
7.1.5	Uncertainty due to limited or unreliable data.....	145
7.2	Implementation guide for the optimization tool in vaccination planning in China.....	147
7.2.1	Adoption process: Justification of the tool.....	149
7.2.2	Implementation process: Three issues.....	154
7.3	Optimization-based vaccination planning as social learning.....	165
8.	Conclusion.....	169
APPENDICES .....		173
REFERENCES .....		187

## LIST OF TABLES

3.1. Design of the DOMI study in Lingchuan County, China.....	37
3.2. Demand elicitation questions used in the DOMI surveys in Lingchuan County.....	39
3.3. Variable definition and descriptive statistics.....	49
3.4. Results of Poisson regression: full and reduced model.....	50
3.5. Comparison of research designs and results: Poulos et al. (2006b) and this research.....	59
4.1. Road distances (in km) between source and destination cells.....	65
4.2. Mean and standard deviation of average income data.....	69
4.3. Outcomes of vaccination at CDC vs. in each cell.....	72
4.4. Results of the set covering models with different maximum distances.....	76
4.5. Results of the p-median models.....	82
4.6. Comparison of set covering and p-median models (if p=USD 1.0) .....	84
5.1. Assumptions for cost estimation by simulation.....	92
5.2. Predicted vaccinations (in hundreds) at price=0.....	95
5.3. Predicted number of vaccinations and required resources for each outpost.....	96
5.4. Estimated costs of vaccination program by category (5 outposts and free vaccination).....	97
5.5. Simulated outcomes for different vaccination program designs.....	98
6.1. Number of vaccinations and travel distance to 14 outposts in “globally-optimal” solution.....	111
6.2. Vaccination program outputs vs. number of outposts.....	113
6.3. Order of the outposts dropped out of “globally-optimal” solution.....	118
6.4. Sensitivity analysis by parameters in demand function.....	119



6.5. Sensitivity analysis by parameters in cost function.....	120
6.6. Sensitivity analysis by number of outposts: zero vs. non-zero cost of vaccine purchase.....	124
6.7. Output of two optimization models with different objectives (If $K = 6$ ).....	128
6.8. Output of two optimization models with different objectives (If $K = 3$ ).....	131
7.1. Possible vaccination alternatives by price and number of outposts.....	163
7.2. Desirable vaccination alternatives for different situations.....	164

## LIST OF FIGURES

3.1. Map of Daxu Township, Lingchuan County, Guangxi Province, China.....	33
3.2. Cumulative distribution of one-way distance to CDC (km): straight-line vs. road distance.....	46
3.3. Raw results: Average number of vaccinations per household by user fee and distance.....	48
3.4. Predicted number of vaccinations per household by user fee and distance.....	52
3.5. Average number of vaccines demanded for a household in each sampled village.....	53
3.6. Average per household demand for vaccinations at the CDC and at each village.....	56
4.1. Map of 29 cells and population size of each cell.....	63
4.2. Scatter plot of straight-line vs. road distances.....	64
4.3. Average annual household income for each cell (in USD).....	67
4.4. Cumulative distributions of average household incomes .....	68
4.5. Vaccination outcomes of two extreme cases by price.....	73
4.6. Optimal locations from the set covering models ( $p=USD 1$ ).....	78
4.7. Optimal locations from the $p$ -median models ( $p=USD 1$ ).....	83
4.8. Comparison of the results between set covering vs. $p$ -median models.....	84
4.9. Comparison of optimal locations by set covering vs. $p$ -median models.....	85
5.1. Map of 29 cells in Daxu Township.....	94
5.2. Locations of 5 outposts provided by $p$ -median model.....	97
5.3. Vaccination delivery costs vs. number of vaccinations (free vaccination).....	101
5.4. Average vaccination delivery costs vs. number of vaccinations.....	102
6.1. Locations of 14 vaccination outposts in “globally optimal” solution.....	109

6.2. Travel pattern to 14 outposts in “globally optimal” solution.....	110
6.3. Results of sensitivity analysis.....	113
6.4. Total benefits and costs vs. number of outposts.....	115
6.5. Association between the required price and the number of outposts.....	116
6.6. Percentage of travelers and travel distance by travelers vs. the number of outposts.....	117
6.7. Typhoid incidence in Daxu Township.....	127
6.8. Optimal locations from two optimization models.....	129
6.9. Optimal locations from two optimization models (If $K = 3$ ).....	131
6.10. Ranks of cells by population size vs. population weighted by incidence.....	132
6.11. Population size and population $\times$ incidence in each cell.....	134
7.1. Flowchart of implementation process.....	148
7.2. Hierarchy of vaccination systems in China.....	156
7.3. Interaction process between task force team and each level of the CDC agencies..	157
7.4. Results of the piecemeal approach (LP models by assumed price (USD)).....	159
7.5. Underlying mechanism in optimization process.....	162
7.6. Planning as social learning.....	167

## ABBREVIATIONS

BME	Bayesian Maximum Entropy
CDC	Center for Disease Control
CM	Choice Modeling
CV	Contingent Valuation
DOMI	Disease of Most Impoverished
EPI	Expanded Program on Immunization
GIS	Geographic Information Systems
IVI	International Vaccine Institute
LP	Linear Programming
OPLV	Optimal Price and Locations of Vaccination
OR	Operations Research
RMB	Ren-Min-Bi (Chinese currency)
USD	U.S. Dollar
WTP	Willingness-To-Pay

## **Chapter 1**

### **Introduction<sup>1</sup>**

Despite a century of prevention and control efforts, infectious diseases remain an important global problem in public health, causing over 16 million deaths each year (including HIV/AIDS). Infectious diseases are thought to account for nearly 25% of all deaths worldwide, occurring disproportionately in developing countries (World Health Organization, 2003). The costs borne by people with infectious diseases have strained private resources, diverting them from alternative investments that may improve standards of living. The negative impact of these diseases is exacerbated by the increasing prevalence of antibiotic resistant strains (Bahl et al., 2004). Some cases of these infectious diseases can be prevented by safe and effective vaccines, such as those against typhoid fever and cholera. The fact that other ways of intervention to reduce the diseases such as water and sanitation improvements are both expensive and unlikely to be used in the near future in the developing world underscores the importance of immunization. The size of the global market for vaccines for diseases in developing countries is growing rapidly at a rate of more than 20% per year. DeRoeck et al. (2005) discovered that there is significant interest in immunization for those diseases in developing countries among health decision-makers, although the lack

---

<sup>1</sup> This dissertation is part of the Diseases of the Most Impoverished (DOMI) Program, administered by the International Vaccine Institute (IVI) with support from the Bill and Melinda Gates Foundation. The DOMI program works to accelerate the development and introduction of new generation vaccines against cholera, typhoid fever and shigellosis. The Program involves a number of parallel activities including epidemiological studies, social science studies, and vaccine technology transfer. The results of the program will support public decision-makers as they make decisions regarding immunization programs for typhoid fever.

of public sector resources for immunization programs is expected to slow the introduction of national immunization programs.

In spite of the enormous success of vaccinations in decreasing the burden of morbidity and mortality caused by a variety of pathogens, there are still millions of deaths from vaccine-preventable diseases worldwide, especially in the developing world (Global Alliance for Vaccines and Information, 2005). For instance, typhoid fever remains a major public health problem in the developing world, causing an estimated 21-22 million cases and more than 200,000 deaths annually (Acosta et al., 2005). This situation is largely caused by the failure to implement vaccine delivery programs in a number of developing countries. As advanced technologies allow for the development of new vaccines against diseases for which no vaccines currently exist and improved vaccines against diseases for which a vaccine currently does exist, it is imperative that a vigorous effort is mounted to assure the delivery of such vaccines for the populations at risk (Fauci, 2001). Since the link between people and immunization can only be forged and maintained by an effective system of delivery, a careful choice of strategies for this delivery system is vital.

In recent years, numerous studies have attempted to identify the determinants of low vaccination coverage in developing countries. Xie and Dow (2005) examined the effects of child, household, and community health facility characteristics on child immunization rates in China, and found that the most important determinants were service price and maternal education. The education factor is one of the well-known determinants of vaccination rates (Streatfield et al., 1990; Rahman et al., 1995), but it is not directly associated with the design of delivery strategy and needs to be addressed within a broader policy framework to achieve vaccination objectives in the long run. Poore (1988) argues that two major problems have

confronted the delivery strategy of health services in developing countries: lack of funds and limited accessibility of susceptible populations to the services. Approaches to the lack of funds problem include user charge, taxation, better management of existing resources, reallocation of health resources, and increased funding from donor nations. Approaches to improve accessibility include frequent and convenient vaccination schedules, financial incentives, channeling by members of the community, and improved proximity to vaccination locations. Among these, much attention has been given to user fees in the literature.

Although the Addis Ababa Consensus (1997)<sup>2</sup> stated explicitly that immunization services should be provided free of charge to the consumer due to positive externalities<sup>3</sup>, user fees have been charged for most vaccines that were not added to the national immunization program in developing countries such as China (Jing, 2004). For such vaccines, setting the level of user fee is an extremely important decision for vaccination policy-makers because it affects the quantity of the vaccinations demanded by the households and ensures the financial sustainability of vaccination programs. Furthermore, it influences all relevant policy outcomes such as number of people vaccinated, revenue from and costs of vaccination programs, cases of disease avoided, and general cost savings incurred in situations where illness was prevented (i.e. cost of illness avoided). The existing literature presents much empirical evidence dealing with the effect of user fees on immunization rate (e.g. price elasticity of demand), program revenue and cost-recovery schemes, and health outcome.

---

<sup>2</sup> The Addis Ababa Consensus on principles of cost-sharing in education and health resulted from a forum convened under the auspices of the United Nations Economic Commission for Africa (UNECA), in collaboration with UNICEF (the United Nations Children's Fund) and the World Bank in Addis Ababa in June 1997. The forum addressed cost-sharing in the social sectors of sub-Saharan Africa.

<sup>3</sup> Positive externalities arise because immunization can benefit not only the immunized individual but also the population in which he or she lives. At high levels of coverage, immunization against a disease may stop the spread of the disease in the community, which is known as herd immunity.

However, the literature has also shown that immunization coverage depends on how vaccinations are delivered (Zhang et al., 1999; Zeng et al., 1999; Xie and Dow, 2005). Among other factors, proximity to vaccination sites or time needed to travel to the sites has been often associated with immunization coverage in less developed countries, particularly in rural areas. In this case, locations of vaccination services play important roles in determining relevant outcomes in vaccination policy. Researchers have also found that the costs of vaccination differ based on vaccination locations (Linkins et al., 1995; Routh and Khuda, 2000; Walker et al., 2004). These findings lead one to consider that a vaccination policy focusing only on user fees while ignoring the location factor is short-sighted and could produce distorted or undesirable outcomes, such as under-immunization in remote rural areas. If the number of vaccinations demanded depends on where vaccinations are offered and the cost of vaccine delivery is affected by the number and location of vaccination sites, important policy questions about vaccination delivery will be raised, such as<sup>4</sup>:

- (1) How many vaccination sites in a region (e.g. state, county, township, etc.) should be used to offer vaccinations?
- (2) Where should these sites be located?
- (3) Given the spatial configuration of vaccination locations and other factors, how much should users be charged for vaccinations?

These are the main questions that my dissertation research addresses. Answering these questions constitutes the goal of this research, which is to aid the development of

---

<sup>4</sup> Of course, the question “With what frequency should vaccinations be offered at the sites and clinics?” also would be important, but this question is not addressed in this research.



vaccination policy in developing countries by addressing two planning decision variables: user fees and distance to the vaccination delivery site. Of course, there are other factors that affect vaccination rates such as user's or parental education and wealth (Gwatkin and Deveshwar-Bahl, 2001). However, these factors are not directly controllable by the government, and thus this dissertation limits its inquiry to the two planning decision variables, user fees and vaccination locations, which can be implemented in the design of vaccination planning once the best solutions are determined.

The effect of vaccination location on vaccine uptake has not been systematically addressed in prior research. Although demand studies have reported the negative effect of vaccination user fee level on demand for vaccinations (Whittington et al., 2002, 2003; Cropper et al., 2004; Suraratdecha et al., 2005; Canh et al., 2006; Kim et al., 2007), the effect of vaccination locations on demand has not been examined. Previous studies did not pay sufficient attention to the potential effect of vaccination location and simply mentioned in the contingent valuation scenario that vaccinations are offered at convenient locations. However, in reality, vaccinations have been delivered at different locations in most countries, and thus travel distance to vaccination locations varies across households, in particular in rural and remote areas. Once vaccination locations have been determined, some households might have to spend substantial time and costs to travel to them. For some households, the cost of travel to the vaccination site, including the opportunity cost of travel as well as actual travel expenses, might be a bigger economic burden than the vaccination user fee itself. In other words, the vaccination policy could be flawed if only the effect of user fees on demand is considered. Without careful consideration of vaccination locations, the quantity of the vaccinations demanded might be overestimated in remote rural areas. Therefore, it is

worthwhile to examine how the demand for vaccination is affected by location and how the location effect should be taken into account in policy decisions.

The five specific objectives (tasks) of this dissertation research are:

- (1) To assess whether or not user demand for vaccinations depends on the number and location of vaccination sites, and if it does, to what extent;
- (2) To determine where to locate vaccination sites in order to meet certain policy objectives, and examine how the number and locations of vaccination sites affect the potential outcomes of a vaccination program;
- (3) To estimate the cost function to investigate how delivery cost of vaccination is affected by the number of vaccination sites as well as vaccination coverage (the number of vaccinations);
- (4) To develop a methodology that can be used to find systematically the optimal user fee levels and locations of vaccination services in order to meet a specific policy objective;
- (5) To discuss how the optimization-based quantitative tool of this research can best be used in actual vaccination planning processes in developing countries such as China.

To address these objectives, this dissertation uses a case study of typhoid vaccination in a rural area of southern China as part of the Diseases of the Most Impoverished (DOMI) research program, which is administered by the International Vaccine Institute (IVI) and funded by the Bill and Melinda Gates Foundation. Data were collected in 2004 from

collaborative fieldwork by the Center for Disease Control (CDC<sup>5</sup>) officials in Guangxi Province, Lingchuan County, and Daxu Township in China, and researchers from IVI and the University of North Carolina at Chapel Hill.

The following chapters of this dissertation address the above five objectives. Chapter 2 is a review of the literature concerning four major topics in this research: (1) stated preference methods for estimating household demand for vaccination, (2) the effect of travel distance on the demand for vaccinations, (3) location models that have been used to seek the optimal spatial distribution of health services, and (4) costs of vaccination due to the spatial configuration of vaccination sites.

To deal with the first objective, Chapter 3 presents the findings from a contingent valuation study of household demands in Daxu Township, a rural township in southern China, focusing on the effects that user fees, distance to vaccination sites and household income have on the number of typhoid vaccinations demanded. The household demand survey data and geographic data collected in the fieldwork are integrated to estimate the demand function to assess the distance effect on household demand for vaccinations. The negative effects of user fee and distance, and the positive effects of income and household size on demand for vaccinations are highlighted in this private demand study since they underpin the entire research in this dissertation.

Relating to the second objective, Chapter 4 applies location models from the operation research (OR) literature to the case study for Daxu Township. The number and locations of vaccination clinics (also called outposts) are identified using two different

---

<sup>5</sup> Throughout this dissertation, the term “CDC”, an abbreviation of Center for Disease Control or Center for Disease Control and Prevention, has two different meanings: (1) the governmental institution of the CDC, and (2) the actual physical location of CDC office/clinic. To avoid ambiguity, when referring to the governmental institution of the CDC, terms such as “CDC agency”, “CDC staff”, or “CDC officials” are used. When it is used without any clarification, “CDC” denotes the physical location of the CDC office/clinic.

location models, set covering and p-median. A simulation approach predicts vaccination outcomes for different solutions, including the number of vaccinations, number of cases of illness avoided, total revenues from user charges, distance users have to travel, and so on. It also shows how the outcomes would change for different levels of user fees and locations of vaccination outposts.

Dealing with the third objective, Chapter 5 integrates data and information from the relevant literature to estimate a cost function for a mass vaccination campaign in Daxu Township. The function indicates how the cost of vaccination delivery changes with the number of vaccination locations and the number of people vaccinated. It also explores whether economies of scale or diseconomies of scale exist for the vaccination program in this township.

For the fourth objective, Chapter 6 develops the optimization models to determine the optimal level of user fee and outpost locations for a vaccination program in Daxu Township by using demand and cost functions estimated in the previous chapters. These formal optimization models employ mixed integer programming to determine the optimal user fee and outpost locations for two different planning objectives: maximizing vaccination coverage and maximizing cases of illness avoided. Sensitivity and regression analyses are performed to examine how the “globally optimal” solution compares with alternative solutions and how the solutions change with additional constraints and requirements.

Relating to the last objective, Chapter 7 deals with how the tool developed in the previous chapters for determining the optimal user fee and location of vaccination sites can best be applied in the vaccination planning processes in developing countries such as China. The chapter contains a review of the literature which examines how optimization tools have

been used in different planning practices in developing countries and identifies the obstacles standing in the way of adopting and implementing such tools. Based on this literature review, the chapter then includes a proposal. The proposal is a practical plan intended to encourage policy-makers to adopt the optimization-based tool of this research to their vaccination planning design. The chapter also includes suggestions dealing with how to address some of the key issues pertaining to the implementation of this tool using examples from the case study in Daxu Township.

The final chapter, Chapter 8, summarizes principal findings and major contributions of this dissertation research, and also mentions some key limitations.

## **Chapter 2**

### **Literature review**

This chapter summarizes the literature for four main topics of this research. Section 2.1 describes two stated preference methods that have been used to estimate private demand for vaccinations and compares them to each other. Section 2.2 gives an overview of demand studies for vaccinations that take into account location or travel distance, and then it summarizes studies of demand for other health services that take into account travel to the service locations. It focuses on the literature that shows the effects of accessibility on the quantity of health services demanded. Section 2.3 reviews the literature on the optimal location of vaccination and other service centers. Section 2.4 deals with the literature concerning how delivery costs of vaccination programs vary with the locations of vaccination clinics. It also reviews the literature that discusses how the costs of delivering other health services change with different spatial configurations for points of services. The last section, section 2.5, summarizes the entire chapter and highlights the gaps in this field of study that this dissertation addresses.

## 2.1. Stated preference methods for vaccinations: contingent valuation (CV) vs. choice modeling (CM)

Two different stated preference methods have been used to determine individual and household demand for vaccinations in developing countries: contingent valuation (CV) and choice modeling (CM). CV for vaccinations are frequently-used hypothetical approaches for eliciting information on private demand when vaccines are currently unavailable or not widely used (Whittington et al., 2002, 2003; Cropper et al., 2004; Suraratdecha et al., 2005; Canh et al., 2006; Kim et al., 2007). CV methods have been used to estimate vaccination demands not only for the respondent but also for entire households. Whittington et al. (2002) measured the private demand for a hypothetical vaccine against HIV/AIDS by using CV surveys with 234 adults in Guadalajara, Mexico, and found the mean willingness to pay (WTP) of the respondents to be about USD 670. Suraratdecha et al. (2005) also conducted a similar study for hypothetical AIDS vaccines with two different efficacies in Thailand, and revealed that the respondents' demand for both high and low efficacy vaccines is substantial. Again Whittington et al. (2003) conducted a CV survey, this time in Marracuene, Mozambique, to estimate adults' perceived economic benefits of avoiding malaria, and reported that the average respondent's WTP to avoid the risk of contracting malaria for one year was about USD 14.

In a different vein, Cropper et al. (2004) estimated a household demand function for a hypothetical malaria vaccine, and measured the household's maximum WTP to provide vaccines for all family members, which turned out to be about USD 36 per household per year. Canh et al. (2006) estimated private demand for typhoid vaccines with different

characteristics (i.e. efficacy and duration) in Hue, Vietnam for both the respondent only and all members of the household. Mean respondent WTP for a single vaccine ranged from USD 2.3 to 4.8, and mean household WTP ranged from USD 21 to 27. Kim et al. (2007) reported the results of a companion study for cholera vaccines in Hue, and found that mean respondent WTP for a 50% effective/3-year cholera vaccine was about USD 6 while mean household WTP was about USD 40 for the vaccine with the same attributes.

These studies have provided vaccination planners with economic data regarding potential vaccination coverage through the private market, predicted revenue based on user fees, and the economic benefits of preventing a disease. This information can be included in cost benefit and cost effectiveness analyses (Poulos et al., 2004). CV is the simplest stated preference technique (Johnson et al., 1996). When the scenarios given to respondents differ in terms of attributes (e.g. price, effectiveness), CV relies on comparing responses between the subjects in order to infer the importance of these attributes.

CM, however, has evolved in the context of market research and has been applied to non-market valuation as an alternative or complement to CV (Johnson et al., 2000). In general, a CM experiment asks respondents a series of questions to choose among multiple alternatives with different levels of attributes (including the status quo). CM can thus be used to estimate private household demand for vaccinations, and to explore the respondents' choice dynamics among different sets of attributes of the vaccine (e.g. efficacy and duration) and vaccination program (e.g. price and delivery method). CM thus provides researchers with tradeoff information about the attributes which helps in understanding what dynamics actually drive the respondents' choices, while CV typically offers more limited tradeoff information between a good or service in itself and its price (Stevens et al., 2000). Some



argue that the purchase decision exercise in CM is more realistic to the respondents and thus better simulates their purchasing behavior in the real market (Hall et al., 2004). However, most of the CM studies have estimated the demands only for an individual (e.g. respondent itself), not for an entire household. The development of CM methods in estimating household demands is still under development.

Relatively few studies explicitly compare the results of CV and CM studies. Boxall et al. (1996) reported that the demand estimates for the improvements at a wildlife management unit in Alberta, Canada were over twenty times higher using CV than CM. They concluded that the difference arises from the respondents who seemed to ignore substitution possibilities when answering CV questions. However, Adamowicz et al. (1998) measured passive use values for preserving caribou in Alberta, Canada and found that the differences of welfare estimates between the two methods were not statistically significant. Foster and Mourato (2003) examined the differences between CV and CM estimates of the value of charitable services in the United Kingdom. Unlike other comparison studies, they used a split-sample experiment (i.e. one part of the sample completed a CV question, while the other sample completed a CM survey), and found a statistically significant difference between the CV and CM results. They found that economic values to save the housing sector *alone* estimated by CV are more than ten times larger than those from CM, while values to save *all* charitable sectors for CM was almost five times larger for CV. They suggest that this difference is mainly due to an “adding-up” problem. They also found from the scope test much stronger evidence for sensitivity to scope in the CM approach than the CV approach.

Cook et al. (2007) compared the demand for cholera and typhoid vaccines using the CM approach with those from a companion CV study that was done concurrently in Hue,

Vietnam. They found the results are quite different. Overall, the CV welfare estimates are remarkably similar across different levels of attributes of vaccines (efficacy, duration), while the welfare estimates for the vaccines using the CM approach range more widely (i.e. much larger demand for the most effective and durable vaccine, but much lower demand for the least effective and durable vaccine). For instance, the estimated economic value of a currently available cholera vaccine (i.e. 50% effective for 3 years) from CM is much lower than that from CV, while the CM estimates are about two times higher than CV estimates for the most protective hypothetical vaccine (i.e. 99% effective for 20 years).

In summary, in the literature there seems to be no consensus on how CV and CM results differ and no clear explanation as to why they are different. However, the literature comparing CV and CM indicates that the two methods can produce significantly different outputs, depending on the characteristics of the estimated goods or services as well as demand elicitation scenario design and context of the study. For application to the case of vaccines, the results from the two methods could be different in the event that respondents had some knowledge and information about the characteristics of the vaccines they have already received or about the availability of other substitute vaccines with different characteristics.

## 2.2. Effect of travel distance on demand

This section investigates demand studies for vaccinations that have taken travel distance into account. Although a number of recent stated-preference studies have measured private demand for vaccinations, few private demand studies have explicitly considered

travel distance as a determinant of demand for vaccinations. Hall et al. (2002) used stated preference discrete choice modeling to examine how people in Sydney, Australia would demand the varicella (chicken pox) vaccination based on its attributes including the vaccination location. They found that provision of the vaccination at schools or early childhood clinics did not influence respondents' choices. However, while their study did address people's preferences about the types of vaccination locations, it did not deal with the direct effect of travel distance on vaccination demand.

There are a few other demand studies that have addressed the issue of accessibility, but they do not explicitly discuss the geographic accessibility to vaccination sites. Zhang et al. (1999) conducted surveys among people in an area in southern China that had both high and low quality immunization service delivery to find out which major factors were associated with immunization coverage. Their study found that providing multiple sessions frequently was the most effective way of improving accessibility for vaccinations, but it did not address the issue of spatial accessibility. Xie and Dow (2005) used longitudinal survey data to explore the determinants of child immunization in China, and found that rural travel time to a regular clinic was negatively related to immunization (i.e. the farther they had to travel to the clinic, the less likely they were to be immunized). However, travel time was measured by asking the respondents how long they traveled to usual sources of access to care, not to the actual places where vaccinations were offered. Thus, in their analysis, the travel time factor was used as a proxy for measuring availability of local health facilities, not for estimating the direct effect of travel distance to vaccination sites on the demand for vaccination.

Concerning health services other than vaccinations, a growing number of stated-

preference demand studies have recently been dedicated to the examination of the effect of location and travel cost on private demand. Among others, McIntosh and Ryan (2002) used a discrete choice experiment to estimate the residents' marginal rates of substitution between location, waiting time and travel cost for the provision of elective surgery in the United Kingdom. They found that the respondents would prefer their treatment with low waiting time and travel cost, although they did not measure the effect of travel distance on the demand for the health service. Clarke (1998; 2002) developed a contingent valuation scenario with two free mammogram alternatives in rural Australia, New South Wales. The first alternative involved using a mobile screening van that came to the women's own town (funded by paying higher taxes) while the second alternative required women to travel to a different town to have a mammogram at any time of the year. Clarke also used the travel cost approach to construct a demand curve for mammogram screening by using access costs, including travel time and expenses. Although his models implicitly found that people were less willing to seek services that required higher travel cost, the main goal of his analysis was to estimate the economic benefits of the service by using hypothetical taxes or travel cost. Thus, he failed to assess the quantity of service demanded using an objective measure of travel distance.

Although only a few stated-preference demand studies have focused on travel distance in estimating demand for health services, a number of studies analyzing service utilization data from health facilities have provided enormous evidence that the use of a health service depends on distance from a health facility. Since Acton (1975) initially emphasized the importance of non-monetary cost factors, such as travel time and distance, in determining the private demand for health services in the absence of user fees, numerous

studies have supported his argument by examining utilization patterns of public or private health facilities in developed or developing nations (Rahman et al., 1982; Muller et al., 1998; Noorali et al., 1999; Field et al., 2001). Among other things, Muller et al. (1998) presented a distance decay function for attendance at a rural health center in Papua New Guinea. Noorali et al. (1999) assessed whether use of government services for treatment of an acute childhood illness was influenced by the physical accessibility of the government primary health centers in a rural district of Pakistan. They found that children living near a governmental facility were less likely to use the facility than those living farther away. Yet this distance effect became insignificant after controlling for the effects of distance from a private facility and treatment cost. Field et al. (2001) showed the relationship between distance and utilization of the general practitioner surgery in the United Kingdom. They all highlighted the proximity factor as one of the primary determinants of use of health services, but their data were not based on an actual survey or experiment that was specifically designed to find out explicit distance effects.

### 2.3. Optimal location of vaccination sites

If distance is a determinant of the demand for vaccinations, it would be important to find out how it affects the optimal location of vaccination sites. The existing literature reports that vaccinations have been usually offered at three types of locations: (1) health centers or clinics, (2) homes of those being vaccinated, and (3) schools. In most developing countries, vaccinations are usually offered at designated health facilities, either as part of mass vaccination campaigns or in routine programs, except for school-based vaccinations for

school-aged children and occasional doorstep vaccination (i.e. house-to-house vaccination) (Zhang et al., 1999). However, there has been little evidence from research on which to base their decisions as to where to deliver vaccinations.

Models from operations research (OR) have often been used in problems to determine where points of supply should be located to be matched with points of demand. They involve simultaneously selecting a set of locations for facilities and assigning spatially distributed sets of demands to these facilities to optimize some specified measurable criterion (Rahman and Smith, 2000). The location models can be classified into three different kinds based on objective: set covering models, p-center models, and p-median models (Jia et al., 2005). Set covering models aim to minimize the number of facilities while providing coverage to all demand points within a specified maximum distance (Toregas and ReVelle, 1973). P-center models have an objective to minimize the maximum distance (or travel time) between the demand points and the facilities (Chen and Handler, 1993), while p-median models help locate a specified number of facilities so that the total travel distance or time between the demand points and their nearest facilities weighted by population size is minimized (ReVelle and Swain, 1970). The p-median model is often attractive since the smaller the total population-weighted travel distance or time, the more convenient for the users to get to the nearest facility, but it allows the facilities to be located beyond some maximum travel distance. When enhancing coverage in hard-to-reach areas is a central concern in locating facilities, the set covering model may provide a better solution since it restricts all users from traveling more than a specified maximum distance. To sum up, location models could provide a framework for finding the optimal number of vaccination sites, evaluating the effectiveness of existing decisions about location of vaccination sites, and generating

alternative sets of locations that would improve outcomes of vaccinations.

There is very little literature dealing with attempts to find out the optimal location of vaccination sites by using OR models. Only one article has been found which used OR models to optimize the locations of preventive health facilities. Verter and Lapierre (2002) developed a generic model to determine where to put health care facilities that provide preventive services such as childhood immunizations, flu shots, blood tests, and cancer screening exams. They let  $I (i \in I)$  denote the set of population centers and  $J$  denote the set of alternative facility sites. In general, the expected number of  $i$  residents who would seek services at facility  $j$  ( $c_{ij}$ ) can be determined as:

$$c_{ij} = f(d_{ij}^*/D) \cdot P \cdot h_i = (P - (P/D) \cdot d_{ij}^*) \cdot h_i \quad \text{eq. 2.1}$$

where  $D$  = maximum distance an individual would travel for preventive care

$d_{ij}^*$  = distance between population center  $i$  and facility sites  $j$  ( $D$  if it is beyond  $D$ )

$f(\bullet)$  = function of participation probability with distance;  $f(0)=1$ ,  $f(D)=0$ ; assumed linear

$P$  = probability of participation when travel distance is negligible

$h_i$  = number of residents in population center  $i$ .

The decision variables are  $y_j$  (1 if a facility is open at site  $j$ , 0 otherwise) and  $x_{ij}$  (1 if population center  $i$  is served by a facility at site  $j$ , 0 otherwise). Let  $S_{ij}$  denote the set of alternative facility sites, indexed by  $l$ , that are closer to population center  $i$  than site  $j$ . Let  $W_{\min}$  denote the minimum required workload at a facility. The following is a mathematical formulation of the preventive health care facility location problem.

$$\text{Maximize: } \sum_i \sum_j c_{ij} x_{ij} \quad \text{eq. 2.2}$$

$$\text{Subject to } \sum_j x_{ij} \leq 1, \quad i \in I, \quad \text{eq. 2.3}$$

$$\sum_i c_{ij} x_{ij} \geq W_{\min} y_j, \quad j \in J, \quad \text{eq. 2.4}$$

$$x_{ij} \leq y_j, \quad i \in I, j \in J, \quad \text{eq. 2.5}$$

$$x_{ij} \leq 1 - y_l, \quad l \in S_{ij}, i \in I, j \in J, \quad \text{eq. 2.6}$$

$$x_{ij} = 0 \text{ or } 1, \quad i \in I, j \in J, \quad \text{eq. 2.7}$$

$$y_j = 0 \text{ or } 1, \quad j \in J, \quad \text{eq. 2.8}$$

The objective of this model is to maximize the expected number of people who participate in preventive programs (eq. 2.2). The six constraints of the model are: (1) at most one facility can serve a population center (eq. 2.3)<sup>6</sup>, (2) the number of facilities is restricted to a level that produces an acceptable minimum workload at each facility (eq. 2.4), (3) a population center can only be served by an open facility (eq. 2.5), (4) each population center is assigned to the closest open facility (eq. 2.6), (5) the decision variable  $x_{ij}$  is binary (zero or one) (eq. 2.7), and (6) the decision variable  $y_i$  is binary (zero or one) (eq. 2.8). This model shows that they regarded proximity to facilities as an important factor in the success or failure of a preventive health care program. Their efforts constitute a step towards the development of a comprehensive framework for designing a system of preventive health care facilities, along with a mathematical formulation and alternative solution approach.

However, there are a few shortcomings of this model. As Verter and Lapierre (2002) remarked in the concluding section of their paper, more research is needed to better understand the factors that attract people to participate in preventive programs. The distance-participation function assumed in this model,  $f(\bullet)$ , was not based on actual data, but instead

---

<sup>6</sup> Eq. 2.3 indicates some population centers could be left unassigned if there are no open facilities within a maximum distance  $D$ .



they simply assumed its functional form and parameters. This limitation underscores an important role of the stated-preference demand study in location analysis for vaccinations as it improves the reliability of the location models by providing the demand function based on the actual survey data. Furthermore, their linearity assumption on the functional form of distance decay function in eq. 2.1 is not supported by other research in the field (Rahman et al., 1982; Farhan and Murray, 2006). Additionally, eq. 2.4 imposes an equity constraint of workloads among the open facilities, but it might be difficult to enforce it because some people may not want to be forced to receive services at a specific site assigned by government.

Unlike the scarcity of research done regarding vaccinations as mentioned above, a great amount of literature deals with the development of location models to optimize the locations of health facilities in the private and public sector (Abernathy and Hershey, 1972; Parker and Srinivasan, 1976; McLafferty and Broe, 1990; Drezner, 1990; Gusein-Zade, 1992). Recently, Revelle and Eiselt (2005) provided an in-depth review of the literature that uses location-allocation models in health service development planning in developing nations. Among other things, Oppong and Hodgson (1994) used location models to demonstrate that substantial improvement in accessibility can be achieved with better location choices and without additional facilities in Ghana. These models were upgraded by Moller-Jensen and Kofie (2001) by applying GIS-based data collection and analysis. They conducted location allocation analysis with two different objectives: to minimize total weighted distance and to maximize health coverage within 8 km. The distance-minimization model chose the locations that provide the lowest total weighted distance, while the coverage-maximization model found locations for new health centers in a way that ensures

that the fraction of people living within an 8 km distance limit is maximized. Their models were used to select optimal locations and provide statistics on average distance to health centers and percentage of population covered.

Rahman and Smith (1999) used location-allocation models to find the optimal locations for health and family welfare centers and community clinics in one “thana” (i.e. county) in Bangladesh, which has a population of tens to hundreds of thousands, to ensure that as many people as possible are within a specified maximum service distance. They showed that the implementation of their solutions would make a health delivery system 35% less costly, and thus their model results can be used as a guideline as to how health facilities should be deployed to maximize physical accessibility and population coverage. They chose the maximal covering location problem rather than a p-median problem because they argued that the p-median model would consider the whole population including those who might be too far from a facility. However, the maximum covering location model would be suitable only for locating the facilities providing routine health services of which service distances are well known. Furthermore, their models simply assumed that all people living within a maximum service distance are users of the services provided by the health facilities. This assumption, however, is often not true.

#### 2.4. Cost of vaccination programs

In countries with decentralized health systems such as China, the introduction or expansion of vaccinations that are not part of the national immunization program into the public health sector is likely to be financed by local governments. If subsidies are not

available, the program costs must be covered by the revenue from user fees and the cost savings available to public health services by reductions in disease incidence. Therefore, estimates of vaccination costs are needed for determining user fees to ensure the financial sustainability of the vaccination program.

Locating vaccination sites at optimal locations might increase vaccination coverage while using fewer vaccination sites, and thus save delivery costs incurred in the vaccination program. A number of cost or cost-effectiveness studies investigate how delivery costs are different by spatial arrangements of vaccination locations. Such information would be valuable to help in the determination of where to offer vaccinations. Compared to the limited amount of research dealing with how private demand for vaccinations is affected by location of vaccination clinics, there is a plethora of literature examining the costs and cost-effectiveness of vaccination programs according to the location where the vaccinations are delivered. Yet a majority of cost-related studies focus on how the costs of immunization change by the type or volume of immunization (Walker et al., 2004; Robertson et al., 1984; Phonboon et al., 1989), or vaccination schedule (Jacobson et al., 1999).

There are two studies that compare costs of vaccinations at home and at fixed sites. Linkins et al. (1995) compared the vaccination coverage and vaccination costs per child for house-to-house and fixed-site delivery in a mass campaign in Egypt. They found that the cost per child vaccinated was similar on average since house-to-house vaccination achieved high levels of vaccination coverage and reduced the amount of vaccine wastage in spite of higher personnel costs. However, for children at the highest risk of infection, vaccination cost was actually 25-50% less on a per-child basis using house-to-house vaccination since such children were less likely to visit fixed sites. They concluded that home delivery may prove to

be the most cost-effective eradication strategy by ensuring universal access to immunization. However, Routh and Khuda (2000) reported that unit cost per child care output, including child immunization, by doorstep provision (about USD 150) were found to be roughly twice as much as that by fixed-based provision at primary health care clinics (USD 50-80) in urban Dhaka, Bangladesh. But they remarked that the static-clinic based delivery of immunization services should be complemented with a scaled-down group of outreach workers with a redefined role of undertaking selective home visits to provide information and motivation to target segments. Although both of the two studies compare costs of vaccinations at fixed sites with those at home, the fixed sites defined in Linkins et al. (1995) were temporarily established for mass campaigns, while Routh and Khuda (2000) defined the fixed sites as primary health care clinics that are routinely available.

There are a few studies that compare the costs of delivering vaccinations at permanent routine sites with those of a mass campaign (Creese, 1984; Shepard et al., 1989; Brenzel, 1994). Creese (1984) showed that mass campaigns for polio immunization required less salaries and capital costs but more publicity and transportation costs in Brazil. Shepard et al. (1989) compared the costs and effectiveness of routine vaccination efforts conducted in medical facilities versus mass immunization campaigns, and found that the costs for fully vaccinating a child were USD 4.39 for routine services compared with USD 8.60 for mass campaigns. Those two vaccination delivery strategies should correspond with different spatial configurations of vaccination sites, but they did not report how much spatial factors (i.e. locations or distance) affected the difference in supply costs.

There are several studies that compare the immunization costs between fixed centers and mobile (or outreach, satellite) units (World Health Organization, 1979; Shepherd et al.,

1982; Phonboon et al., 1989; Brenzel, 1994; Khan et al., 2004). According to Shepherd et al. (1982), salaries took 62% of total costs of fixed-center immunization, while supervision and transportation costs were much higher with mobile immunization than with fixed immunization. Phonboon et al. (1989) showed that average cost per immunized child turned out to be smaller for fixed services than for outreach services. Brenzel (1994) reviewed seven cost and cost-effectiveness studies on three different delivery strategies of the EPI (Expanded Program on Immunization)<sup>7</sup>, and found that the cost per child who was fully immunized by the six EPI vaccines was highest for the campaign (USD 23.08 on average), followed by the mobile team (USD 19.24 on average) and fixed-facility immunization (USD 13.87 on average). On the contrary, Khan et al. (2004) estimated the costs of providing child immunization services in Bangladesh, and found that the outreach facilities provided immunization services at a much lower cost than the permanent static facilities. Khan et al.'s finding implies that the cost of immunizing children can be reduced significantly through better targeting.

Other than vaccination, a number of studies reported that the cost of delivering services changes according to the spatial configurations for points of services. Among others, Khan et al. (2001) provided a framework of incorporating a cost function into an OR location model. They showed that average facility-based costs tend to decline with increasing radius from emergency obstetric care facilities in Bangladesh. This supply-cost function was summed with the cost function incurred by households which tends to increase with the increasing radius of a facility's service area, which generates a U-shaped cost curve. In so

---

<sup>7</sup> In most developing countries, the EPI program is run by the Ministry of Health in close cooperation with WHO, UNICEF and other partners, and implemented in each region by the regional health bureaus. The six initial target diseases of the EPI program include diphtheria, tetanus, pertussis (whooping cough), polio, measles, and tuberculosis (WHO, 1989). All vaccines included in the EPI program were provided for free.

doing, they defined the optimal radius of a health facility at the minimum point of the aggregated average cost curve (i.e. 6 to 12 km). Their approach is quite impressive in the sense that it incorporates costs incurred by both health service providers and households into the model. However, their model is contingent upon a series of assumptions. In particular, it estimated the need for the services in the locality based on assumptions about the number of high-risk patients and the probability that they will use the facility. This might have created bias in estimating costs for households and for the health centers.

## 2.5. Conclusions

The purpose of the literature review in this chapter is to show both what has been done already and also to highlight what is left undone in the field of my dissertation research. I found that researchers have produced a great amount of evidence showing that accessibility or proximity is one of the most significant factors that determine the demand for health services. However, it turns out that only a limited amount of research has been done to explicitly measure the effect of travel distance on private demand for vaccinations. Recently, stated-preference methods have been used for estimating the private demand for vaccinations, but travel distance has not been incorporated into the methods to measure distance effect on vaccination demand. Furthermore, although there is a great deal of OR literature aimed at putting health facilities in optimal locations, relatively little research has been carried out on developing optimization models which can be applied appropriately to locating vaccination sites in developing countries.

## **Chapter 3**

### **Stated preference demand study for typhoid vaccinations in Daxu Township**

This dissertation research aims, among other things, at providing a viable and practical way of determining the best number of and most suitable location for vaccination sites in a specified study area. If user demand were not affected by where vaccination sites are located and how far users travel to get to them, the location of vaccination sites would not be in need of research. This research, therefore, starts by assessing the extent to which the demand for vaccinations depends on the location of vaccination sites and the distance users have to travel to be vaccinated.

To address this question, this research expanded on a case study in southern China undertaken by the University of North Carolina at Chapel Hill (UNC-CH) for the International Vaccine Institute (IVI) under the auspices of the Diseases of the Most Impoverished (DOMI) program. The major goal of that study was to assess the amounts of money households were willing to pay for typhoid fever vaccinations in Lingchuan County, China. My dissertation research focuses in on one of the most remote and mountainous areas in the county, Daxu Township, to investigate whether or not the demand for typhoid vaccinations depends on travel distance from the household's dwelling to the vaccination site, and if so, to what extent.

### 3.1. Background

China has made noticeable progress in its immunization status, yet problems still exist due to imbalanced regional development and shortage of funds (Xinhua News Agency, 2005). Vaccination status has regressed in some economically backward and remote areas and failed to reach national coverage targets. Many national and local reports in China have suggested that special attention should be given to immunization in rural and remote areas so as to make the vaccination projects beneficial to more people. Most researchers who have examined the reasons for the low immunization rate in China argue that vaccine price is a key determinant of low demand because users are charged fees in China for all vaccinations except in the Expanded Program of Immunization (EPI). However, the literature also shows that the location of vaccination sites is another important factor that affects vaccination coverage in rural China (see Chapter 2).

This chapter examines how much user demand is affected by a series of determinants, such as price of vaccine, travel distance, household income, household size, and so on, using data from a case study for vaccinations against typhoid fever in a rural township in China. Typhoid fever is still endemic in this area, but the proportion of people covered by vaccination is small. This township is a remote and mountainous region where villagers spend considerable time traveling to central health facilities, such as the CDC, where vaccinations are routinely offered. Travel distance might thus be an important factor when people make decisions about getting vaccinated if such vaccinations are offered far from their homes. This section first presents background information about typhoid fever and vaccines against typhoid fever, and then describes typhoid vaccination practices and their



costs in southern China to discover where and how typhoid vaccinations have been offered in the area and what costs have been involved in delivering vaccinations to users.

Typhoid fever is a systemic infection with the bacterium *Salmonella typhi*, and is usually transmitted by contaminated food or water (Parry, 2002). The incidence of typhoid fever has dramatically decreased in industrialized regions due to the provision of clean water and sanitary sewage systems, but the disease continues to be a major public health problem in many developing countries where sanitary conditions are still poor. The case fatality rate has been typically estimated at 1%, but sometimes reported up to 30% in some developing countries, even though they have access to antibiotics (Hessel et al., 1999; Crump et al., 2004).

There are two licensed vaccines available for typhoid fever immunization programs: Ty21a and the Vi polysaccharide vaccine (i.e. Vi vaccine). Ty21a is generally considered to be unsuitable for routine immunizations due to its widely varying effectiveness (53 to 95%), high price (USD 10-30 per series), and need for multiple doses (Ivanoff et al., 1994). The Vi vaccine is a new generation vaccine with a well-established safety profile and low incidence of mild side effects when administered alone or with other vaccines (Hessel et al., 1999). It is administered in one dose as an injection, with revaccination recommended after 3 years (Hessel et al., 1999). The price per dose is typically in the range of USD 1-5 in the public sector (USD 5-10 in the private sector) in Southeast Asia. Studies in endemic areas have found that the efficacy of the Vi vaccine ranges from 50 to 80% (Hessel et al., 1999; Yang et al., 2001). In most countries it is indicated for use in adults and children over 24 months of age, but its efficacy in very young children remains to be determined (Hessel et al., 1999). The Vi vaccine is widely held to be the best typhoid vaccine for use in public health

programs in developing countries (IVI, 2007).

In the past when the Vi vaccine was exported to developing countries, high costs were incurred for delivery and storage. However, the technology for production of the Vi vaccine has recently been transferred to Vietnam and India where the vaccine has been locally produced at a lower cost than the Western version in these countries (DeRoeck et al., 2005). Local production has an added benefit as it reduces delivery and maintenance costs. Once vaccines are produced, if a cold chain is not maintained from manufacture to the place of use, vaccine efficacy suffers greatly. While the Ty21a requires a strict cold chain (2°C to 8°C), the Vi vaccine is relatively heat-stable and has less stringent requirements, which is one of its distinct advantages. Immunogenicity of the vaccine is maintained after storage at 37°C for 6 months and at 22°C for 3 years. However, it needs to be stored in a refrigerator to minimize degradation (WHO, 2000).

In China, the Vi vaccine has been locally produced in six different vaccine production institutes, following a technology transfer from the United States National Institutes of Health (IVI, 2001). Some provincial and district governments in high-incidence areas have used the locally-produced vaccine in school-based campaigns financed by user fees (Acosta et al., 2005). In 1996, the Guangxi Zhuang autonomous region (i.e. Guangxi Province) in southern China, where Daxu Township is located, introduced the Vi vaccine for school-aged children and for use during typhoid outbreaks. However, since 2001, the Vi vaccine was no longer promoted or administered in school or routine immunization programs, and thus there have been very few Vi immunizations in the province. The vaccine is currently available only upon demand at major health facilities such as higher-level or township hospitals, municipal clinics and county/township CDC, which are mainly located in urban areas. Unlike

EPI vaccines, the Vi vaccines are not available in village clinics, where most households receive primary health care including EPI and other optional vaccinations. Although typhoid cases have been decreasing in this area over the past decade, there is still a large risk of typhoid outbreaks unless progress is made in improving environmental health conditions, health infrastructure, sanitary personal behavior, and vaccinations (Lin et al., 2003). Public health officials are considering mass inoculations using the Vi vaccine for all age groups to help prevent typhoid fever in high-risk populations in China. Guangxi province now plans to expand Vi vaccinations beyond school-based programs (DeRoeck et al., 2005).

To show the feasibility of mass immunization in controlling typhoid fever for both adults and children in areas with high incidence or potential of outbreaks, Yang et al. (2005) reported the logistics of Vi vaccination that targeted a population aged 5-60 years in Hechi City in Guangxi Province, China. Their campaign started with a pilot phase when a few clusters were initially vaccinated in order to test and fine-tune the system and for training. They reported that a large-scale vaccination program was then conducted at selected posts such as schools, health facilities, factories and town squares, although they did not provide the information on which criteria shaped their decisions as to how many posts to select and where to locate them. The Vi vaccination program yielded coverage of more than 70%. Those who were not vaccinated did not get vaccinated for various reasons, but it turned out that they were more likely to be adults living in remote locations. This result suggests that one of the major impediments to vaccination coverage would be proximity (or travel costs) to vaccination sites. In spite of knowing that vaccinations would be offered for free, some people apparently decided not to participate, perhaps because the location of vaccination sites was not convenient to them (Yang et al., 2005).

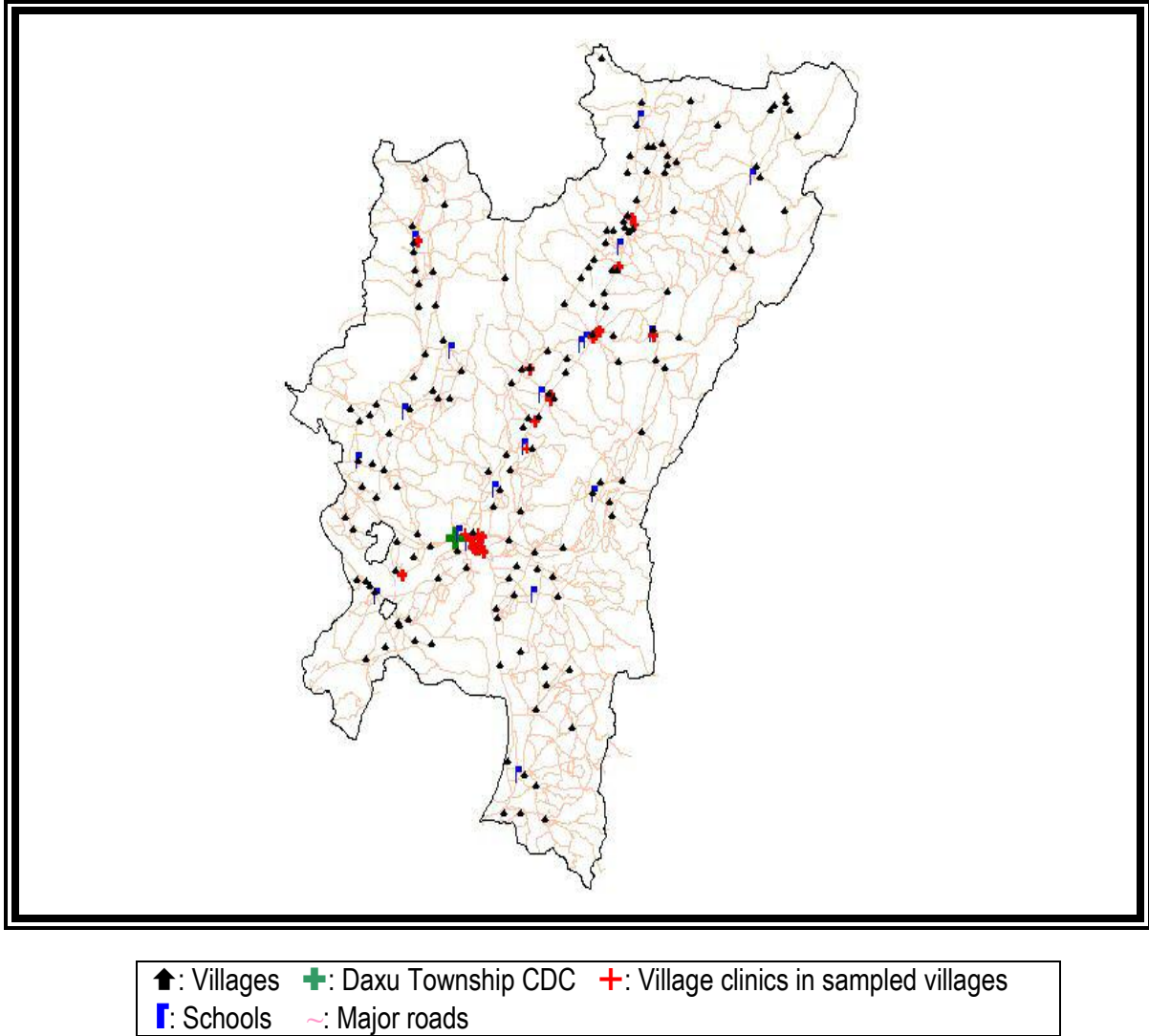
Unfortunately, there is no published article that reports the actual costs or cost-effectiveness of the Vi vaccination program in China. Instead of reporting actual cost data, Yang et al. (2005) argued that the Vi vaccinations through mass campaign were found to be affordable in China when the vaccine is locally produced. They provided information on the resources used and time required to vaccinate the target population. These data are helpful in estimating costs, at least approximately. During the campaign, each vaccination team consisted of a leader (physician), 1 to 2 vaccinators (nurses), a recorder (health workers), and 2 to 3 community helpers. A set of vaccination teams (5-10 teams) were supported by a vaccine storage manager, data manager, field health worker for home visits in the case of serious adverse events, driver, and supervisor. Each team vaccinated about 200 persons per day on average and covered 3 or 4 village clusters in about 30 days. Each vaccination team was equipped with 1 or 2 cold boxes (for storing the vaccines), injection supplies such as syringes, emergency kits, and one safety disposal box. All supplies, including the vaccines, were stored at the logistic hub at a centralized vaccination center which was equipped with refrigerators and freezers. Transportation from the center to the vaccination posts required a variety of modes of transport: by foot, bicycles and motorized vehicles (motorcycles, cars, buses or ambulances).

### 3.2. Study site: Daxu Township, Lingchuan County, Guangxi Province, China

Daxu Township is one of thirteen rural townships in Lingchuan County located in southern China. It is approximately 8 km wide and 16 km long, with 141 villages and approximately 54,000 inhabitants. Most of the villages are located in remote and mountainous areas, and are connected by major or minor roads. About 200-500 people live in

each village. The township CDC is located in the southern part of the township and village clinics are located in nearly half of the villages. Nineteen schools are located throughout the township. The map is shown in Figure 3.1.

Figure 3.1. Map of Daxu Township, Lingchuan County, Guangxi Province, China



The township CDC, where most vaccinations are available including the Vi vaccine, manages and controls all preventive health programs in the township. Most households

receive primary health care including EPI vaccinations at village clinics usually located at the center of the village. The typical village clinic is privately owned and located in its owner's home. These home-based clinics are usually staffed by one practitioner who is the owner of the clinic. Each clinic consists of two rooms, one for reception and the other containing one or two beds for those requiring a short stay. Village doctors, generally self-employed, sometimes rent a village clinic for their private or group practice (Anson and Shifang, 2005).

Lingchuan County is one of the high-risk counties for typhoid fever in China experiencing an outbreak almost every year (Chen et al., 2005). On top of that, Daxu Township has the highest incidence of typhoid fever in the county. From the years 2000-2004, there were 245 cases of typhoid or paratyphoid fever annually per 100,000 inhabitants in the township. While there is no detailed data on the age distribution of cases of typhoid fever in Lingchuan County, officials report that the majority of typhoid fever cases in China are found in 5-30 year olds (IVI, 2001). The risk factors for typhoid fever which is primarily waterborne in China (IVI, 2001) are still present in Daxu Township. Furthermore, Lingchuan County has a high and growing rate of antibiotic resistant *Salmonella typhi* and *paratyphi*. In most cases in China, patients of typhoid fever have to pay for treatment costs in full on their own unless they are enrolled in the EPI insurance program by paying about USD 4.3 annually (IVI, 2001). The government does not pay anything for treating cases of typhoid fever in China.

Although the Vi immunization programs were successful in reducing typhoid fever rates between 1996 and 2000, school-based immunizations and promotion were discontinued in 2001 in Lingchuan County. Since then the Vi vaccines have been available only on demand at the township CDC and used in response to outbreaks. They are not available from

village clinics nor delivered to residents' homes. People living anywhere in the township who want typhoid vaccinations have to travel to the township CDC. Due to the limited access to the Vi vaccines, the proportion of immunized persons has dropped off considerably in recent years (2001-2003) in this township. Since the Vi vaccine is only effective for three years, less than 10% of the population in this township was protected by the Vi vaccine in 2004, the year of our study. The Vi vaccine is sold for RMB5-6 (USD 0.6-0.7)<sup>8</sup> with an additional service fee of RMB2.5 (USD 0.3) for both adults and children in Lingchuan County. The profits earned from the service fee are distributed to the provincial, county, and township health centers (i.e. CDC agencies), as well as to village doctors (IVI, 2001).

The incidence data collected and managed by the Lingchuan County CDC staff do not separate typhoid fever and paratyphoid fever. However, Ochiai et al. (2005) reported that decreases in typhoid fever incidence rates in China coincided with an increase in the paratyphoid fever incidence rate. This trend of paratyphoid and typhoid incidences is also found in other areas of the world (Ochiai et al., 2005; Yang et al., 2001). The dramatic incidence shift from typhoid fever to paratyphoid fever from 1999 might be interpreted as an impressive success of vaccination since the Vi vaccine is effective only for typhoid fever, not paratyphoid fever. In fact, it is difficult to distinguish paratyphoid fever from typhoid fever without a blood culture test. In general, typhoid fever and paratyphoid fever are similar in presentation, and thus cases of paratyphoid fever and typhoid fever are indistinguishable, in most cases, to patients and even physicians without a medical test (Vollaard et al., 2004). However, they follow distinct routes of transmission. The risk factors for typhoid fever are mainly associated with the household (e.g. no soap for washing hands, no toilets), while

---

<sup>8</sup> The exchange rate in 2004 was USD1.0 = RMB8.2

those for paratyphoid fever are associated with things outside the household (e.g. food from street vendors, flooding). Incidence profiles are different between the two diseases: a majority of typhoid fever cases occur in school-aged children, while there does not seem to be a specific age group vulnerable to paratyphoid fever<sup>9</sup>. In spite of the differences, the patients of both diseases are treated about the same.

### 3.3. Research Design

In July and August 2004, as a part of the DOMI studies, fieldwork was conducted in Lingchuan County, Guangxi Province, China. The field research team included Drs. Christine Poulos, Xun Wu, Christine Boyle and myself, along with Chinese collaborators, Drs. Dong Baiqing, Gong Jien, and Yang Jin. I was involved in the entire process of field research, including interviewing CDC staff, developing survey instruments, training enumerators, supervising data collection in the field, developing data entry programs, and managing data entry. There are four different sub-studies in the entire DOMI stated-preference study in Lingchuan County, using different demand elicitation questions based on contingent valuation (CV) and choice modeling (CM) methods. These are included in two different kinds of questionnaires titled as “CV questionnaire” and “CM questionnaire”. Table 3.1 shows the entire design of the DOMI stated-preference study in Lingchuan County and also shows how they are different from each other.

---

<sup>9</sup> The recent paratyphoid outbreak in Lingchuan County occurred mostly in those between the ages of 15-30 years old.



Table 3.1. Design of the DOMI study in Lingchuan County, China

Title of questionnaires	“CV questionnaires”		“CM questionnaires”	
	<i>Individual CV</i>	<i>Household CV</i>	<i>Individual CM</i>	<i>Household CV</i>
Type of demand elicitation				
Sample size	951	638	300	160
Target area	5 townships and urban districts		3 townships and urban districts	Daxu Township
Vaccination locations	Nearest health facility vs. Home (Split sample)		Home vs. Vaccination center	Township CDC
Reference	Poulos et al. (2006a)	Poulos et al. (2006b)	Work in progress	This dissertation

The “CV questionnaires” included two types of demand elicitation questions: (1) asking a referendum question whether or not the respondent would be willing to buy a Vi vaccination for self or a child at a certain price (called *individual CV*), and (2) asking how many Vi vaccines the respondent would buy for the entire household at a certain price (called *household CV*). These surveys were administered in 5 rural townships (Daxu, Lingtian, Sanjie, Lingchuan, and Tanxia) and several other urban districts in Lingchuan County<sup>10</sup>. The respondents were told that vaccinations would be delivered at the nearest health facility, except for one sub-sample for which home vaccinations were offered. Split-sample design allowed the team to test whether or not the respondents prefer home vaccination to vaccination at the nearest health facility which on average was about 0.8 km away (see Appendix 1). However, it did not take into account the actual distance from the sample households to the nearest facility but just used a dummy variable indicating those who were offered the home vaccination option. The results from these studies are reported in Poulos et

<sup>10</sup> CV questionnaires were also used in six villages in Ziyuan County to address the issue of paratyphoid fever, but were not included here since they are beyond the scope of this dissertation research. See Poulos et al. (2006a) for details.

al. (2006a; 2006b). Poulos et al. (2006a) measured respondent's demand for the vaccine for himself separately from his demand for a vaccine for a specific child in the household in Lingchuan County. They reported that average WTP for a vaccine for himself was USD 9, and that for his focal child was USD 11. These results indicate that there is significant private demand for a vaccine to prevent typhoid fever in the area, and the private demands for improvements in children's health are higher than those for improvements in adult health. They also reported that delivery of the vaccines at the respondents' homes instead of the nearest health facility increases the probability of the respondents' willingness to purchase the vaccine for themselves by about 8%.

The "CM questionnaires" were collected in three rural townships (Daxu, Tanxia, and Lingchuan) and other urban districts in Lingchuan County. The "CM questionnaires" comprised eight sections: (1) demographic characteristics of the respondent and the household; (2) the respondent's health service utilization behavior; (3) perceptions and attitudes regarding typhoid fever; (4) perceptions and attitudes regarding vaccination; (5) choice experiments for individual demand, (6) "household CV" question; (7) socioeconomic information; and (8) the interviewer's assessment of the quality of the interview. The choice experiment (the 5<sup>th</sup> section) asked the respondents to choose for themselves (called *individual CM*) between the two alternative hypothetical vaccines against typhoid fever with different levels of effectiveness, duration, vaccination location, and price. For example, one alternative location of vaccination was home, and the other was a vaccination center. They were allowed to opt out (i.e. choose nothing) as well. However, the data from this choice experiment were not used in my dissertation research.

For my dissertation research, I chose Daxu Township as a case study site to investigate the effect of travel distance on stated demand for vaccination, as shown in the last column in Table 3.1. To the “CM questionnaires” used in Daxu Township, I appended the household CV question (the 6<sup>th</sup> section in the questionnaire as shown above) which is the same as the one in “CV questionnaire”. However, this household CV question used for my dissertation was asked after informing the respondents that Vi vaccinations would be offered only at the township CDC. Table 3.2 shows the four different types of CV and CM questions asked in Lingchuan County.

Table 3.2. Demand elicitation questions used in the DOMI surveys in Lingchuan County

Title of questionnaires	Type of demand elicitation	Actual question asked
“CV questionnaires”	Individual CV	If a Vi vaccine cost X, would you be willing to buy for yourself?
	Household CV	If a Vi vaccine cost X, how many vaccines would you buy for your household members?
“CM questionnaires”	Individual CM	Suppose typhoid vaccine A is X <sub>1</sub> % effective for Y <sub>1</sub> years, and offered at home for price Z <sub>1</sub> , and typhoid vaccine B is X <sub>2</sub> % effective for Y <sub>2</sub> years, and offered at vaccination center for price Z <sub>2</sub> . Which one would you choose for yourself? A, B, or neither?
	Household CV	If a Vi vaccine were offered at township CDC for price X, how many vaccines would you buy for your household members?

Among 141 villages in Daxu Township, 16 villages were randomly selected to be surveyed using the “CM questionnaires”. In each selected village, about 30-50 households meet our sampling criteria: (1) at least one child younger than 18 years of age lives in the household, and (2) either the head of the household or his/her spouse is younger than 65 years of age. Among the 30-50 candidate households in each selected village, ten households were chosen at random and either the head of the household or his/her spouse was randomly selected to be interviewed. As a result, 160 completed “CM questionnaires” were collected in

Daxu Township. Interviews took an average of 70 minutes. As explained above, this dissertation research uses the responses to the household CV question described in the last row in Table 3.2. The offer price ( $X$ ) was randomly assigned to each respondent from four different prices, RMB 2, 10, 40, and 120 (USD 0.24, 1.2, 4.8, and 14.4 respectively), and thus 40 surveys were collected per price using split samples. For the households that would buy vaccines, they were asked to indicate for which family members they would buy them.

Due to the survey design in which the choice experiment preceded the household demand question, there was a need to examine whether or not the responses to the household CV question were biased by the information given in the choice experiment. In the choice experiment, half of the respondents who were interviewed using the “CM questionnaires” were informed of hypothetical typhoid vaccines that would theoretically perform much better (i.e. 99% effective for 20 years) than the currently available Vi vaccine which was asserted to be 70% effective for 3 years. The other half was not informed of the nearly-perfect hypothetical vaccines. This information was used to test whether their responses were affected by the choice experiment.

Because the Vi vaccine is not effective for paratyphoid fever, the results of private demand study for Vi vaccination in Daxu Township where paratyphoid fever incidence rates are also high must be interpreted with caution. Thus, immediately after the household CV question, three debriefing questions were asked of all respondents to investigate whether or not their responses were influenced by their perception or knowledge of paratyphoid fever; (1) Have you heard about a disease called paratyphoid fever? (2) Is paratyphoid fever different than typhoid fever? and (3) If so, how is paratyphoid fever different than typhoid fever? Only 12% of respondents had heard about paratyphoid fever, but none of them was

able to distinguish between the two diseases, and thus all respondents were included in data analysis. This finding indicates that the respondents might have answered the demand questions based on their experiences with both diseases because they are very similar in symptoms. Poulos et al. (2006a) reported that the demand function in the area where paratyphoid fever rates are very high is similar to the demand function for vaccines in the area where there is almost no paratyphoid. This paratyphoid versus typhoid situation in Lingchuan County has little impact on the main thrust of this dissertation, which is the effect of vaccination location on demand for vaccination.

Along with the household surveys, global positioning systems (GPS) were used to collect location data for all sample households in Daxu Township and the township CDC. Most of the households were located close to each other within a village, and thus it was assumed that all households in a village are located at the center of the village in all subsequent analyses. I also obtained an electronic map of Daxu Township that includes the point data for the locations of all 141 villages in the county and the line data for road networks. Using the data in the ArcGIS program, straight-line distances and the shortest road network distances from each village to the township CDC were calculated. The two types of distances were compared to each other to examine how they were dissimilar. In the econometric analysis, the shortest road network distances were used for the value of travel distance assuming that people travel to the township CDC to receive vaccinations by the shortest road. In so doing, unlike Poulos et al.'s study, this research measures the effect of actual travel distance to the CDC on stated household demand in the model.

All together, the "CV questionnaires" were used in 14 villages and the "CM questionnaires" were used in 16 villages in Daxu Township, but never in the same village.

My dissertation research does not use data from the “CV questionnaires” with only one exception: household income data collected from 14 villages surveyed by the “CV questionnaire” were combined with those from 16 villages surveyed by the “CM questionnaires”. The combined income data from 30 surveyed villages were used to predict the household income for all 141 villages in Daxu Township, as described in Chapter 4.

### 3.4. Econometric models

Assuming the respondent is the decision-maker for a household, household demand for typhoid vaccinations can be estimated from the respondent’s stated preference for vaccinations as it relates to maximizing household utility in preventing the disease (Cropper et al., 2004). Thus, the respondent makes a decision on how many typhoid vaccinations ( $q$ ) he or she would purchase for all household members to maximize the utility for the household. It is assumed that the respondent’s decision relates to his or her socioeconomic characteristics, such as household income and household size, and the characteristics of vaccination such as user fee and travel distance to vaccination site. Like Cropper et al. (2004) and Canh et al. (2006), econometric analysis was used to fit a Poisson model to explain the number of vaccinations each household  $i$  would purchase ( $Q_i = q$ ) at user fee ( $p_i$ ), travel distance to the CDC ( $d_i$ ) (by road, not straight line distances), household income ( $I_i$ ), and household size ( $H_i$ ), which is as follows:

$$P[Q_i = q] = \frac{e^{-\lambda_i} \lambda_i^q}{q!} \quad (q = 0, 1, 2, \dots) \quad \text{eq. 3.1}$$

where

$$\lambda_i = \exp(\alpha + \beta_p \cdot p_i + \beta_d \cdot d_i + \beta_I \cdot \ln(I_i) + \beta_H \cdot H_i). \quad \text{eq. 3.2}$$

$Q_i$  is a random variable for the number of vaccinations that a household  $i$  would purchase and  $\lambda_i$  is the expected number of vaccinations that will be purchased by household  $i$  with income  $I_i$  and size  $H_i$ , if it were required to travel  $d_i$  and pay user fee of  $p_i$  for vaccination. Note that the model in eq. 3.2 uses the natural log of household income  $I_i$ . The dependent variable of the Poisson demand model is the probability that the household  $i$  will buy  $q$  vaccinations depending on  $\lambda_i$ , and the probability is assumed to be a random draw from a Poisson distribution with mean and variance of  $\lambda_i$ .<sup>11</sup> Note that  $\lambda_i$  is a continuous variable.

Using the Poisson regression function, the private benefits of vaccination can be calculated by a measure of WTP (willingness-to-pay). When price is zero, the WTP for vaccinating all household members in household  $i$  ( $WTP_i$ ) is the area under the inverse household demand curve<sup>12</sup> from the Poisson model in eq. 3.2. This area can be calculated by integrating the Poisson demand function over prices from zero to the choke price  $c$  less than infinity:

$$WTP_i = \int_0^c \exp(\alpha + \beta_p \cdot p_i + \beta_d \cdot d_i + \beta_l \cdot \ln(I_i) + \beta_H \cdot H_i) dp \quad \text{eq. 3.3}$$

$$= \frac{1}{\beta_p} [\exp(\alpha + \beta_p \cdot c + \beta_d \cdot d_i + \beta_l \cdot \ln(I_i) + \beta_H \cdot H_i)]$$

$$- \frac{1}{\beta_p} [\exp(\alpha + \beta_d \cdot d_i + \beta_l \cdot \ln(I_i) + \beta_H \cdot H_i)] \quad \text{eq. 3.4}$$

---

<sup>11</sup> The Poisson distribution has equal values of the mean and variance.

<sup>12</sup> This is a Marshallian demand function which assumes that the marginal utility of income is constant.

If price is not zero ( $p^* > 0$ ), the household WTP for the entire family is the sum of the expenditure on the vaccine and the remaining consumer's surplus, which is calculated as follows:

$$\begin{aligned}
 WTP_i = & p^* \cdot \exp(\alpha + \beta_p \cdot p^* + \beta_d \cdot d_i + \beta_l \cdot \ln(I_i) + \beta_H \cdot H_i) \\
 & + \frac{1}{\beta_p} [\exp(\alpha + \beta_p \cdot c + \beta_d \cdot d_i + \beta_l \cdot \ln(I_i) + \beta_H \cdot H_i)] \\
 & - \frac{1}{\beta_p} [\exp(\alpha + \beta_p \cdot p^* + \beta_d \cdot d_i + \beta_l \cdot \ln(I_i) + \beta_H \cdot H_i)] \quad \text{eq. 3.5}
 \end{aligned}$$

Both eq. 3.4 and eq. 3.5 include distance  $d_i$ , which indicates that the private benefits measured by the WTP would be different by locations of vaccinations (i.e. amount of travel to vaccination sites) as long as the coefficient of distance,  $\beta_d$ , is significantly different from zero in statistical analysis. The detailed mathematical derivations of the WTP are included in Appendix 2.

### 3.5. Results

The results from the contingent valuation study in Daxu Township are shown below.

#### 3.5.1. Characteristics of the sample

Forty nine percent of respondents were male, and their average age was 42 years. The mean household size was 4.5 persons, including 3.0 adults and 1.5 children. Median



household size was 4 persons, and half of sample households had only one child. The average respondent completed about 6 years of education, 54% did not complete primary school, 25% completed primary school only, 20% completed secondary school, and only 1% completed university or postgraduate studies. Twenty four percent of respondents could not read a newspaper. The average annual household income was USD 1,163 (about USD 3.2 per calendar day) mostly from farming, and nearly all respondents (98%) were farmers. Fifty two percent of households owned color televisions, 42% had a telephone, and 11% had a refrigerator. Eighty six percent of households had a bicycle, and 16% had a motorbike.

In this township, water and sanitation conditions were generally poor. Only 8% of households had a private water connection, and 74% drank water from private wells. Seventy seven percent used private or shared open pit latrines and 17% used a flush toilet. Sixty three percent of respondents reported that they normally boiled water before drinking, while 8% said that they never boiled drinking water. Eighteen percent of respondents said that they always washed their hands before eating. Sample households were on average 0.5 km from the nearest health facility, most of which were village clinics. They usually walked or rode a bicycle to travel to health facilities, but sometimes took a bus when they were located far from their homes.

The straight-line distances from each village to the township CDC show an average (mean) of 4.6 km (median = 4.5 km). By straight-line distance, about 31% of the sample households were located more than 5 km from the township CDC. By road network distance, mean one-way travel distance to the township CDC was about 6.3 km (median was 6.1 km), and more than half (56%) of the sample households had to travel more than 5 km one-way to the township CDC. The straight-line and road network distances were highly correlated with

each other (correlation coefficient = 0.98); on average, road network distance was 1.36 times as long as straight-line distance.

Figure 3.2. Cumulative distribution of one-way distance to CDC (km): straight-line vs. road distance<sup>13</sup>

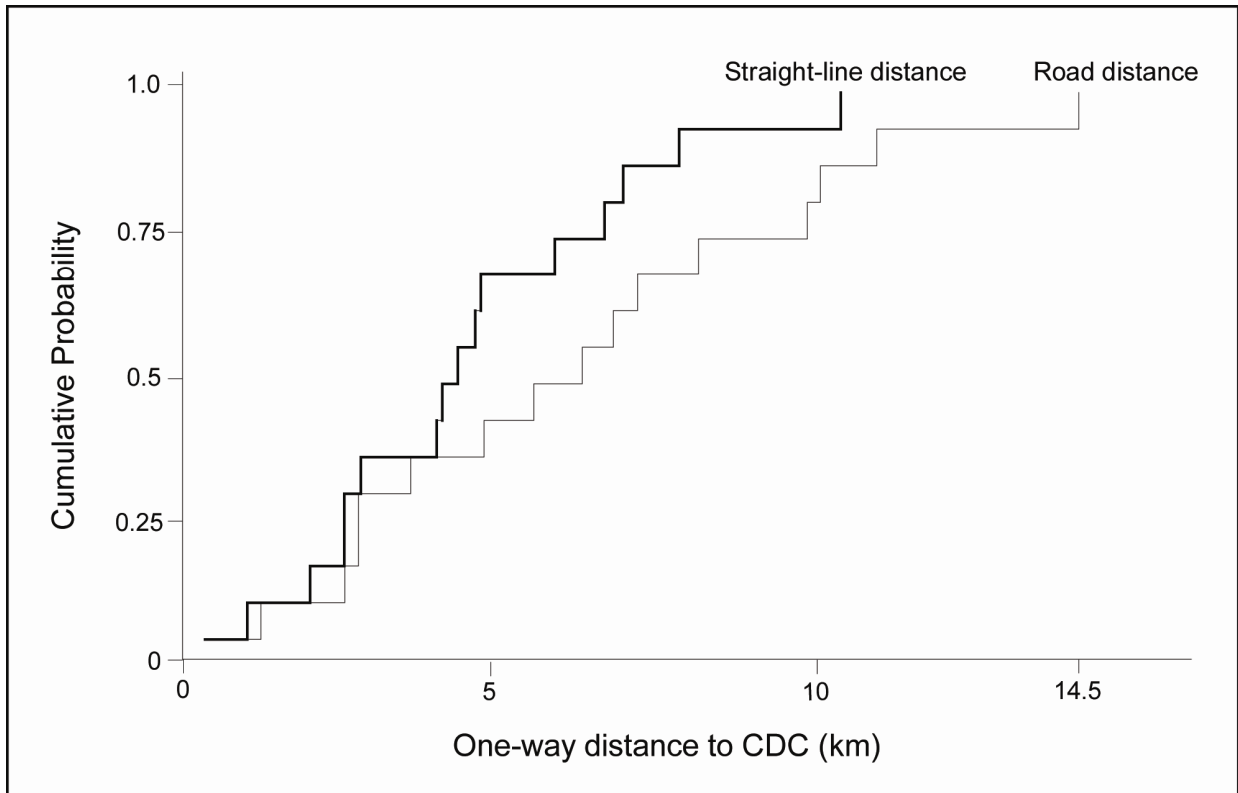


Figure 3.2 shows how the cumulative distributions of straight-line distances and road network distance to the CDC are different from each other. All the measurements presented in this dissertation are based on distances by the road network from the villages to the CDC.

<sup>13</sup> This cumulative distribution function is a step function because of the assumption that all sample household in a village are located at the center of the village.

### 3.5.2. Knowledge and perceptions about typhoid and vaccination

Ninety three percent of the respondents reported that they previously had heard about typhoid fever. Thirty one percent of the respondents reported that there had been an outbreak of typhoid fever in their villages. Although only about 9% of respondents believed typhoid was common in their villages, 64% reported knowing someone who has had typhoid fever, and 31% reported that a household member had actually contracted typhoid fever. Only 9% of respondents believed that it was likely they would get typhoid fever within the next three years, while 14% believed that it was likely their children would get typhoid fever within the next three years.

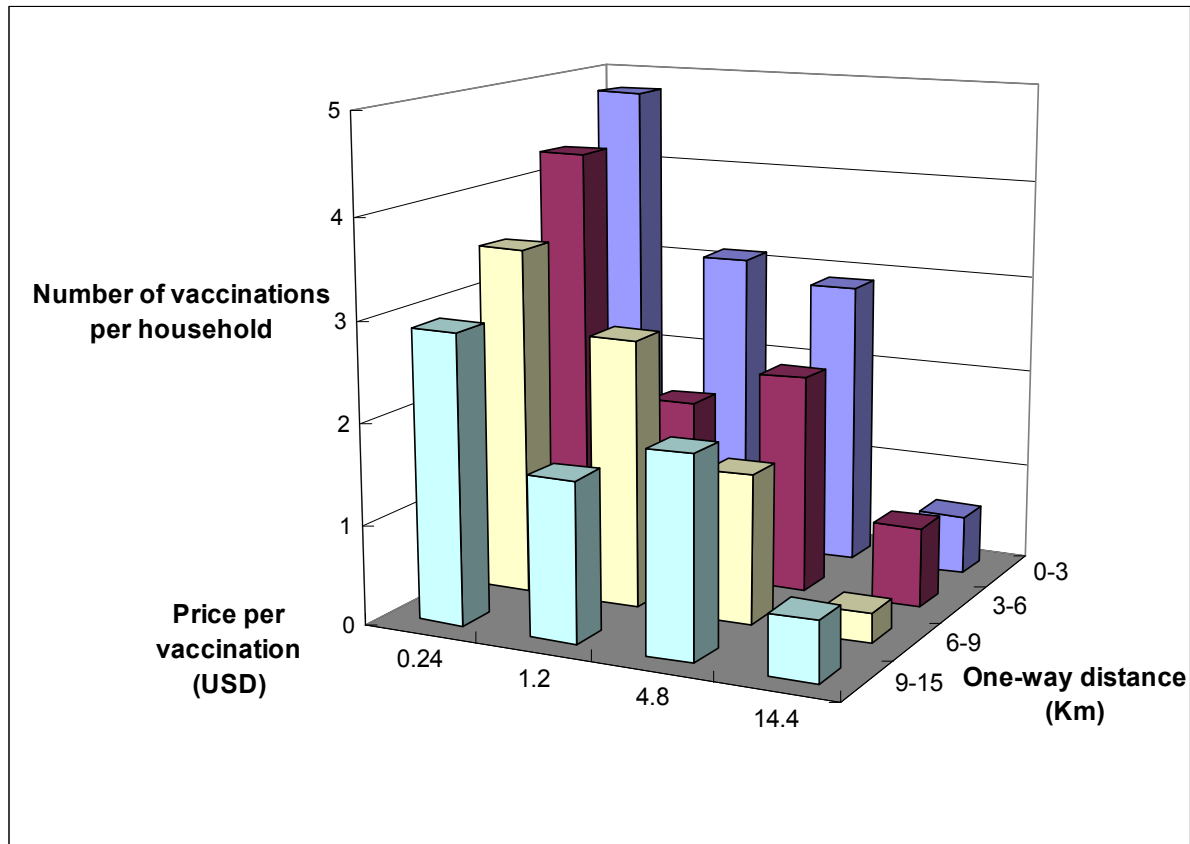
Ninety-seven percent of respondents had heard about vaccines, and among them, about 54% reported that at least one of their family members had received Vi vaccines within the past five years. Seventy-four percent of the respondents reported they were satisfied with the immunization services available to their household members. Yet this result should be interpreted with care since only respondents who had been vaccinated in the past five years were asked questions about satisfaction. Little is known if the rest of the respondents were satisfied with the vaccination services, and it is likely that people who were not satisfied with the vaccination service decided not to take part in the service again.

### 3.5.3. Demand for Vi Vaccines

Figure 3.3 illustrates that the average number of vaccinations that households would buy changes in proportion to the one-way road distance from each household to the CDC and

user fee. Although some data points behave abnormally due to small sample size, the “distance decay” effect appears in this raw data plot, i.e. people would buy fewer vaccinations on average if they had to travel greater distances to get them. This distance effect looks more pronounced for the lowest price (USD 0.24).

Figure 3.3. Raw results: Average number of vaccinations per household by user fee and distance



The Poisson probability density function was fitted to the responses of 160 sample households. The number of vaccinations that would be purchased by the respondent was regressed against a series of potential explanatory variables of the demand for vaccinations. Table 3.3 presents the descriptions and statistics of the variables.

Table 3.3. Variable definition and descriptive statistics

Variable name	Description	Mean	S. D.	Range
Distance	Road distance to CDC (one-way; km)	6.3	3.8	0.6-14.5
Income	Annual household Income (continuous; USD)	1163	991	84-7483
Ln(income)	Natural log of annual household income (USD)	6.8	0.8	4.4-8.9
Household size	Number of household members (continuous)	4.5	1.1	2-9
Respondent's education	Years of school completed (continuous)	5.6	3.1	0-15
Respondent's sex	1=if respondent is male; 0=otherwise	0.49	0.5	
Respondent's age	Respondent's age (continuous; years)	42.0	8.2	29-62
Number of rooms	Number of rooms in home (continuous)	4.3	2.9	1-17
Refrigerator	=1 if household owns a refrigerator; 0 otherwise	0.11	0.3	
Bicycle	=1 if household owns a bicycle; 0 otherwise	0.86	0.3	
Phone	=1 if household owns a phone; 0 otherwise	0.42	0.5	
Wash hands before eating	=1 if respondent always washes hands; 0 otherwise	0.18	0.4	
Boil drinking water	=1 if respondent normally boils water; 0 otherwise	0.63	0.5	
Risk perception for self	=1 if respondent believes it is likely he/she will get typhoid in the next three years; 0 otherwise	0.09	0.3	
Risk perception for children	=1 if respondent believes it is likely his/her children will get typhoid in the next three years; 0 otherwise	0.14	0.4	
Outbreak	=1 if village had typhoid outbreak in last 3 years; 0 otherwise	0.31	0.5	
HH members had typhoid	=1 if a household member has ever had typhoid; 0 otherwise	0.31	0.5	
Know someone with typhoid	=1 if respondent knows someone who has had typhoid; 0 otherwise	0.64	0.5	

Table 3.4 presents the results of the two final Poisson regression models: full vs. reduced models. The fit of the Poisson model is adequate because there is no evidence of overdispersion (mean number of vaccinations demanded =2.4; standard deviation = 1.8)<sup>14</sup>. In the full model including all potential predictors of the demand, only three variables are significant at the 5% level: user fee, road network distance to the CDC, and the number of people in the household. Note that the two risk perception variables (one for self, the other for their children) have opposite signs, but neither of those is significant at the 10% level. The T-tests also show that the demand for vaccinations is not statistically different between those who believe typhoid risk is high and those who do not, both for self and for their

<sup>14</sup> In the case of overdispersion, running the negative binomial regression instead of the Poisson regression is adequate.

children. Also note that neither of the two variables of risk-averse behavior (e.g. washing hands before eating, boiling drinking water) is significant. These results indicate that the respondents might be willing to buy vaccinations not based on their actual risk of contracting typhoid fever, but rather as a kind of insurance policy.

Table 3.4. Results of Poisson regression: full and reduced models

Variables	Full model (N=160)			Reduced model (N=160)		
	Coef.	Std. Err.	P>z	Coef.	Std. Err.	P>z
User fee per vaccination (USD)	-0.10	0.01	***	-0.10	0.01	***
Road distance to CDC (km; one-way)	-0.04	0.02	**	-0.05	0.01	***
Ln of household income (USD)	0.11	0.07		0.13	0.04	*
Household size (number of HH members)	0.19	0.05	***	0.18	0.07	***
Years of education of respondent	0.02	0.02				
Male respondent	-0.12	0.13				
Age of respondent	-0.01	0.01				
Number of rooms	0.03	0.02				
Own refrigerator	-0.03	0.19				
Own bicycle	0.03	0.15				
Own phone	-0.08	0.13				
Washes hands before eating	0.17	0.13				
Boils drinking water	-0.03	0.11				
Respondent believes typhoid risk is high for self	0.25	0.27				
Respondent believes child's typhoid risk is high	-0.22	0.22				
Village had an outbreak	-0.10	0.15				
Any HH member had typhoid fever	0.05	0.13				
Know someone who had typhoid fever	0.00	0.12				
Constant	-0.13	0.57		-0.20	0.49	
Log likelihood	-255.04			-258.98		
Pseudo R2	0.21			0.20		

\*\*\*: Significant at 1% level \*\* : Significant at 5% level \* : Significant at 10% level

As shown in Table 3.4, the reduced model excludes all insignificant variables, except for the income variable since it is one of the typical predictors of private demand. Once a number of asset variables which are correlated with household income were excluded from the model, the variable of annual household income became significant at the 10% level ( $p=0.055$ ). These results support the conclusion that the reduced model performs as sound as

the full model because the model fit is not so different (i.e. R-squared is almost the same), and the constant term is not significant in either model. Therefore, the results of the reduced model are used in all of the following analyses in this dissertation.

The coefficients of all variables in the reduced model have expected signs. The price of the vaccine has a negative effect, and household income and household size have positive effects on vaccine demand. Road distance to the vaccination center (i.e. CDC) has a negative effect on household demand, and thus it needs to be taken into account in determining the number and locations of vaccination sites. The resulting demand function based on the reduced model is as follows:

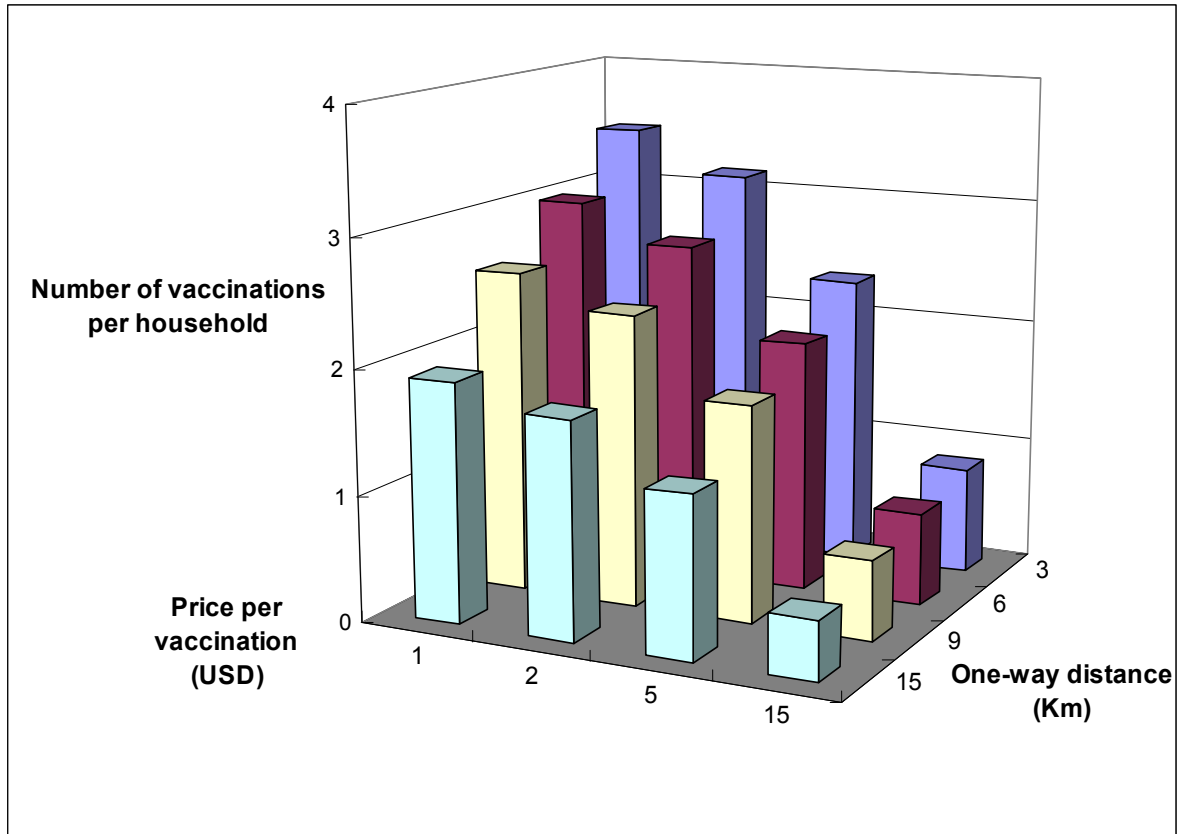
$$\lambda = \exp[-0.2 - 0.1 \cdot p - 0.05 \cdot d + 0.13 \cdot \ln(I) + 0.18 \cdot H] \quad \text{eq. 3.6}$$

where  $\lambda$  is the expected number of vaccinations that a household in Daxu Township would purchase if it were given the option to buy any number and had to pay a price of  $p$  (USD) per vaccination, travel  $d$  km one-way to the vaccination site, had average annual income of  $I$  (USD), and had  $H$  persons in the household. For example, a five-person household with annual income of USD 800 would be expected to receive a total of 4.8 vaccinations if the price they had to pay were zero and if they did not have to travel to obtain them.

In order to illustrate the price and distance effect more clearly, the proportion of vaccination by distance to vaccination site and by price was calculated using the results of the Poisson model, assuming average annual household income of USD 1,163 and average household size of 4.5. Figure 3.5 shows that approximately 77% of the people in Daxu Township would be vaccinated when the price is USD 1 and one-way travel distance is 3 km.

However, the proportion drops to 10% when they have to pay USD 15 and travel 15 km one-way for vaccination.

Figure 3.4. Predicted number of vaccinations per household by user fee and distance

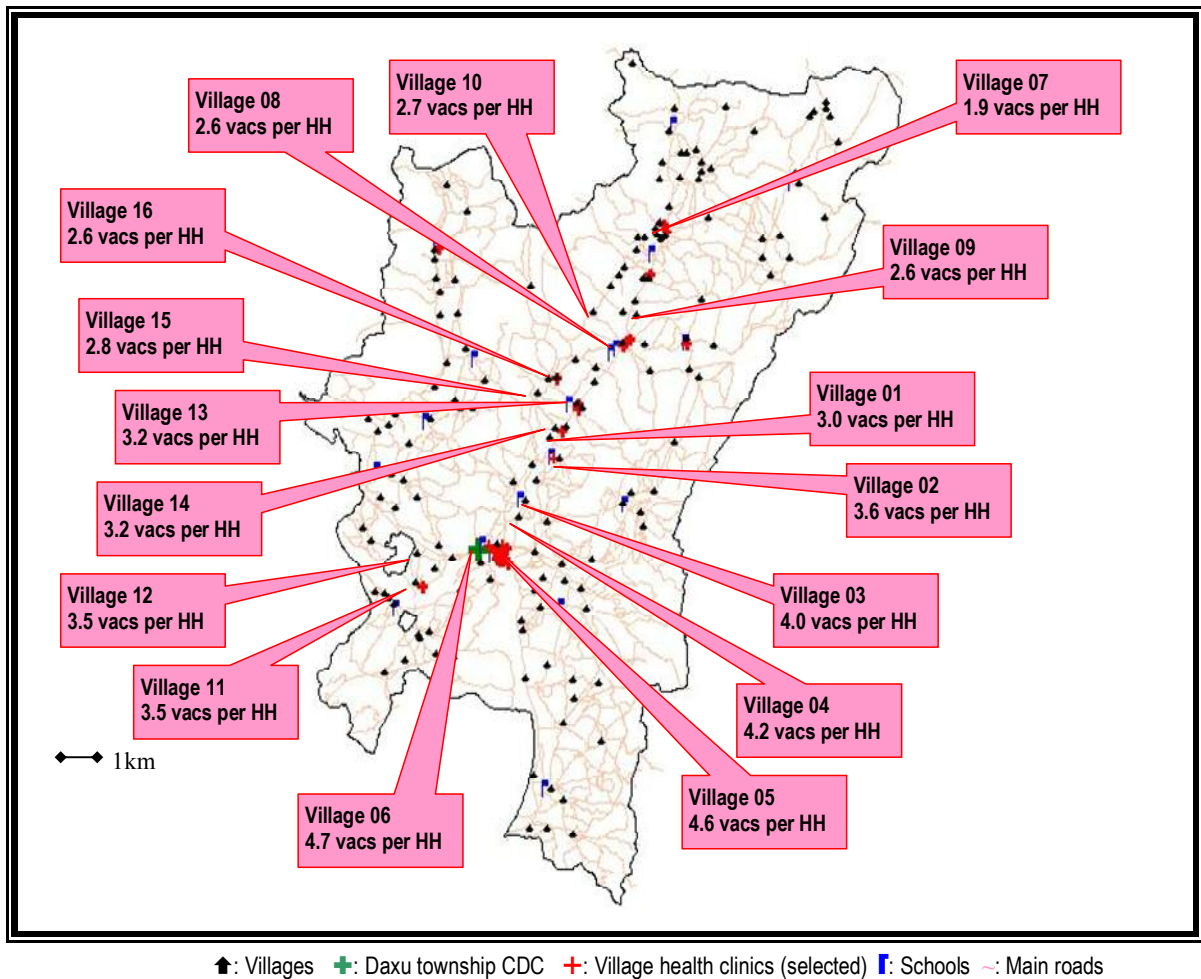


This figure helps demonstrate that household demand decreases by both price and travel distance. This finding implies that, when respondents answered about their demands for vaccinations, they considered not only user fee which they would have to pay, but also burden to travel to CDC such as pecuniary travel cost and non-pecuniary travel cost measured as opportunity cost of travel time. Figure 3.5 presents a map showing the average number of vaccines demanded for a household in each of 16 sampled villages in Daxu Township, if the vaccine were only available in the CDC at a price of USD 1. This figure shows a spatial pattern of household demand by distance to the CDC, i.e. households living



near to the CDC would purchase more vaccinations than those living far from the CDC, on average.

Figure 3.5. Average number of vaccines demanded for a household in each sampled village



Although the actual data of travel time and costs are not available, it can be inferred from this result that the size of travel cost may be substantial regardless of the mode of travel. Considering that walking or bicycling is associated with low pecuniary travel cost but high non-pecuniary travel cost due to longer travel time while taking a bus is associated with relatively high pecuniary travel costs, total travel costs might be similar for different modes

of travel. Assuming that total travel cost is USD 0.1 per km regardless of the mode of travel, a person in this township would save USD 1.3 on average by receiving vaccinations at home (or village) instead of traveling about 13 km roundtrip to the CDC. If user fee were less than USD 1 per vaccination, travel cost might be more burdensome than user fee to some of those who want vaccinations. This finding indicates that not only user fee but also the number and location of vaccination sites are important issues for further research.

These results, based on stated preference, are consistent with recent findings from the revealed preference results about demand for vaccination. Jeuland et al. (2007) estimated travel cost models of the revealed household demand for cholera vaccines in the free vaccination trial in Beira, Mozambique. They found that the quantity of vaccines obtained by households and the likelihood of participation decreased with the increase of travel time and costs, which depends on travel distance from household to vaccination site. The per capita willingness to pay for cholera vaccination, which was revealed as travel costs incurred by households, is estimated at about USD 1 in this area, which turns out to be somewhat lower than that from the stated-preference willingness-to-pay method. They reported that average distance for those that received vaccination was 2.8 km, and thus per-kilometer travel cost can be calculated as more than USD 0.36 in this area ( $= 1 / 2.8$ ). Assuming that the per-kilometer travel cost in Daxu Township is similar to this estimate in Beira, households' burden to travel costs would be even greater in Daxu Township in China.

The dummy variable for indicating whether the respondent was informed of a hypothetical typhoid vaccine with 99% effectiveness for 20 years in the choice experiment was tested for its significance in the full and reduced models above, and it turns out to be insignificant in both models ( $p=0.6$ ). This result helps confirm that the responses to the

household CV question were not biased by the information on the superior hypothetical vaccines given in the preceding choice experiment.

#### 3.5.4. Private benefits of vaccination

The fitted demand function in eq. 3.6 predicts the average number of vaccinations that will be purchased by a household as a function of four variables: the price (USD) it has to pay, the one-way travel distance (km) from the household to the vaccination outpost, the natural log of the household's annual income (USD), and the number of members in the household. If vaccinations were available in or near households, the travel distance would be zero. In this case, using average household size of 4.5 persons and average natural log income of 6.8, eq. 3.6 can predict the number of vaccinations demanded by a typical household for a range of prices between USD 0 and 14. The result is shown in Figure 3.6 in the curve labeled 'Village.' On the other hand, the average one-way travel distance for "all" households in Daxu Township to the CDC is about 6.8 km, shown in Chapter 4 below (note that average distance for "sample" households in Daxu Township to the CDC is about 6.3 km). Inserting this value for distance in eq. 3.6 results in the demand curve for a typical household in Figure 3.6 labeled 'CDC.'

Figure 3.6. Average per household demand for vaccinations at the CDC and at each village

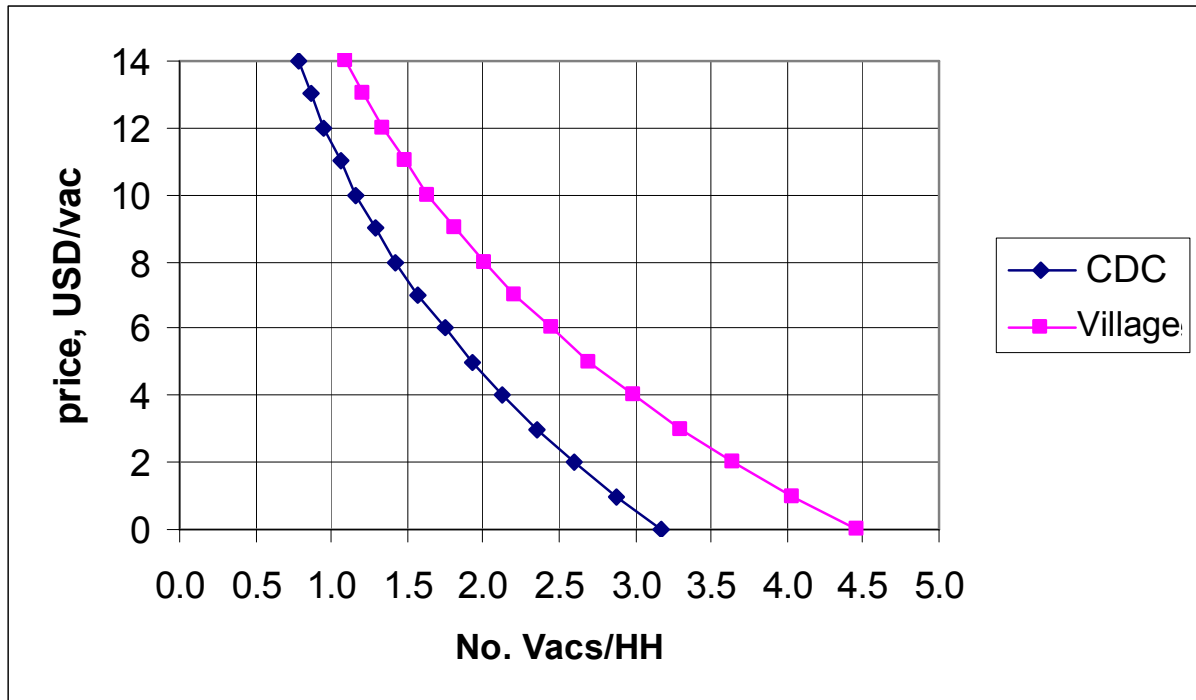


Figure 3.6 shows that the demand curve shifts for different values of travel distance. If the price is USD 1 and vaccinations are available at each village so that no substantial travel is required, the quantity demanded for a typical household is about 4 vaccinations, or about 400 vaccinations for each 100 households, which implies per capita coverage of about 89% ( $=400/450$ ). If a household has to travel to the CDC for vaccinations, the expected quantity demanded is about 2.8, or about 280 vaccinations for each 100 households (62% per capita coverage). Currently, these vaccines are available only “on demand” at the CDC for about USD 1, but only about 10% of the people has been vaccinated because no public vaccination campaign or promotion has been conducted in this township since 2001. This gap between the estimated demand and actual coverage could be explained mostly by

implementation factors affecting actual vaccination coverage, such as publicity campaigns and social mobilization for vaccination promotion.

As described in Section 3.4 (Econometric models), the area under the demand curves in Figure 3.6 is a measure of the private economic benefit derived by a “typical” household (not sample household) from purchasing vaccinations for all household members. Figure 3.6 indicates that the choke price is less than infinity because vaccinations come in discrete numbers from zero to the number of household members. Less than one vaccine would be purchased at prices higher than about USD 15. It also demonstrates the choke price would be similar between the two different delivery strategies. Thus, the choke price is assumed to be USD 20, the same for both cases, because the primary goal of this analysis was to work toward a reasonable (approximate) estimate of private benefits and not a precise, finely-tuned number. Eq. 3.4 was used to calculate the private benefits for the entire household for free vaccination, and eq. 3.5 was used if price were not zero, based on the parameter values in eq. 3.6. If vaccinations were free ( $p=0$ ), the private benefits for the entire household would be USD 27 for vaccinations at the CDC, but USD 39 for vaccinations at each village. The private benefits from vaccinations at each village are significantly larger than those from mega-site vaccination, by about USD 12 per household (44%). For non-zero prices, these private benefits show little change. They change by only less than USD 1 even with the price of USD 2.

These results help to show that the private benefits from vaccinations are different according to where vaccinations are delivered. In Figure 3.6, the area between the two demand curves represents additional benefits that result from receiving vaccinations at their own villages instead of traveling to the CDC for vaccinations, a benefit estimated at around

USD 12 on average. It indicates that the respondents factored in not only price but also the non-pecuniary travel cost and opportunity cost of lost work due to travel and queue time into their responses when they answered the questions about their demand for vaccinations. This finding implies that having more sites would bring a substantial amount of private benefits, and having a single or fewer sites might not be the best for society since it overlooks these private benefits. However, it does not necessarily indicate that the best alternative is always to deliver vaccinations at every village because it does not consider other important factors such as vaccination costs and budgetary constraints under which governments must function.

### 3.5.5. Comparison with the results of Poulos et al. (2006b)'s household CV study

In order to make sure that the findings from the two household CV studies in Lingchuan County (3<sup>rd</sup> and 5<sup>th</sup> columns in Table 3.1) do not contradict each other, the household CV results for Daxu Township presented in my dissertation research are compared with those for Lingchuan County as reported in Poulos et al. (2006b). This comparison is significant since both studies estimated the household demand function for typhoid vaccination in southern China but using different research designs. As described in Table 3.5 (2<sup>nd</sup> and 3<sup>rd</sup> columns), the two major differences in research designs between the two studies are: (1) samples of Poulos et al.'s study were collected from both urban and rural areas, while those of my dissertation research were collected only from rural areas, and (2) Poulos et al. performed a split sample study that offered vaccinations at home to one group and at the nearest health facility to the other, while my research informed all respondents that vaccinations would be offered only at the CDC. The detailed description of the variables and

results of the models in Poulos et al. are included in Appendix 1. Note that average annual household income in the Poulos et al.'s sample is substantially larger than that of my research in Daxu Township (USD 1,796 vs. 1,163), but average household size and other demographic variables are quite similar between the two studies.

Table 3.5. Comparison of research designs and results: Poulos et al. (2006b) and this research

Household demand studies	Research Design		Poisson model (coefficients) <sup>15</sup>			
	Sample area	Location of vaccination delivery	Price	Natural log of income	Household size	Distance to vaccination site
Poulos et al. (2006b)	Urban and rural areas	Home vs. nearest facility (Split sample)	-0.09	0.07	0.14	N/A
This dissertation research	Rural areas (Daxu)	Township CDC	-0.10	0.13	0.18	-0.05

The last four columns in Table 3.5 show how the two demand models differ in the coefficients of key variables. The effects of price and household size are similar for both studies, while income effect is greater in this research. Note that mean household income of the samples in Daxu Township is only 65% of the mean household income of the samples in Poulos et al.'s study. This implies that household income is a more important determinant of demand for vaccinations in rural areas with many low-income households than it is in urban areas. According to Poulos et al. (2006b), the dummy variable indicating whether home vaccination was offered to the respondent was not significant. This finding indicates that respondents in their study were indifferent between getting vaccinations at home and at the

<sup>15</sup> Poulos et al. (2006b) reported six different model specifications, as shown in Table A1.2 in Appendix 1. The results presented here are based on Model (4) which has the most similar model specification compared to the full model in my research.

nearest health facility which on average was about 0.8 km away. By comparison, the distance effect is significant in my dissertation research where vaccinations are offered only at the township CDC, which on average required a one-way travel distance of 6.3 km.



## Chapter 4

### **Simulation analysis examining the effects of user fees and vaccination locations on the vaccination program**

Chapter 3 showed that the number of vaccinations demanded depends among other things on travel distance to the vaccination center. It showed that the quantity of Vi vaccinations demanded by household members in Daxu Township decreased as distance to the vaccination center increased. This finding leads to the next question of where vaccination sites should be located in an area like Daxu Township. One may consider two extreme alternatives: (1) in every village, and (2) only at the vaccination center in the township (the township CDC). However, vaccination policy-makers might consider a more reasonable alternative of having more than one site but something less than in each and every village<sup>16</sup>. This raises the question of how many vaccination sites are needed and where they should be located. Should planners simply use their own professional judgment to determine locations for vaccination sites, or can their judgment be aided by analytic tools?

This chapter takes a systematic approach to determining the optimal number and location of vaccination sites, using location models from operations research (OR) to screen candidate locations. These models cannot provide definitive answers about where to locate vaccination sites, but they are valuable aids in making this judgment. Using OR models,

---

<sup>16</sup> Yang et al. (2005) reported that the mass vaccination campaign of the Vi vaccine conducted at one outpost in each village cluster was found to be feasible in Hechi City, Guangxi province.

simulation analyses indicate the effects that different numbers and locations of vaccination sites have on the outcomes of a vaccination program.

This chapter employs a cell-based framework in which households are clustered into villages and villages are clustered into a grid of cells that is superimposed onto the map of Daxu Township. This chapter describes the cell-based analysis, and it predicts the outcomes of a vaccination program for the two extreme cases described above (i.e. vaccination outposts in every cell or only at the central vaccination office). Then it employs two location models, the set covering model and the p-median model to obtain solutions under different assumptions. The results from repeated use of the two models are used in a simulation approach to investigate how the locations change with different assumptions and to map the effects of alternative locations, along with user fee levels, onto outcomes. The outcomes of the simulations are then compared to determine the best plan.

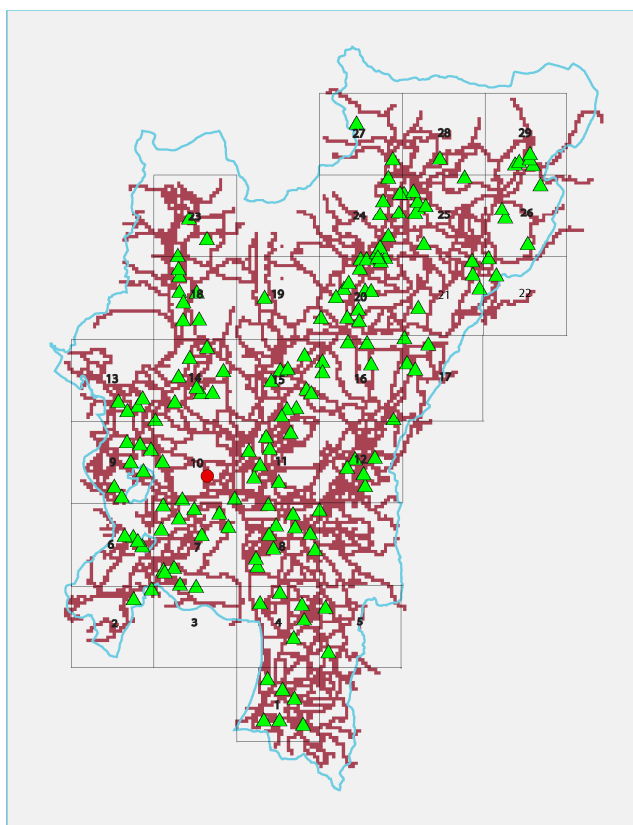
#### 4.1. Cell-based analytic framework

Although it is theoretically possible for all 141 villages in Daxu Township to be used as locations for vaccination sites, it is not particularly useful to do so, in consideration of not only computational complexity but also the fundamental role of mathematical models. Mathematical models often abstract and simplify the systems since they should be used as aids to judgment, not as tools to give absolutely correct and definite answers. All villages in Daxu Township were thus aggregated into 29 cells, each about 8 km<sup>2</sup> (2.8 km by 2.8 km), an identification number was assigned to each cell, and the total population in each cell was assumed to be located at its center. Road distances were measured between all the pairs of

cells using the shortest path, assuming people take the shortest path to an outpost.<sup>17</sup> In order to minimize the uncertainty due to different road conditions, only major roads were used to measure distances. The ArcGIS network analysis tool was used to calculate minimum distances between cells. Figure 4.1(a) is the map showing how the 29 cells containing 141 villages are connected by the road network. Figure 4.1(b) shows the total population of each cell.

Figure 4.1. Map of 29 cells and population size of each cell

(a) Map of 29 cells connected by road network



● : Township CDC ▲ : 141 Villages — : Major roads  
 \* Numbers in the cell are the cell IDs.

(b) Population by cell

			Cell #27	Cell #28	Cell #29
			848	180	615
	Cell #23		Cell #24	Cell #25	Cell #26
	1097		2938	2097	674
	Cell #18	Cell #19	Cell #20	Cell #21	Cell #22
	1094	443	4669	1568	85
Cell #13	Cell #14	Cell #15	Cell #16	Cell #17	
1417	2443	4397	1523	1143	
Cell #9	Cell #10	Cell #11	Cell #12		
2801	1377	2951	1230		
Cell #6	Cell #7	Cell #8			
3164	4884	4496			
Cell #2	Cell #3	Cell #4	Cell #5		
604	517	1193	348		
		Cell #1			
		2541			

<sup>17</sup> This assumption might be too approximate because actual travel patterns are sometimes too complex to be simplified as such (i.e. various road conditions or atypical travel preference).

The straight-line distances between all pairs of cells were compared to the actual travel distances by road. Figure 4.2 shows the scatter plot of road versus straight-line distances. The correlation coefficient is 0.96, and on average, road distance is about 1.4 times greater than straight-line distance. For most of the dots in Figure 4.2, the difference between road and straight-line distances is less than 2 km. For some dots, however, road distance is longer than 20 km for straight-line distances of only 6-7 km. The road distances from cell  $i$  to cell  $j$  were calculated and stored into the matrix with 29 rows and 25 columns shown in Table 4.1. Four cells located near the northeast side border (#22, #27, #28, and #29) were dropped out of the destination columns because they contain relatively small populations and are located so far from other cells. Travel distance within any cell is assumed to be zero although in fact, the distance from villages in the cell to the center of the cell is around 0.7 km on average.

Figure 4.2. Scatter plot of straight-line vs. road distances

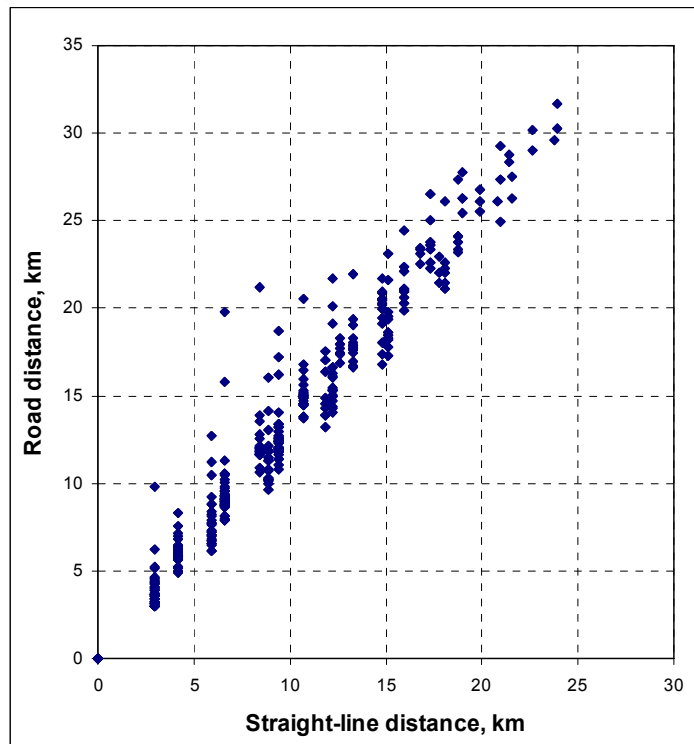


Table 4.1. Road distances (in km) between source and destination cells

From / To	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	23	24	25	26
1	0	9	8	5	3	11	10	8	13	11	12	12	16	16	16	17	18	20	19	20	21	24	23	25	26
2	9	0	2	7	10	3	5	8	6	6	9	13	9	11	13	16	18	14	16	18	20	18	21	24	26
3	8	2	0	5	8	3	3	6	6	4	7	10	9	10	11	14	16	13	15	16	18	17	19	22	24
4	5	7	5	0	3	8	6	4	9	7	7	8	12	12	11	13	14	15	15	15	17	19	19	21	22
5	3	10	8	3	0	8	9	8	12	11	13	13	17	19	19	19	20	24	24	24	24	29	28	30	29
6	11	3	3	8	8	0	3	7	3	3	7	11	6	8	11	14	16	11	13	15	18	15	18	21	24
7	10	5	3	6	9	3	0	5	4	1	5	8	6	7	8	11	13	10	12	13	16	14	16	19	21
8	8	8	6	4	8	7	5	0	8	5	4	5	10	8	7	9	10	12	11	12	13	16	15	17	19
9	13	6	6	9	12	3	4	8	0	3	6	11	3	6	9	13	15	9	11	14	17	12	16	19	22
10	11	6	4	7	11	3	1	5	3	0	4	8	5	6	7	11	12	9	11	12	15	13	15	18	20
11	12	9	7	7	13	7	5	4	6	4	0	5	7	5	4	7	9	8	8	9	11	12	12	14	17
12	12	13	10	8	13	11	8	5	11	8	5	0	11	8	5	5	6	11	9	8	9	14	11	13	14
13	16	9	9	12	17	6	6	10	3	5	7	11	0	4	8	12	13	6	9	12	15	9	14	17	20
14	16	11	10	12	19	8	7	8	6	6	5	8	4	0	4	8	10	4	6	8	11	7	11	13	17
15	16	13	11	11	19	11	8	7	9	7	4	5	8	4	0	4	6	6	4	5	8	9	8	11	13
16	17	16	14	13	19	14	11	9	13	11	7	5	12	8	4	0	2	10	5	4	4	12	6	8	10
17	18	18	16	14	20	16	13	10	15	12	9	6	13	10	6	2	0	11	6	4	3	13	6	7	8
18	20	14	13	15	24	11	10	12	9	9	8	11	6	4	6	10	11	0	5	8	12	4	10	12	16
19	19	16	15	15	24	13	12	11	11	11	8	9	9	6	4	5	6	5	0	3	7	6	5	8	12
20	20	18	16	15	24	15	13	12	14	12	9	8	12	8	5	4	4	8	3	0	4	9	3	6	9
21	21	20	18	17	24	18	16	13	17	15	11	9	15	11	8	4	3	12	7	4	0	12	4	5	6
22	23	24	22	20	26	22	19	16	20	18	15	12	19	15	11	8	6	15	10	7	4	15	6	4	2
23	24	18	17	19	29	15	14	16	12	13	12	14	9	7	9	12	13	4	6	9	12	0	9	12	16
24	23	21	19	19	28	18	16	15	16	15	12	11	14	11	8	6	6	10	5	3	4	9	0	3	7
25	25	24	22	21	30	21	19	17	19	18	14	13	17	13	11	8	7	12	8	6	5	12	3	0	4
26	26	26	24	22	29	24	21	19	22	20	17	14	20	17	13	10	8	16	12	9	6	16	7	4	0
27	26	24	23	22	33	22	20	18	19	19	15	14	17	14	11	10	9	12	8	7	7	11	4	3	7
28	27	25	24	23	33	23	21	19	21	20	16	15	18	15	12	10	9	13	9	8	7	12	4	2	5
29	29	29	27	25	33	26	24	21	25	23	19	17	23	19	16	13	11	18	14	11	8	17	9	6	3

Household income data were obtained for 30 sample villages in Daxu Township from both the CV and CM questionnaires (see Section 3.3). In each of these villages, a random sample was drawn of 10-20 households<sup>18</sup>, and the income data of each household was obtained using a questionnaire. The average self-reported household income in each of the sampled villages was obtained from an arithmetic average of the sample households. Because

<sup>18</sup> On average, 10 households per village were sampled for the “CM questionnaire”, while 20 households per village were sampled for the “CV questionnaire” in Daxu Township.

household income is an important determinant of demand for vaccination, several techniques were used for estimating the household income for unsampled villages, such as synthesis (Birkin and Clarke, 1989) multiple imputation (Raghunathan et al., 2001), and spatial interpolation (Flowerdew et al., 1991). The Bayesian Maximum Entropy (BME) method was ultimately used to predict income in unsampled villages by using the spatial dependency pattern of the existing data from the 30 sampled villages. Spatial clustering or dependence of income data in a small area has been written about frequently (Flowerdew et al., 1991; Anselin, 2003; Longley and Tobon, 2004). The detailed description of spatial interpolation methods and the actual process and validation of the BME estimation of household income for unsampled villages in this research are found in Appendix 3.

After average annual household income was estimated for all 141 villages using BME, the village values were aggregated to estimate average annual household income for each cell. Simple arithmetic averages of village data were used to calculate cell averages because more sophisticated approaches could not be justified on the basis of having only 10-20 household observations for each of the 30 sample villages. Figure 4.3 shows average annual household income for each cell.

Figure 4.3. Average annual household income for each cell (in USD)

			<b>Cell #27</b> <b>1098</b>	<b>Cell #28</b> <b>1123</b>	<b>Cell #29</b> <b>1132</b>
	<b>Cell #23</b> <b>1024</b>		<b>Cell #24</b> <b>1424</b>	<b>Cell #25</b> <b>1141</b>	<b>Cell #26</b> <b>1132</b>
	<b>Cell #18</b> <b>901</b>	<b>Cell #19</b> <b>1251</b>	<b>Cell #20</b> <b>1015</b>	<b>Cell #21</b> <b>1196</b>	<b>Cell #22</b> <b>1132</b>
<b>Cell #13</b> <b>707</b>	<b>Cell #14</b> <b>1124</b>	<b>Cell #15</b> <b>858</b>	<b>Cell #16</b> <b>994</b>	<b>Cell #17</b> <b>1123</b>	
<b>Cell #9</b> <b>1189</b>	<b>Cell #10</b> <b>1051</b>	<b>Cell #11</b> <b>1424</b>	<b>Cell #12</b> <b>895</b>		
<b>Cell #6</b> <b>1214</b>	<b>Cell #7</b> <b>992</b>	<b>Cell #8</b> <b>1375</b>			
<b>Cell #2</b> <b>838</b>	<b>Cell #3</b> <b>1108</b>	<b>Cell #4</b> <b>1127</b>	<b>Cell #5</b> <b>1134</b>		
		<b>Cell #1</b> <b>1122</b>			

In order to assess the validity of the BME income prediction and aggregation of income data by cells, the cumulative distributions of observed incomes for 30 sample villages, predicted incomes for all 141 villages based on BME estimation, and aggregated incomes for 27 cells are compared as shown in Figure 4.4. As seen from both Figure 4.4 and Table 4.2, the mean values are quite similar among observed incomes for sampled villages, predicted incomes for all villages, and aggregated incomes for all cells, although variances

are reduced by both prediction and aggregation. The BME income prediction reduces standard deviation by USD 185, and the cell-based aggregation reduces standard deviation by USD 108, which seems not too substantial. Furthermore, judging from the natural log of income, which was used in the econometric model in Chapter 3, the reduction in variance by prediction and aggregation is minimal. Additionally, as shown in Table 4.2, natural log income does not change much from one village (or cell) to another (standard deviation = 0.2-0.4), which could explain why income effects were not so strong in the Poisson regression models in Chapter 3 and indicate that income effects would not be substantial in the following cell-based analyses.

Figure 4.4. Cumulative distributions of average household incomes

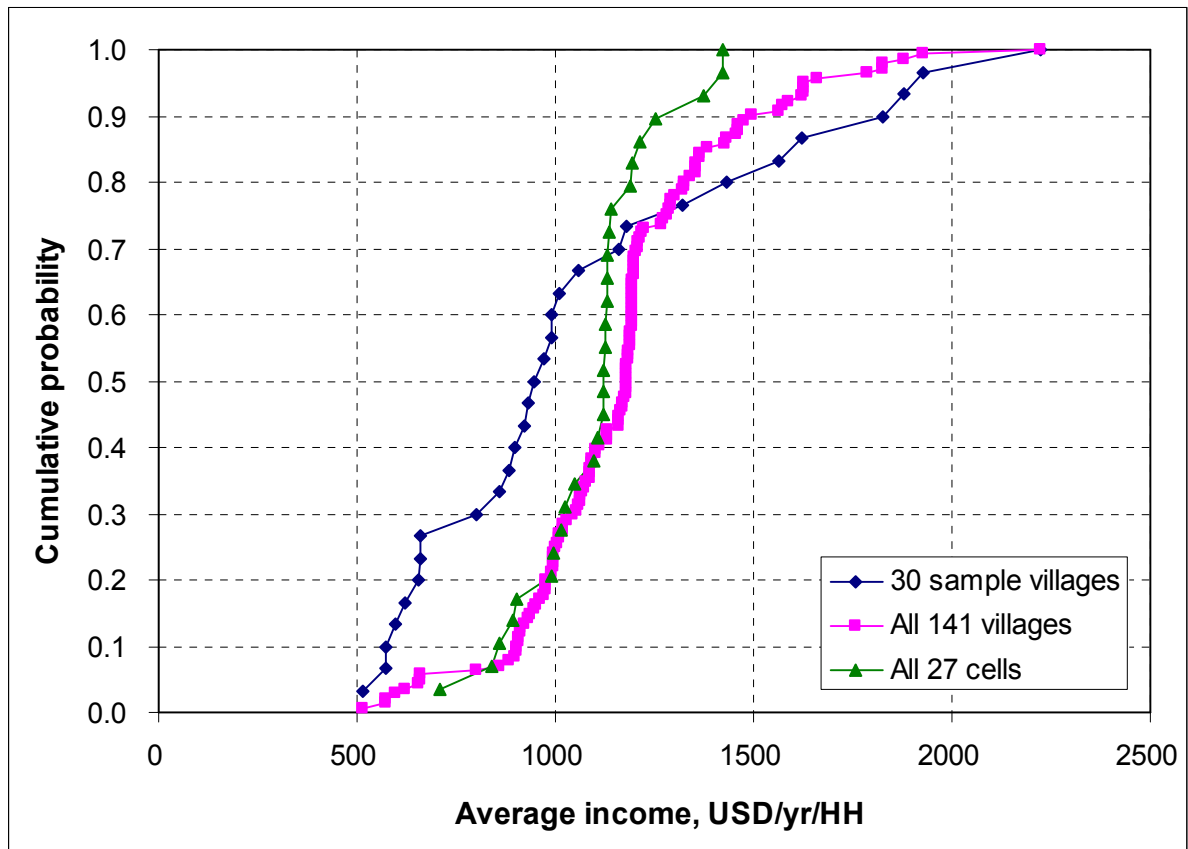




Table 4.2. Mean and standard deviation of average income data

	30 sample villages		All 141 villages		All 27 cells	
	Income (USD)	Ln(income)	Income (USD)	Ln(income)	Income (USD)	Ln(income)
Mean	1075	6.9	1171	7.0	1098	7.0
Standard deviation	457	0.4	272	0.2	164	0.2

In principle, estimates can be made of the quantities of vaccinations demanded by each cell and the revenues that would be generated by any selected vaccination fee for any assumed arrangement of vaccination outposts. The number of vaccinations can be estimated using the household demand function eq. 3.6, cell population data (in Figure 4.1(b)), average logs of annual household income by cells (in Figure 4.3), and travel distances by road (in Table 4.1). The revenue can be calculated by multiplying the estimated number of vaccinations by the selected fee for vaccination. Assume, for example, that it is decided to have a single vaccination center in cell #10 at the CDC. Assume further that the vaccination price is USD 1.0. Consider cell #1 that has 2,541 persons, or about 570 households using the average of 4.5 persons per household. The average income in the cell is USD 1,122 per household per year (from Figure 4.3). The road distance of households in cell #1 to the outpost in cell #10 is 11 km (from Table 4.1). Using the demand function in eq. 3.6, it is predicted that households on average will purchase about 2.3 vaccinations. Thus, for the case of a single outpost in cell #10, the total quantity demanded in cell #1 is about 1,313 vaccinations, and the revenue generated is USD 1,313. Repeating this calculation for all other cells, the total demand and revenue can be obtained for the entire vaccination program.

In addition, using the estimates of the number of typhoid vaccinations demanded by each cell and the incidence data for each cell, the number of typhoid cases avoided by

vaccinations during the period that the Vi vaccine remains effective can be obtained for each cell in Daxu Township. The number of cases avoided in each cell is calculated by subtracting the number of cases with a vaccination program in each cell from the number of cases without the program in each cell<sup>19</sup>. Lauria et al. (2005) showed that the number of cases avoided by a vaccination program can be calculated by multiplying the predicted number of vaccinations by efficacy of the Vi vaccine (70%), incidence rate (in each cell), and duration of vaccine efficacy (3 years). For the example above, the number of cases avoided by Vi vaccinations in cell #1 for 3 years is about 7 ( $= 1,313 \text{ vaccinations} \times 0.7 \text{ efficacy} \times 0.00245 \text{ incidence rate} \times 3 \text{ years}$ ). Adding these values for all cells produces the total cases avoided by vaccinations in Daxu Township.

Furthermore, using the estimates of the number of typhoid vaccinations demanded by each cell, the private benefits can be calculated. Chapter 3 (Section 3.5.4) showed how to estimate the private benefits of vaccinating the entire household for a “typical” household in the township, and reported that the private benefits per household is USD 27 when vaccinations are delivered at the CDC, and USD 39 when vaccinations are delivered in or near households so that they do not need to travel, regardless of price. Because these values are per household, the predicted number of “households with all household members being vaccinated”<sup>20</sup> is calculated in each cell by dividing the predicted number of vaccinations in each cell by average household size in each cell (4.5). The total private benefits in each cell

---

<sup>19</sup> The number of cases that occur without a program in a 3-year period in each cell is a product of population in the cell, the incidence rate in the cell, and duration of vaccine efficacy (3 years). The number of cases that occur with a vaccination program in a 3-year period in each cell is the sum of (1) the number of people who contract typhoid fever in the cell because they are not vaccinated, and (2) the number of cases among people who have been vaccinated but the vaccinations were not effective in the cell. The detailed explanation of this calculation is found in Chapter 6 and in Lauria et al. (2005).

<sup>20</sup> Note that the private benefit per household estimated in Section 3.5.4 is the WTP for vaccinating “all” household members.

can be calculated by multiplying the predicted number of households with all household members being vaccinated by the private benefits per household estimated in Chapter 3.

#### 4.2. Extreme cases: vaccination in each cell vs. a mega-site at CDC

Two extreme cases are considered: vaccination in each cell versus vaccination only in cell #10 where the township CDC is located. Table 4.3 shows that users on average would need to travel nearly 7 km<sup>21</sup> one-way (about 14 km roundtrip) if vaccinations were delivered only at the township CDC. Travel distance is zero if vaccinations are offered in each cell. If the price were zero, 69% of the people in Daxu Township would be immunized, and 179 cases of typhoid would be avoided over 3 years. However, if vaccinations were offered at each cell for free, 98% of the people in Daxu Township would be vaccinated (an increase of more than 15,000 persons), and 243 cases would be avoided. Hence, provision of outposts in each cell has the marginal effect of increasing vaccination sales by many thousands but cases avoided by only 64 if the price is zero, decreasing to about 50 if the price is USD 2. Revenue would be zero with free vaccination, but if USD 2 were charged per vaccination, it would amount to about USD 62,000 when vaccinated at the township CDC and about USD 87,500 when vaccinated in each cell. Moreover, the private benefits by offering vaccinations in each cell (about USD 400,000) are about twice as large as those by offering vaccinations only at the CDC (about USD 200,000). Since these values of private benefits are almost linearly

---

<sup>21</sup> This value (more accurately, 6.8km) is an average one-way distance between the center of each cell and the township CDC. Note that average one-way distance from each “sample” village to the township CDC was 6.3km, as reported in Chapter 3.

associated with the number of vaccinations, the number of vaccinations can be a surrogate of the private benefits.

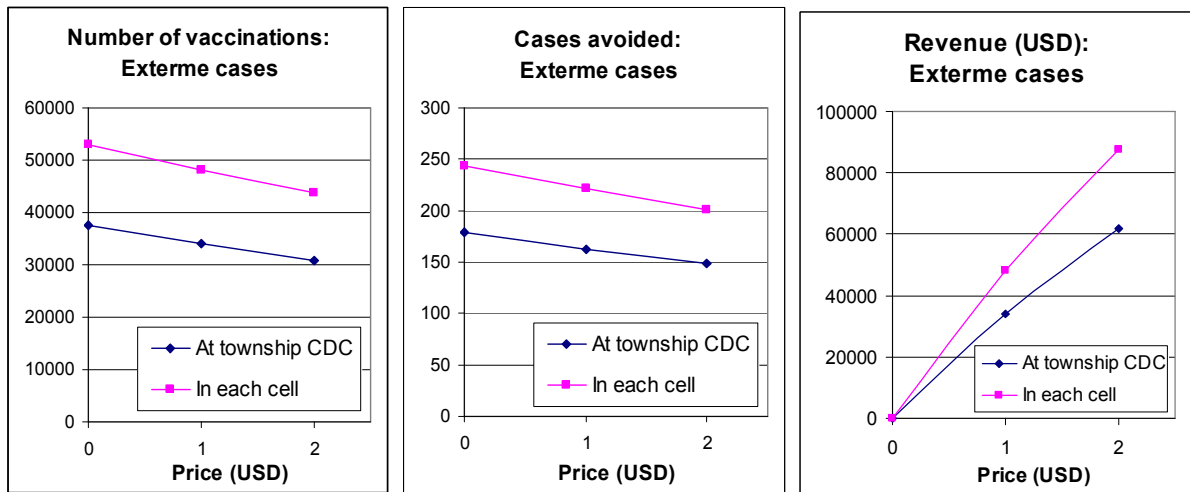
Table 4.3. Outcomes of vaccination at CDC vs. in each cell

Vaccination outposts	Average one-way travel distance (km)	Price (USD)	Number of vaccinations	Coverage (fraction)	Cases avoided	Revenue (USD)	Private benefits (USD)
At township CDC	6.8	0	37,438	0.69	179	0	224,628
		1	34,034	0.63	163	34,034	204,204
		2	30,940	0.57	148	61,880	185,640
In each cell	0	0	52,944	0.98	243	0	458,848
		1	48,131	0.89	221	48,131	417,135
		2	43,755	0.81	201	87,510	379,210

¶ Total population in Daxu Township in 2004 = 54,000

Figure 4.5 compares three outcomes of the two vaccination cases by price. About 41% more people would be vaccinated if vaccines were offered in each cell instead of at the CDC, and about 9% fewer people would be vaccinated if price increased by USD 1 (see Figure 4.5(a)). As a result, about 36% more cases would be avoided if vaccines were offered in each cell instead of only at the CDC, and about 9% fewer cases would be avoided by a price increase of USD 1 (see Figure 4.5(b)). As long as a user fee is charged, about 41% higher revenue would be generated if vaccines were offered in each cell instead of the CDC (see Figure 4.5(c)).

Figure 4.5. Vaccination outcomes of two extreme cases by price



(a) Number of vaccinations

(b) Cases avoided

(c) Revenue

How can each of these indicators be used to address the research questions on how many outposts to have and where to locate them? From the standpoint of government that may focus primarily on health, the public health benefits, indicated by cases avoided, seem to increase very little by increasing the number of outposts from one to 29. It is likely that government argues that a single outpost at the CDC is entirely proper because the marginal health benefits from adding more outposts do not seem worthwhile to pursue.

But from the standpoint of the users, who in fact are paying for the vaccination program, the pertinent indicators are the numbers of vaccinations sold, the revenue generated, the distance traveled, and the private benefits, all of which improve and argue for more rather than fewer outposts. Without this kind of study, it would not be possible to evaluate their vaccination strategy of employing only a single outpost because in many cases government lacks the information on how much users are willing to pay for vaccinations. However, in light of the findings about user demand from this study, it seems that the number

of outposts should be more than one and that vaccinations should be brought closer to the users.

Although a full benefit-cost analysis is not the purpose of this research, if it were made, it would be necessary to account for all the benefits and costs to whoever they accrue. Then, the small marginal increase in cases avoided by having more rather than fewer outposts could not make a convincing argument that vaccinations should only be provided at a single or fewer sites. Instead, the substantial increases in all other indicators, such as the number of vaccinations sold, revenues from vaccination sales, and private benefits, argue that a single outpost does not meet society's demands. Hence, it seems clear that Daxu Township should have more than one outpost, but it is still unclear how many to provide, where to locate them, and how much to charge the users.

#### 4.3. Set covering model

Section 4.2 argues that something more than a single outpost but probably fewer than one in each cell is called for to best serve society if the objective is to achieve economic efficiency, i.e. to maximize net benefits. To help develop this idea, a series of set covering models was developed to obtain insight on how many vaccination sites would be needed in order to offer vaccinations within a certain maximum travel distance. The set covering model determines the minimum number of vaccination sites needed and their locations to ensure that no one in the township would have to travel more than some maximum distance that is selected by the planner.

Assume that a vaccination campaign in Daxu Township targets all people living in 29 cells in the township ( $i = 1, 2, \dots, 29$ ). Recall that 25 of them are candidates for the location of vaccination outposts ( $j = 1, 2, \dots, 25$ ). The objective function of the set covering model is to minimize the total number of vaccination outposts. The decision variable is  $x_j \in \{0, 1\}$ : 1 if a vaccination outpost is located in cell  $j$ , 0 otherwise. The set covering model is formulated as follows:

$$\text{Minimize: } \sum_{j=1}^{25} x_j \quad \text{eq. 4.1}$$

$$\text{subject to } \sum_{j=1}^{25} G_{ij} x_j \geq 1, \forall i \quad \text{eq. 4.2}$$

$$x_j = 1, \text{ for } j = \#10 \text{ where the CDC is located} \quad \text{eq. 4.3}$$

where  $G_{ij}$  equals 1 if villages in cell  $i$  are within the specified distance of a vaccination outpost that could be located in cell  $j$ ; 0 otherwise.

The set covering model for the case of Daxu Township has two constraints: first, each of the 29 cells must be assigned to at least one vaccination outpost (eq. 4.2); and second, the township CDC should be included in the solution (eq. 4.3). The second constraint was added to the model since it appears that the township CDC should be the headquarters for typhoid vaccination in the township even though additional sites may likely be required. Due to the binary feature of the decision variable  $x_j$ , this set covering problem is formulated as a 0-1 integer programming problem which can be solved by the branch-and-bound method (Toregas and ReVelle, 1972). A series of set covering models was solved to determine the best outpost locations for 3 different maximum travel distances (4 km, 7 km, and 10 km) and 3 different user prices (USD 0, 1, and 2). When the maximum distance is set at 3 km or less,

no feasible solution was found because two cells (#27 and #29) are not located within 3 km of any other cell, and could not be candidates for a vaccination outpost. The location set covering problem commonly has multiple alternate optima (Drezner, 1995), but in this case, a single optimal solution was found for each maximum distance. Table 4.4 shows the results<sup>22</sup>.

Table 4.4. Results of the set covering models with different maximum distances

Maximum travel distance	Number of outposts required	Average one-way travel distance (km)	Assumed price (USD)	Number of people vaccinated	Coverage rate (% of total)	Cases avoided	Revenue (USD)
4 km	10	2.0	0	49,354	91	225	0
			1	44,867	83	204	44,867
			2	40,788	75	186	81,576
7 km	5	3.4	0	45,866	85	208	0
			1	41,696	77	189	41,696
			2	37,905	70	172	75,810
10 km	3	3.8	0	44,807	83	205	0
			1	40,734	75	186	40,734
			2	37,030	68	169	74,060

When the maximum distance for one-way travel to vaccination sites was set at 4 km, the set covering model required ten locations (the existing mega-site plus nine additional sites). Note that users have to travel about 7 km one-way on average if vaccines are delivered only at the mega-site, but with these ten sites, the average one-way travel distance drops to 2 km. As a result, vaccination coverage increases by around 20% for all price levels (approximately 10,000 additional vaccinations), but 9% of the people would still not be covered even if vaccinations were free. Cases avoided also increases compared to the outcomes with a single mega-site, but not as much as those of vaccination at every cell.

<sup>22</sup> The private benefits are not presented in this table because the number of vaccination is a surrogate, and there is not much difference in private benefits depending on travel distance. They are not presented in the next section concerning the p-median model either for the same reason.



Similarly, if the maximum distance was set to 7 km and 10 km, five and three sites would be needed, respectively. People on average would have to travel 3.4 km one-way with five sites and 3.8 km with three sites. By having 5 sites instead of 10 sites, vaccination coverage drops about 6% losing only 17 avoided cases. By having 3 sites instead of 5 sites, vaccination coverage drops only an additional 2% and cases avoided would be almost unchanged.

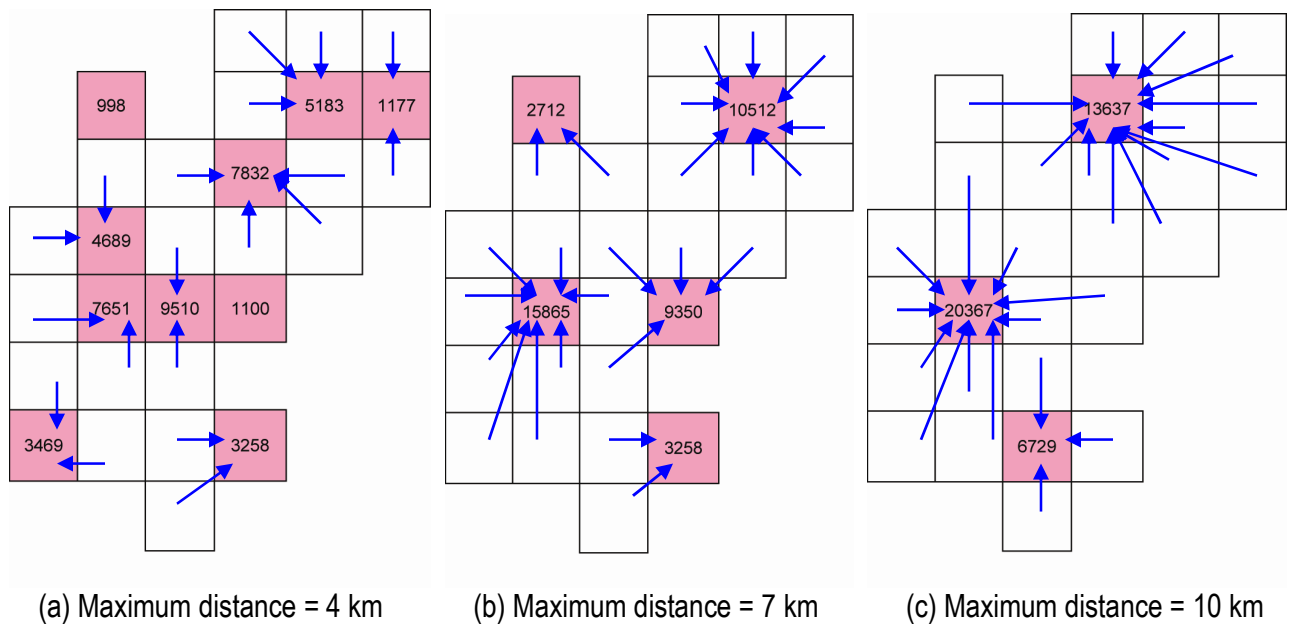
These results provide important insights. Vaccination coverage increases with more sites, but only marginally for more than three sites. Average travel distance continues to decrease with from one to ten sites. However, the marginal returns of cases avoided by adding more sites seem not substantial even compared to the single mega-site vaccination with less than 50 additional cases avoided by having 10 outposts instead of only one. As discussed in the previous section, the cases avoided seems to favor government's single mega-site vaccination plan at the CDC, while the other indicators, such as number of vaccinations, travel distance, revenue and benefits, favor more outposts for the users in need of vaccination. The ultimate decision would be dependent upon what benefits government focuses on (i.e. health benefits vs. private benefits) and how their planning process is structured (top-down vs. bottom-up). Economics and policy literature argue that all the benefits and costs to whomever they may accrue should be accounted for in benefit-cost analysis. If government aims at meeting private demands as well as maximizing public benefits, identifying and analyzing all benefit and cost information would be important to provide the best vaccination policy possible.

Despite the absence of the actual cost information, these results disclose the level of average unit cost of vaccination that can result in the system breaking even. Because there is no cost savings to the public health system by reductions in disease incidence due to

vaccinations, revenue from private sales is the only source of financial benefit for the vaccination program. Thus, the level of user fee should be the same as the average cost to make the system break even financially.

Figure 4.6 also shows how the locations of outposts selected by the set covering models change as the maximum distance increases, and how the set covering models allocate the cells to each of the selected outposts<sup>23</sup>. According to Figures 4.6(a) and 4.6(b), five cells remain selected as optimal as the maximum distance changes from 4 km to 7 km. However, four out of the five selected outposts in Figure 4.6(b) would have to cover more people including those who were covered by other cells in Figure 4.6(a). It indicates that lowering the number of outposts would require larger capacity from the outpost in the selected cells.

Figure 4.6. Optimal locations from the set covering models (p=USD 1)



\*\*\* The optimal cells are shaded.

\*\*\* Numbers are the predicted number of vaccinations in the cell.

\*\*\* Arrows show how cells assign to outposts.

<sup>23</sup> For some cells where multiple outposts are located within the specified distance, it is assumed that people travel to the nearest outpost among them.

Furthermore, considering population size in each cell shown in Figure 4.1(b), some of the selected cells have a very small population, but a much larger number of people in the neighboring cells were assigned to the cells with small population by the set covering model. For instance, cell #5 has a population of only 348, but about 3,000 people in the neighboring cells were assigned to travel to the outpost located in cell #5. This observation raises concerns about (1) limited capacity in small-population cells, and (2) large burden of vaccinees' travel.

#### 4.4. p-median model

While the set covering model provides insights on the optimal number and locations of vaccination sites to ensure that no one is beyond the selected maximum distance, the p-median model suggests where to locate a pre-specified number ( $K$ ) of vaccination sites so that total population-weighted travel distance is minimized (ReVelle, Church and Schilling, 1975). The total population-weighted distance is obtained by summing the products of population of each demand point (e.g. village) and distance to the closest vaccination site. Assuming that those who want to receive vaccinations choose to travel to the closest vaccination site, the p-median model identifies the Pareto optimal solution so that no person can reduce his travel distance without making another person worse off. Unlike the set covering model, the p-median model may produce the solution which requires people in some areas to travel considerable distances to the vaccination outpost since it is not subject to any maximum distance requirement.

As in the set covering model scenario above, let us assume that a vaccination campaign in Daxu Township targets all people living in the 29 cells in the township ( $i = 1, 2, \dots, 29$ ) and only 25 of them are candidates for the location of vaccination outposts ( $j = 1, 2, \dots, 25$ ). The objective function of the p-median model is to minimize the total population-weighted distance between each cell and the nearest cell with a vaccination outpost. In this model, decision variables are  $x_{ij} \in \{0, 1\}$ : 1 if households in cell  $i$  assign to a vaccination site in cell  $j$ , 0 otherwise.

$$\text{Minimize: } \sum_{i=1}^{29} \sum_{j=1}^{25} \{A_i \cdot \Pr(p, d_{ij}, I_i, H_i)\} \cdot d_{ij} \cdot x_{ij} \quad \text{eq. 4.4}$$

$$\text{Subject to } \sum_{j=1}^{25} x_{ij} = 1, \forall i \quad \text{eq. 4.5}$$

$$\sum_{j=1}^{25} x_{jj} = K \quad \text{eq. 4.6}$$

$$x_{ij} \leq x_{jj}, \forall i, \forall j, i \neq j \quad \text{eq. 4.7}$$

$$x_{jj} = 1, \text{ if } j = \#10 \text{ where the CDC is located} \quad \text{eq. 4.8}$$

where  $A_i$  = Population in cell  $i$

$\Pr(\bullet)$  = Probability of being vaccinated based on the demand function in eq. 3.6<sup>24</sup>

$d_{ij}$  = Road distance from cell  $i$  to cell  $j$

$p$  = User fee for typhoid vaccination

$I_i$  = Average household income in cell  $i$

$H_i$  = Average household size in cell  $i$

---

<sup>24</sup> The p-median model developed in my dissertation is slightly different from a typical p-median model since it uses the predicted number of population vaccinated based on the demand function rather than the entire candidate population.

This p-median model has four constraints: first, each cell must be assigned to one vaccination site (eq. 4.5); second, the total number of vaccination sites is  $K$  (eq. 4.6)<sup>25</sup>; third, households in cell  $j$  must self-assign to the vaccination site in cell  $j$  if the vaccination site in cell  $j$  is assigned to households in cell  $i$  by computer (eq. 4.7); and fourth, the township CDC should be included in the solution set of vaccination sites (eq. 4.8). The demand function in eq. 3.6 depends on four variables, such as distance to vaccination site, user fee, average household income, and household size, all of which are exogenous in this model. The number of vaccination sites is specified by the modeler as “ $K$ ”. The p-median problem is formulated as a 0-1 integer problem due to the binary feature of  $x_{ij}$ , but usually (not always) is solved by linear programming. To resolve unusual solutions with fractional assignments produced by linear programming, the branch-and-bound method can be used to find the optimal integer solutions to the p-median model (ReVelle and Swain, 1970). In general, the p-median model is thought to be easier to solve than the set covering model which requires a 0-1 integer programming to solve in most cases.

To begin with, the p-median model can be used to evaluate the current location of the CDC if it is run without the last constraint in eq. 4.8. The result shows that cell #10, where the CDC is currently located, was chosen as optimal if only one outpost is to be located in the township ( $K=1$ ). This finding also ensures the appropriateness of the constraint in eq. 4.8.

Suppose two additional sites are to be used for vaccination in addition to the CDC. Where should they be located to minimize the sum product of population and travel distances between each cell and its nearest vaccination outpost? What if we assign five or more sites? How far would people have to travel on average for each of the alternatives? How would the

---

<sup>25</sup> Since  $x_{ij} = 1$  means that villagers in cell  $i$  receive the vaccine at their own cell, the sum of  $x_{ij}$  should be the same as the total number of open vaccination sites ( $K$ ).

program outcomes change by the number of sites? Table 4.5 addresses these questions. The number of sites was chosen as 3, 5, and 10 to compare the results with those from the set covering models.

Table 4.5. Results of the p-median models

Number of sites assumed ( $K$ )	Average one-way travel distance (km)	Assumed price (USD)	Number of people vaccinated	Coverage rate (% of total)	Cases avoided	Revenue (USD)
10	1.2	0	51,326	95	232	0
		1	46,660	86	211	46,660
		2	42,418	78	192	84,836
5	2.5	0	47,925	89	209	0
		1	43,568	80	190	43,568
		2	39,607	73	173	79,214
3	3.4	0	45,733	84	202	0
		1	41,575	77	184	41,575
		2	37,795	70	167	75,590

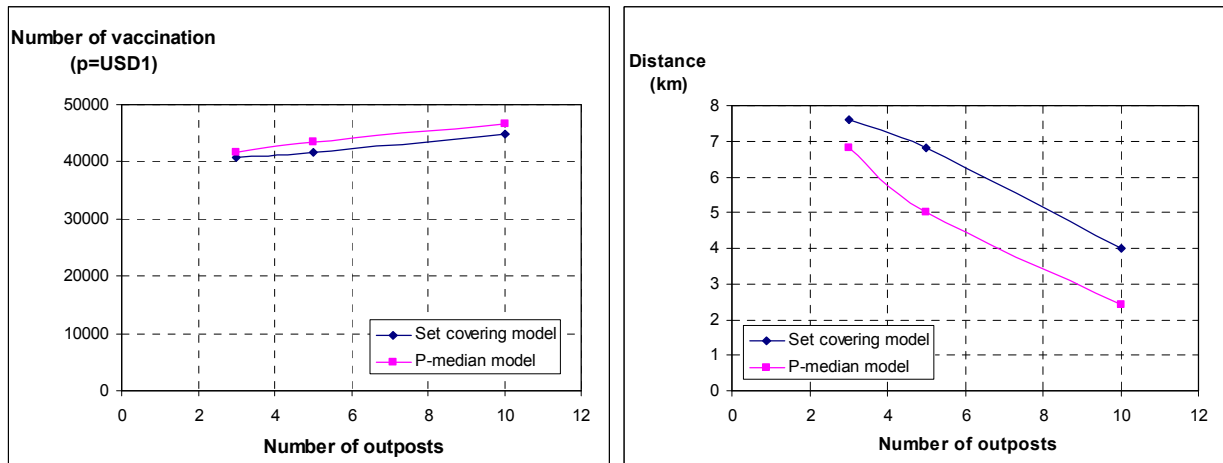
Compared to the single mega-site vaccination in Table 4.3, Table 4.5 shows that about 8,000 more people would be vaccinated by using two more sites in addition to the CDC. However, the number of vaccinations increases by only about 2,000 with two additional sites from  $K=3$  to 5, and increases by only about 4,000 with five additional sites from  $K=5$  to 10. This result clearly indicates diminishing marginal returns with more outposts. Just three sites capture most of the vaccinations and after that, additional sites do not contribute much. Similarly, marginal returns of cases avoided, revenue, and average travel distance also diminish with more outposts. For instance, average roundtrip travel distance drops in half by the first two additional outposts (from 6.8 km with the single mega-site to 3.4 km with three sites), but decreases by only 1 km with the next two additional outposts (from 3.4 km with 3 sites to 2.5 km with 5 sites). Figure 4.7 shows the vaccination sites selected by the p-median models.



Table 4.6. Comparison of set covering and p-median models (if p=USD 1.0)

Number of outposts ( $K$ )	Outcomes	Set covering model	P-median model
3	Average one-way travel distance (km)	3.8	3.4
	Number of vaccinations	40,734	41,575
	Cases avoided	186	184
	Private benefits (USD)	289,664	304,883
10	Average one-way travel distance (km)	2.0	1.2
	Number of vaccinations	44,867	46,660
	Cases avoided	204	211
	Private benefits (USD)	338,995	373,280

Figure 4.8. Comparison of the results between set covering vs. p-median models



(a) Number of vaccinations

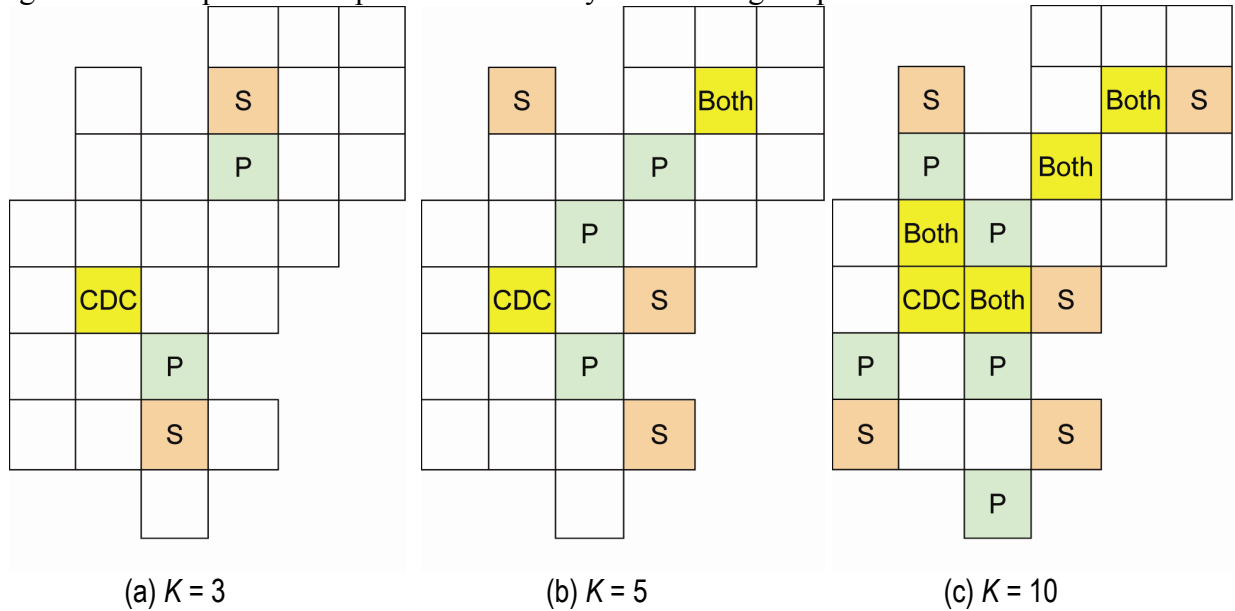
(b) Average roundtrip travel distance

Figure 4.9 shows which cells were selected as optimal outpost locations by each model for  $K = 3, 5,$  and  $10$ . For  $K = 3$ , the cells selected for the two sites in addition to the CDC are different but close to each other. The similar pattern is found for  $K = 5$  and  $K = 10$ . However, it is worth noting that the set covering models tend to locate outposts closer to the border while the p-median models locate outposts in the cells with high population (see Figure 4.1(b)). The difference in the solutions between the two models is due to the different objective of each model. The set covering model minimizes the number of sites while holding all cells within a certain distance, while the p-median model allocates a certain



number of sites to minimize the sum product of population and travel distances between each cell and the selected outpost.

Figure 4.9. Comparison of optimal locations by set covering vs. p-median models



\* S: cell selected by set covering model, P: cell selected by p-median model, Both: cell selected by both

It is a disadvantage of the set covering model to ignore population size in cells. In this particular case in Daxu Township where population sizes do not vary much by cells, the impact seems small. However, if the model is used for an area with large variability in population size, it would be a big deficiency. Furthermore, as already argued before, the set covering model could locate an outpost in a cell with very small population, assigning a large population in the neighboring cells to travel to the outpost. However, in practice, it seems unlikely that an outpost would be located not in but adjacent to a cell with high population. In this regard, one may conclude that the p-median model performs better, at least for this case, since it takes account of not only inter-cell distance but also population size in the cells. One limitation of the p-median model would be to assign households to a specific outpost

assuming users should receive vaccinations at the nearest outpost, which may not be easily enforced in practice.

#### 4.6. Conclusion

This chapter highlights that the two location models presented here, the set covering and p-median models, are powerful tools to assist in planning decisions concerning the suitable number of vaccination sites and locations of multiple sites even in the absence of cost data. It also demonstrates that the p-median model seems preferable to the set covering model for the reasons given above. Decisions being made concerning the number and location of vaccination outposts without the aid of these kinds of analytic tools might be limited and quite possibly would be far from optimal.

The results of these models, however, may not provide complete and absolute guidance on the optimal solutions without considering the cost side unless vaccination cost per person is trivial (e.g. a few pennies per vaccination). An approximate calculation for the model results presented in this chapter may indicate whether the cost of vaccinating a person is trivial or substantial. In Table 4.5, the p-median model predicts that approximately 40,000 people would be vaccinated if five outposts were located and user fee were USD 2. Assuming that a team of five whose daily salary is USD 10 vaccinates 200 people per day, USD 10,000 would be spent for personnel costs. If all non-personnel operation costs (e.g. vaccine storage, publicity, supplies, transportation, etc.) come to a total of USD 50 per outpost per day, another USD 10,000 would be needed. By dividing the total program cost of USD 20,000 by the predicted number of people who would be vaccinated from the model

(40,000 people), the cost per person is calculated as USD 0.5 ( $=20,000/10,000$ ). Such per-person cost of vaccination would quite likely be judged as nontrivial in China, which would argue for the need for greater attention to be paid to estimate a cost function in a more sophisticated fashion and to examine optimization models that seek to improve efficiency in vaccination delivery.

Economists suggest the “marginal approach” to identify the condition where marginal costs and benefits are equal because it maximizes net benefits (i.e. the maximization principle). For instance, if costs are simply assumed to be equal to revenues, the marginal benefits of vaccinations will always be greater than marginal costs with an increasing number of outposts. Then, the optimal solution would be to have an outpost in each cell because the net benefits would increase monotonically when more and more outposts are added. However, it is certainly possible that marginal costs of vaccinations might become larger than marginal benefits when only a few or several outposts are located in the township. Therefore, the optimal number of outposts may not be determined by these models until vaccination cost information is incorporated into the analysis.

## **Chapter 5**

### **Estimation of vaccination delivery costs**

Although the location models presented in Chapter 4 showed substantial strengths in locating vaccination outposts, more comprehensive and definite determination of the best and most feasible vaccination delivery policy in this township would be possible only if vaccination delivery costs are considered along with the other policy indicators. However, in many cases, vaccination delivery cost data are either unavailable or hard to be obtained. Thus, in this chapter we estimate the cost function for a vaccination campaign in Daxu Township based on simulations.

#### **5.1. Background**

The technical literature shows that the costs of vaccination programs are different depending on the delivery method used (Walker et al., 2004; Robertson et al., 1984; Phonboon et al., 1989; Linkins et al., 1995). The two main vaccination delivery methods are (1) fixed (routine) programs, and (2) mass vaccination campaigns. Fixed vaccination programs typically require permanent clinics (health centers) with permanent staff. Daxu Township has only a few permanent clinics and virtually no health staff besides the village doctor in the villages. Therefore, fixed programs are not feasible for Daxu Township, and

therefore this research assumes vaccinations will be delivered in Daxu Township through mass campaigns.

Mass vaccination campaigns are usually offered periodically (once every few years), and they tend to operate from ‘borrowed’ facilities such as schools, workplaces, government buildings, homes, and, if available, village clinics, sometimes requiring rental fees and other times not. Special staff are needed for mass campaigns, and staff salaries are usually the largest portion of the total delivery cost of a vaccination program<sup>26</sup>. Promotion campaigns are needed to make people aware of where and when vaccinations are available. Mass campaigns are often run from an office that is centrally located to the outposts, and vaccination staff gather there each day to be transported to their assigned outposts with vaccines and supplies.

The costs of a mass vaccination campaign falls into two categories: fixed and variable costs. The boundaries for the categories are not always clear, with some costs being classified as fixed which could as easily be considered variable, and vice versa. In this research, fixed costs are assumed to be associated with the number of vaccination outposts, and variable costs depend on the number of persons vaccinated. Hence, it is assumed that the cost of a mass vaccination campaign is a linear function of two explanatory variables as shown in eq. 5.1:

$$TC = a \cdot Z + b \cdot Q \quad \text{eq. 5.1}$$

where  $TC$  = total cost,  $a$  = average fixed cost per outpost,  $Z$  = number of outposts,  $b$  = average cost per dose, and  $Q$  = total number of people vaccinated during the campaign.

---

<sup>26</sup> In this chapter, only “delivery cost” is estimated, assuming that the vaccine dose costs zero.

If vaccinations were offered at one or just a few outposts, travel cost for the vaccination workers might be relatively small, and fixed cost might also be small due to economies of scale. However, vaccination demand with only a few outposts would probably be relatively low due to longer travel times and distances required of vaccinees to go to the vaccination outposts. Delivering vaccinations at a large number of outposts would probably incur a larger setup cost, but it would probably reach more people who would not have to travel so far to be vaccinated. The extreme alternatives are to offer vaccinations: (1) at a single mega-site or (2) in each home. Between these extremes presumably lies the optimal number and location of outposts, which this research aims at identifying.

## 5.2. Cost estimation approach

Because little data and information are available on vaccine delivery cost in China, it is necessary to estimate vaccination program costs based on the simulation of different delivery systems. To the greatest possible extent, the characteristics of mass vaccination campaigns and unit cost values used in the simulations of this chapter were based on data from Daxu Township, but where lacking, they had to be supplemented by other sources. Yang et al. (2005) reported on a cluster-based Vi mass vaccination campaign against typhoid fever in Hechi, Guangxi province in China, where Daxu Township is located. Actual cost information, however, was not included in their report. Jian et al. (1998) and Cavailler et al. (2005) provide data on the unit costs incurred by mass vaccination campaigns in developing countries other than China, which are used in the simulations of this chapter. Based on Yang et al. (2005), it is assumed that each vaccination team that participates in a mass campaign

consists of 1 physician (the leader), 2 nurses (vaccinators), 1 health worker (support staff, record keeping, etc.), and 3 community helpers.

A campaign is assumed to last 30 work days, and each team is assumed to vaccinate 200 persons per day during an 8-hour work day, 2 hours of which are assumed to be spent traveling from the central office where team members assemble each day (called the CDC in China) to its outpost and returning to the CDC. Twenty-five of the 29 cells in Daxu Township (see Figure 5.1) are potential sites for outposts, which are represented by the columns in Table 4.1. Vaccine doses are stored in cold rooms at the CDC and transported daily to outposts by the vaccination teams. Each outpost has a vehicle that is dedicated to transporting a 7-person team plus vaccines and supplies from the CDC each morning and returning in the evening. The required number of teams assigned to an outpost depends on the expected number of vaccinees. The assumed vaccine wastage rate is 11%, as reported by Yang *et al.* (2005).

According to Cavailler *et al.* (2005), the average salary for vaccination staff was about USD 7.7 per day in Mozambique. Considering the purchasing power parity of China and Mozambique, the average daily salary for Daxu staff is about USD 10, which seems to agree with the information for the mass campaign of Vi vaccinations in Hechi City, China in 2003. The cost of vaccine storage per day is assumed to be USD 1.0 per 1,000 doses, following Cavailler *et al.* Based on private communication with the Guangxi provincial CDC staff who have been involved in mass vaccination campaigns in Hechi province, it costs about USD 30 for setup per outpost per day, USD 20 for car and driver rental per day, and USD 0.3 for local transportation per kilometer. Assumptions for the cost simulations performed herein are summarized in Table 5.1.

Table 5.1. Assumptions for cost estimation by simulation

Items	Value	Sources
<b>Logistics</b>		
Members in a vaccination team	7	Yang et al. (2005)
Vaccinations per team per day	200	Yang et al. (2005)
Length of campaign, days	30	Yang et al. (2005)
Wastage rate, % of total doses	11	Yang et al. (2005)
<b>Unit costs, USD</b>		
Average daily salary per worker	10	Cavailler et al. (2005)
Vaccine storage, per 1000 doses per day	1.0	Cavailler et al. (2005)
Publicity, per dose	0.06	Jian et al. (1998)
Training, per dose	0.02	Jian et al. (1998)
Supplies, per dose	0.02	Jian et al. (1998)
Outpost setup/rental, per outpost per day	30	Personal communication with Guangxi CDC staff
Car & driver, per day	20	Personal communication with Guangxi CDC staff
Mileage, per km	0.3	Personal communication with Guangxi CDC staff

The first step in estimating the cost function in eq. 5.1 was to generate alternative vaccination program designs. This was done by selecting a different number of vaccination outposts for each design and then solving the p-median model described in Chapter 4, one solution for each specified number of outposts, to determine (1) the optimal locations of the outposts for each design and (2) the number of people who would seek vaccination at each outpost. For the simulations, the number of outposts was assigned values of 1, 2, 3, 4, 5, 8, and 12, which resulted in 7 different designs and 7 solutions of the p-median model. For each design, the user fee was assumed to be zero, and the vaccination demand function in eq. 3.6 was used with the travel distances in Table 4.1 from source cells to candidate outpost locations and the average household income for each cell in Figure 4.3 to determine the number of vaccinees at each (optimally located) outpost. The average household size of 4.5 is also assumed.

The next step was to estimate the cost of a mass vaccination campaign for each alternative design using the data in Table 5.1. With estimates of the number of vaccinees at each outpost from p-median model solutions, it was possible to determine the number of



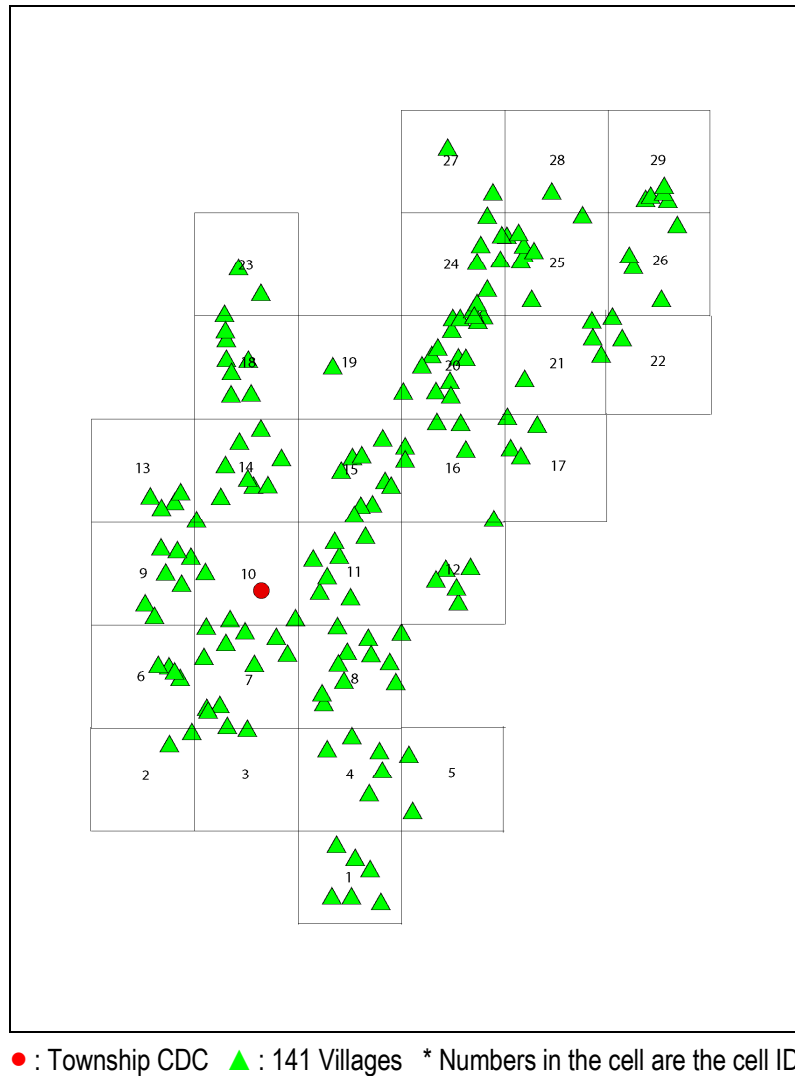
vaccination teams required for each outpost, the number of cars and drivers, the total doses of vaccine, total number of personnel, and similar resources required to deliver the different program designs. Similarly, with the optimal locations of outposts, it was possible to estimate total travel distances and costs. Thus, an estimated cost was produced for each different design, seven in all. After making the simulations with a user fee of zero, the simulations were repeated with using a fee of USD 1.0 per dose to generate an additional seven designs.

The final step was to regress the costs of the different designs against the two explanatory variables in eq. 5.1, the number of outposts and the number of doses, which enabled estimates of the parameters  $a$  and  $b$ . The data for fees of zero and USD 1.0 were pooled and a dummy variable was included in the regression analysis to determine the effect of fee on the cost parameters  $a$  and  $b$ .

### 5.3. Illustrative example

The example in this section illustrates the approach that was used for estimating costs by simulation. The assumed number of outposts was 5 and user fee was assumed to be zero. Recall that Table 4.1 shows the road distances in km between source cells (rows) where the people of Daxu Township live and the 25 candidate locations of outposts (columns), which defines  $d_{ij}$  in the demand function, distance that a person living in cell  $i$  would have to travel to be vaccinated if an outpost were located in cell  $j$ . Figure 5.1 shows the grid that was superimposed on Daxu Township to define the cells for this analysis.

Figure 5.1. Map of 29 cells in Daxu Township



According to Table 4.1, if there were only a single outpost in Daxu Township located in cell #10 at the CDC, then people from, for example, cell #1 would have to travel 11 km to be vaccinated, and people in cell #2 would have to travel 6 km. These distances were measured based on road networks and are not straight-line distances.

Each travel distance  $d_{ij}$  in Table 4.1 was inserted into the vaccination demand function in eq. 3.6 with a price of zero, average household size of 4.5 persons, and the average household income for each cell, and the demand model was solved to predict  $Q_{ij}$ , the

average number of vaccinations that a household in cell  $i$  would purchase if the vaccination outpost were in cell  $j$ . Multiplying each  $Q_{ij}$  value by the number of households in cell  $i$  yields the predicted number of people in cell  $i$  who would be vaccinated if their outpost were in cell  $j$ . Table 5.2 shows the predicted number of vaccinations for all possible combinations of source and destination cells in Daxu Township (the units are hundreds of persons). For example, if residents in cell #1 had to travel to cell #10, about 1,500 of them would be vaccinated if no fee were charged.

Table 5.2. Predicted vaccinations (in hundreds) at price=0

From / To	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	23	24	25	26
1	26	16	17	20	22	15	16	17	13	15	14	14	11	11	12	11	11	9	10	10	9	8	8	7	7
2	4	6	5	4	4	5	5	4	4	4	4	3	4	3	3	3	2	3	3	2	2	2	2	2	2
3	3	5	5	4	4	5	4	4	4	4	4	3	3	3	3	3	2	3	2	2	2	2	2	2	2
4	10	8	9	12	10	8	9	10	8	9	8	8	7	7	7	6	6	6	6	6	5	5	5	4	4
5	3	2	2	3	4	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1
6	19	28	28	22	22	32	28	23	28	27	23	19	24	21	19	16	15	18	16	15	13	15	13	11	10
7	29	38	42	36	31	42	49	39	41	46	39	32	36	34	32	27	25	29	27	25	22	24	21	19	17
8	31	31	35	39	31	33	37	47	31	37	39	37	29	31	32	30	28	26	27	26	24	21	22	20	18
9	15	21	22	18	16	25	24	19	29	24	21	17	24	21	18	15	14	18	16	14	12	15	13	11	9
10	8	10	11	10	8	12	13	11	12	14	11	9	11	10	10	8	7	9	8	7	7	7	6	6	5
11	17	19	21	21	16	22	24	25	22	25	31	25	22	24	25	22	20	20	21	20	18	17	17	15	13
12	7	6	7	8	6	7	8	10	7	8	10	12	7	8	9	10	9	7	8	8	8	6	7	6	6
13	6	8	9	7	6	10	10	8	11	10	10	8	14	11	9	7	7	10	9	7	6	9	7	6	5
14	11	14	15	14	10	16	17	16	18	19	20	16	21	25	20	16	15	21	19	16	14	17	14	13	11
15	19	22	24	24	17	25	28	30	27	30	35	33	29	35	43	35	32	32	36	34	29	27	29	25	22
16	7	7	7	8	6	8	9	10	8	9	11	12	8	10	12	15	14	9	12	13	12	8	11	10	9
17	5	5	5	6	4	5	6	7	6	6	8	9	6	7	9	11	12	7	8	10	10	6	9	8	8
18	7	9	10	9	6	11	11	10	12	12	12	11	14	16	14	12	11	19	15	13	10	16	12	10	8
19	2	2	2	2	1	2	3	3	3	3	3	3	3	3	4	3	3	4	5	4	3	3	4	3	3
20	17	19	21	21	14	22	24	26	24	25	30	31	26	31	37	39	38	31	40	47	39	30	40	35	30
21	6	6	6	7	5	6	7	8	7	8	9	10	7	9	11	13	14	9	11	13	16	9	13	13	12
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	1	1	0	1	1	1
23	3	4	5	4	3	5	5	5	6	6	6	5	7	8	7	6	6	9	8	7	6	11	7	6	5
24	10	11	12	12	7	12	14	15	13	14	17	18	15	18	21	22	23	19	24	26	25	19	31	27	22
25	6	6	7	7	5	7	8	9	8	9	10	11	9	11	13	14	15	11	14	16	17	12	18	21	17
26	2	2	2	2	2	2	2	3	2	2	3	3	2	3	4	4	4	3	4	4	5	3	5	5	7
27	2	3	3	3	2	3	3	3	3	3	4	4	4	4	5	5	5	5	6	6	6	5	7	8	6
28	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1
29	1	1	2	2	1	2	2	2	2	2	2	3	2	2	3	3	4	3	3	4	4	3	4	5	5

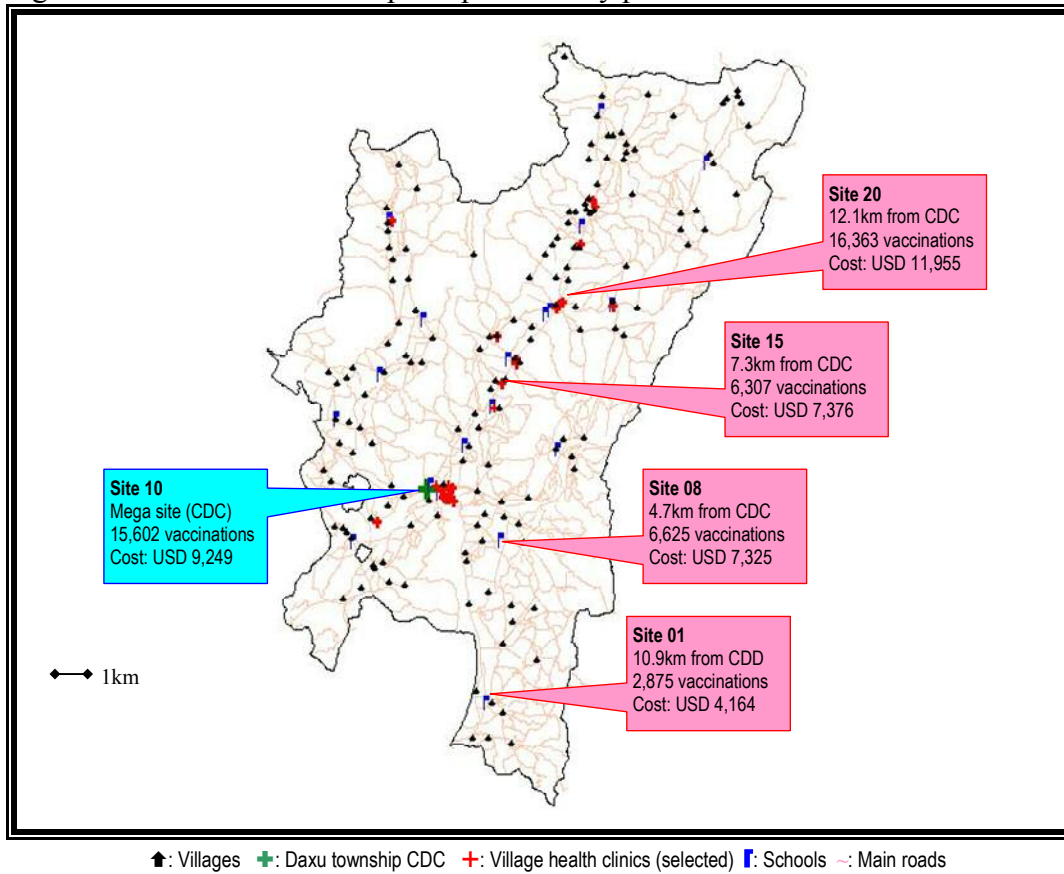
For this illustrative example, the number of outposts was restricted to five. Accordingly, the p-median model was solved to determine (1) their optimal locations, and (2) the number of vaccinations that would be demanded at each one. The results are shown in the first and second columns of Table 5.3.

Table 5.3. Predicted number of vaccinations and required resources for each outpost

Outpost Cell ID	Predicted vaccinations	Required teams	Required cars	Roundtrip distance per day (km)	Total distance (km)
#10	15,602	3	0	0	0
#1	2,875	1	1	22	654
#8	6,625	2	2	19	282
#15	6,307	2	2	29	438
#20	16,363	3	3	73	2,178
<b>Sum</b>	<b>47,772</b>	<b>11</b>	<b>8</b>	<b>142</b>	<b>3,552</b>

Consider the row in which cell #20 is the optimal location for an outpost. The p-median model predicted that about 16,000 people would get vaccinated there. Three vaccination teams would be needed to provide the vaccinations (200 per day per team for 30 days). Three vehicles would be needed to transport the teams to the outpost, and their total roundtrip distance from the CDC would be about 73 km per day or about 2,200 km for the entire campaign. In total, 11 teams would vaccinate about 48,000 people (88% of Daxu population) traveling a total distance of about 3,500 km. The results are shown in Figure 5.2.

Figure 5.2. Locations of 5 outposts provided by p-median model



Using the simulation results in Table 5.3 and the unit costs in Table 5.1, an estimate was made of total program cost for this program design. The result is shown in Table 5.4.

Table 5.4. Estimated costs of vaccination program by category (5 outposts and free vaccination)

Category	Cost (USD)
Personnel Cost (Salaries)	23,100
Publicity Cost (Promotion)	2,866
Training Cost	955
Cost of Supplies	955
Vaccine Storage (Cold room, refrigerator)	1,610
Car / Driver Rental Cost	4,800
Mileage Cost	1,282
Outpost Setup / Rental Cost	4,500
<b>Total Cost</b>	<b>40,069</b>

#### 5.4 Cost summary

The illustrative example was only one of fourteen separate simulations that were made in order to obtain a dataset for estimating eq. 5.1 by the ordinary least square (OLS) method. Half the simulations assumed the user fee was zero and the other half assumed it was USD 1.0. The resulting cost estimates and characteristics of the different vaccination program designs are shown in Table 5.5.

Table 5.5. Simulated outcomes for different vaccination program designs

Run	Number of outposts (Z)	Predicted vaccinations (Q)	Vaccination coverage (%)	Average Vaccinations per outpost	Vaccination costs (USD)	Average costs per dose (USD)	User fee (USD)
1	1	37,438	69	37,438	20,606	0.55	0
2	2	42,828	81	21,914	26,914	0.61	0
3	3	45,435	84	15,145	31,591	0.70	0
4	4	46,610	86	11,653	36,118	0.77	0
5	5	47,772	88	9,554	40,069	0.84	0
6	8	50,012	92	6,252	49,643	0.99	0
7	12	51,850	96	4,321	56,232	1.08	0
8	1	34,034	63	34,034	18,051	0.53	1
9	2	39,843	74	19,922	26,381	0.66	1
10	3	41,304	76	13,768	31,039	0.75	1
11	4	42,371	78	10,593	33,451	0.79	1
12	5	43,428	80	8,686	36,657	0.84	1
13	8	45,465	84	5,683	49,035	1.08	1
14	12	47,136	87	3,928	53,501	1.14	1

Estimated costs in the sixth column of Table 5.5 were treated as the dependent variable in eq. 5.1 and the independent variables are in the second (Z) and third (Q) columns. In addition, a dummy variable with the values in the last column was included to determine whether the different user fees had a significant effect on program costs. Eq. 5.1 was fitted without an intercept (overall R-square = 0.97), and the model was significant at the 1% level (F= 126). The estimated coefficients for  $a$ ,  $b$ , and the dummy variable were 2570, 0.53, and

166, respectively. The two explanatory variables are each significant at the 1% level, but the dummy was not significant ( $t = 0.15$ ). Hence, the model for predicting the costs of alternative vaccination programs based on the number of outposts and total vaccination sales is shown in eq. 5.2:

$$TC = 2570 \cdot Z + 0.53 \cdot Q \quad \text{eq. 5.2}$$

Table 5.5 shows that the predicted number of vaccinations increases as the number of outposts increases, which raises the question of whether multicollinearity exists between these two variables. The partial correlation coefficient is close to 0.7, which, although high, probably is not subject to a serious multicollinearity problem (Kennedy, 1992). It seems obvious that more people would be vaccinated if more outposts are used, but it is also true that delivery costs are a function of not only the number of outposts (i.e. fixed cost) but also the numbers of persons who visit them to be vaccinated (i.e. variable cost). In fact, for the fourteen simulated data points, it is found that the “observed” costs match very well with the “predicted” costs based on eq. 5.2, which indicates that a multicollinearity problem associated with simulated cost data is less important than one might think. Recall that both explanatory variables are highly significant in the regression model for costs above.

A recurring question about vaccination programs is whether they reflect economies of scale. The common belief is that there are economies in such programs, but the data in Table 5.5 suggest otherwise. According to the first seven rows of Table 5.5 for a user fee of zero, the numbers of vaccinations in the third column are shown in increasing order, and the average cost per dose in the seventh column also increases. Hence, the data suggest

diseconomies of scale, not economies. The same is true of the last seven rows of Table 5.5 for which the user fee is USD 1.0. In Daxu Township, the total population is fixed at about 54,000. Because the quantity of vaccinations demanded decreases with increasing travel distance, the only way to vaccinate more people is by bringing outposts closer to them, which incurs additional setup and travel costs. If demand were entirely inelastic with respect to travel, the optimal solution would be to have a single mega-site. In the case of Daxu Township, it turns out that the marginal cost of adding more outposts exceeds the average cost, causing the average to increase.

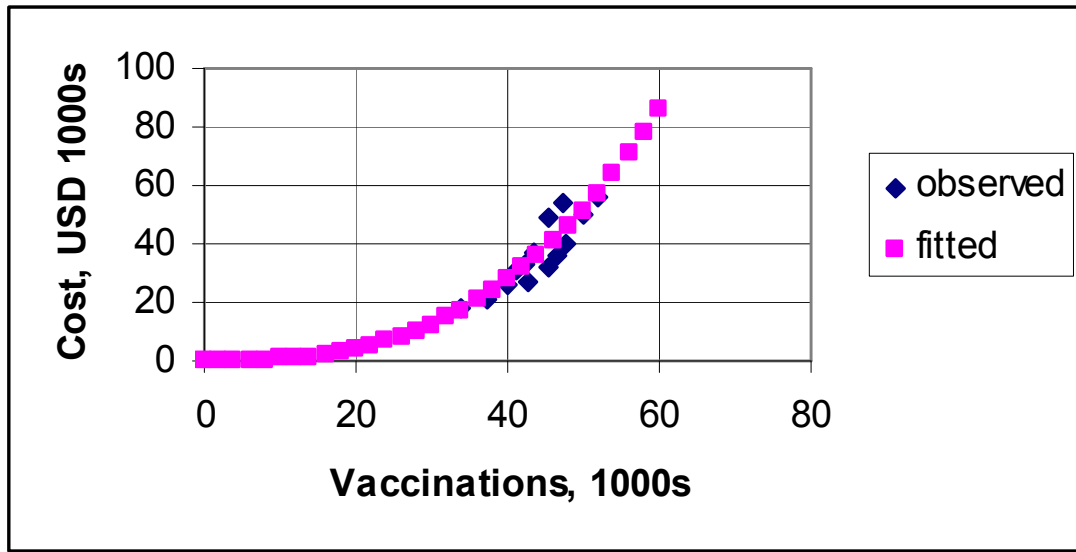
This can easily be seen from the log linear equation that was fitted to total cost (USD 1000s) and total vaccination (1000s) data in Table 5.5. A graph of the cost data from Table 5.5 is shown in Figure 5.3 together with the fitted equation, which is shown in eq. 5.3 (R-square = 0.85);

$$TC = 0.0009 \cdot Q^{2.8} \quad \text{eq. 5.3}$$

where  $TC$  is total delivery cost in thousands of USD and  $Q$  is number of vaccinations in thousands. It is easy to show that the exponent of a power function like the one in eq. 5.3 represents the percentage change in cost per 1% change in the number of vaccinations, which is sometimes called the economy of scale factor. For economies to exist, the exponent would need to be between zero and one. In this case, there is nearly a 3% increase in cost for every 1% increase in vaccinations, which implies quite large diseconomies of scale.



Figure 5.3. Vaccination delivery costs vs. number of vaccinations (free vaccination)

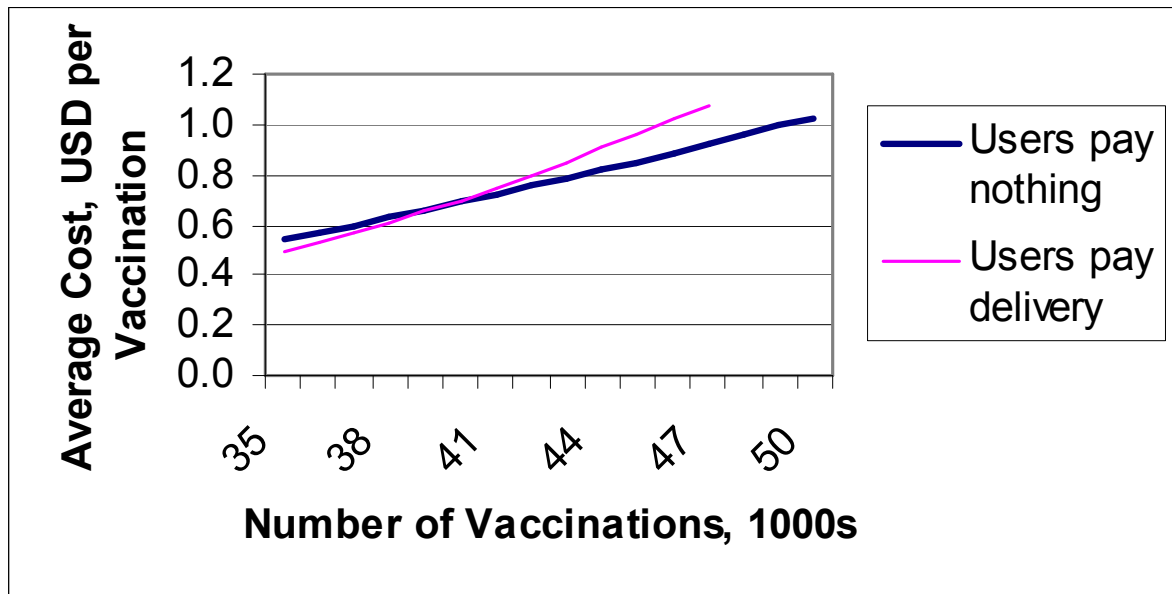


The analysis presented so far in this chapter has assumed that vaccinations are offered free of charge and users pay nothing, but users would have to pay a price that would cover delivery cost. Figure 5.4 compares delivery costs in which users pay nothing (the seventh column in Table 5.5) to delivery costs in this case where users are responsible for covering them. In both cases, vaccines are assumed to be available without charge. The differences between the two curves in Figure 5.4 do not appear to be large, yet this is not entirely accurate. First, we notice that the range of average delivery cost is a little larger when users pay than when they do not (USD 0.5 to 1.1 when they pay). However, note that the user-pay curve in Figure 5.4 ends at about 47,000 vaccinations, which is the maximum number that can be obtained when users are charged and which occurs when there are 14 outposts. It is not possible to vaccinate more than this if users must pay, unlike the case when users do not have to pay. Another important difference can be seen by comparing eq. 5.4 (R-square = 0.84) that underlies the user-pay curve in Figure 5.4 with eq. 5.3 that underlies the no-pay curve:

$$TC = 0.00004 \cdot Q^{3.7} \quad \text{eq. 5.4}$$

where  $TC$  is total delivery cost in thousands of USD and  $Q$  is number of vaccinations in thousands. The larger exponent in eq. 5.4 than in eq. 5.3 indicates even larger diseconomies of scale in mass vaccination campaigns when users have to pay, which is also seen from the steeper slope of the user-pay curve in Figure 5.4.

Figure 5.4. Average vaccination delivery costs vs. number of vaccinations



## **Chapter 6**

### **Models for determining optimal user fee and locations**

The previous chapters presented the key information for the design of a vaccination program in Daxu Township in China. Chapter 3 provided estimates of the private demand for vaccinations based on user fee, travel distance to the vaccination site, and household income. Chapter 4 presented two locations models, the set covering model and p-median model, for the initial understanding of how many vaccination outposts might be needed and where they should be located. Chapter 5 provided estimates of costs.

This chapter pulls together all the pieces from the previous chapters and uses them to address the main policy questions concerning the number and locations of vaccination outposts and the price to charge for typhoid vaccinations in China. It first develops an optimization model in which the planning objective is to maximize vaccination coverage. Analyses are made to examine how sensitive the solutions are to different constraints and assumptions about the demand and cost functions. Next, an alternative model is formulated and solved in which the objective is to maximize the number of cases that can be avoided with a vaccination program. The results from this model are compared with those from the model in which coverage was maximized.

## 6.1. Optimization model for maximizing vaccination coverage

The optimization model of this section assumes that the objective is to maximize the number of vaccinations (i.e. coverage) in Daxu Township, subject to the constraint that program costs should be entirely covered by revenue from user fees. Considering the private benefits associated with getting vaccinated, this objective implies primary concern with maximizing private benefits and not necessarily with maximizing health effects. Hence, this model takes no special account of variations in disease incidence in the target area, and thus does not prioritize the areas with high incidence<sup>27</sup>.

Assume that the vaccination campaign targets all people living in  $N$  cells in the township ( $i = 1, 2, \dots, N$ ) and that  $M$  of the cells are candidate locations for vaccination outposts ( $j = 1, 2, \dots, M$ ), where  $M \leq N$ . The decision questions are: What price should be charged to the users, what is the optimal number of vaccination outposts, and where should they be located under the financial constraint that revenue covers cost? Let  $x_{ij} = 1$  if people in cell  $i$  are served by a vaccination outpost at cell  $j$  and 0 otherwise and  $Q_{ij}$  = the number of people in cell  $i$  who would be vaccinated at the outpost in cell  $j$ .  $Q_{ij}$  is a function of the price charged for a vaccination ( $p$ ), the distance between cells  $i$  and  $j$  ( $d_{ij}$ ), average household income in cell  $i$  ( $I_i$ ), and average household size in cell  $i$  ( $H_i$ ).  $Q_{ij}$  is derived from lambda in eq. 3.6.  $x_{ij}$ ,  $Q_{ij}$  and  $p$  are decision variables whose optimal values are to be determined by model solution, and  $d_{ij}$ ,  $I_i$  and  $H_i$  are known parameters. It is assumed that people use the shortest distance to travel from their cell to an outpost for vaccination. Since the objective is

---

<sup>27</sup> In a sense that this coverage-maximization model does not prioritize the areas with high incidence without considering the incidence distribution, it seems similar to the set cover model in Chapter 4 because it does not prioritize the areas with large population without considering the population distribution in the region.

to maximize coverage, the model seeks to maximize the sum product of  $Q_{ij}$  and  $x_{ij}$  (i.e. the total number of vaccinations) similar to the objective of the p-median model in Section 4.4:

$$\text{Maximize: } \sum_{i=1}^N \sum_{j=1}^M Q_{ij} \cdot x_{ij} \quad \text{eq. 6.1}$$

where  $x_{ij}$  = binary (0 or 1) and  $Q_{ij} = f(p, d_{ij}, I_i, H_i)$ .

This model requires four constraints plus an optional fifth. First, each cell must be served by only one vaccination outpost. That is, all the people in the region who choose to do so must go somewhere to be vaccinated.

$$\sum_{j=1}^M x_{ij} = 1 \quad \text{for } \forall i \quad \text{eq. 6.2}$$

Second, if people in cell  $i$  travel to the outpost in cell  $j$  for vaccination, people in cell  $j$  must be served by the outpost in their own cell. This constraint is complicated and it derives from the p-median model presented in Chapter 4:

$$x_{jj} \geq x_{ij} \quad \text{for } \forall i, \forall j, i \neq j \quad \text{eq. 6.3}$$

Third, the total cost of the mass vaccination program must be covered by revenue from vaccinations. Total vaccination cost, as defined in Chapter 5, is the sum of fixed cost ( $a \cdot Z$ ) which depends on the number of outposts ( $Z = \sum_{j=1}^M x_{jj}$ ), and variable cost ( $b \cdot Q$ ) which

depends on the number of vaccinations that are sold ( $Q = \sum_{i=1}^N \sum_{j=1}^M Q_{ij} \cdot x_{ij}$ ). This model does not include public sector cost savings from not having to treat cases of typhoid avoided because, in most cases, people in China have to pay for treatment cost on their own when they are sick. It is thus assumed that there is no public cost for treatment that is incurred by the government. Revenue from vaccinations is the product of the total number of vaccinations (which is the same expression in the objective function) and the price charged ( $p$ ), which creates a quadratic function that is nonlinear in the decision variables:

$$p \cdot \sum_{i=1}^N \sum_{j=1}^M Q_{ij} \cdot x_{ij} \geq a \cdot \sum_{j=1}^M x_{jj} + b \cdot \sum_{i=1}^N \sum_{j=1}^M Q_{ij} \cdot x_{ij} \quad \text{eq. 6.4}$$

In the case of Daxu Township, the CDC is the headquarters for vaccinations, where the doctors and health staff work on a regular basis. Thus, for this case in China, it is reasonable to add a fourth constraint that the township CDC must be included in the solution set of vaccination sites<sup>28</sup>.

$$x_{cc} = 1, \text{ if the CDC is located at cell } c \quad \text{eq. 6.5}$$

Solution of the model in equations 6.1–6.5 would in principle produce the “globally optimal” solution. However, a fifth constraint can be added to this model which strictly speaking would result in suboptimal solutions. Nevertheless, in some cases it might be reasonable to specify the required number of vaccination outposts ( $Z$ ) in advance. Thus we

<sup>28</sup> In Chapter 4, the current location of the township CDC was confirmed as optimal in Daxu Township.

have the fifth constraint in eq. 6.6, where  $K$  is a user-selected number between 2 and  $M$ , the solution for  $K=1$  being the outpost at the CDC<sup>29</sup>.

$$Z = \sum_{j=1}^M x_{jj} = K \quad \text{eq. 6.6}$$

In the results below, the “globally optimal” solution will be obtained first without this constraint, and then a series of suboptimal solutions with the constraint will be obtained to see how they change with different values of  $K$ .

## 6.2. Parameter values

As described in Chapter 4, 141 villages in the township are aggregated into 29 cells (see Figure 4.1), 25 of which are assumed to be candidate locations for vaccination outposts (i.e.  $N=29$ ,  $M=25$ ). The decision problem for health officials in the township is to choose the optimal outpost locations among the 25 candidate sites, together with the optimal price to be charged to the users, given the vaccination campaign target of 54,000 inhabitants in the township. Thus, this model has 725 binary decision variables  $\{x_{ij}\}$  for inter-cell assignment ( $29 \times 25$ ) plus one decision variable for price.

In spite of the assumption that the entire population knows about the campaign and is eligible to receive vaccinations, not all of the population will participate in the vaccination campaign. The number of people in cell  $i$  who would be vaccinated at the outpost located at

---

<sup>29</sup> Note that “ $Z$ ” stands for the number of outposts and “ $K$ ” stands for the specified number of “ $Z$ ”, throughout this dissertation.

cell  $j$  ( $Q_{ij}$ ) is calculated by multiplying the total number of households at cell  $i$  ( $S_i$ ) by the expected number of vaccinations purchased by a household in cell  $i$  derived from the demand function in eq. 3.6 as follows:

$$Q_{ij} = S_i \cdot \exp(-0.2 - 0.1 \cdot p - 0.05 \cdot d_{ij} + 0.13 \cdot \ln(I_i) + 0.18 \cdot H_i) \quad \text{eq. 6.7}$$

where  $S_i$  = number of households in cell  $i$ ,  $p$  = price per vaccination,  $d_{ij}$  = road distance from cell  $i$  to cell  $j$ ,  $\ln(I_i)$  = natural log of average household income at cell  $i$ , and  $H_i$  = average household size at cell  $i$ . Average household size is assumed to be the same for all cells, which is about 4.5. The two parameters in the cost function in eq. 6.4 were estimated in Chapter 5:  $a = 2,570$  and  $b = 0.53$ , which, after rounding, yields the total cost ( $TC$ ) of the vaccination program shown in eq. 6.8.

$$TC = 2500 \cdot \sum_{j=1}^M x_{jj} + 0.5 \cdot \sum_{i=1}^N \sum_{j=1}^M k_{ij} \cdot x_{ij} \quad \text{eq. 6.8}$$

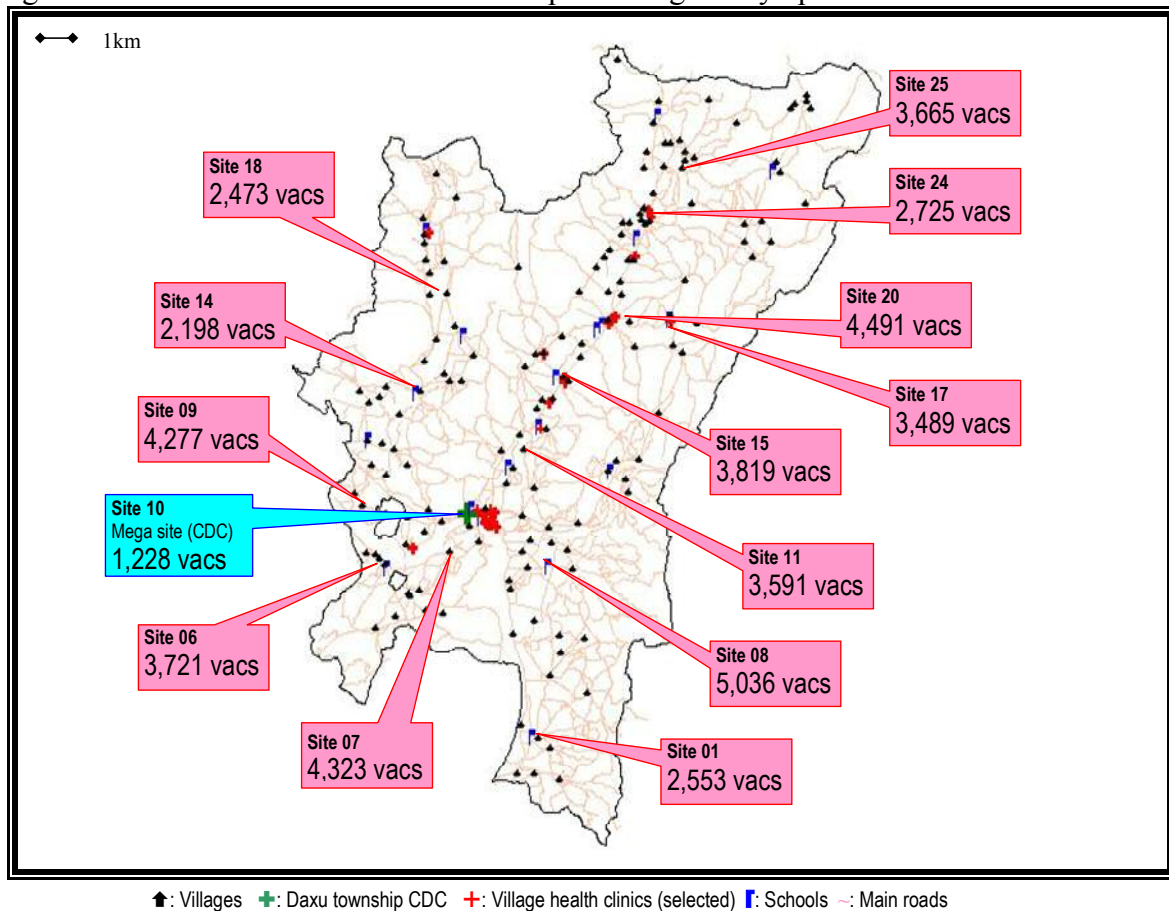
### 6.3. Solutions

Price is a continuous decision variable, and the location decision variables  $\{x_{ij}\}$  are binary integers. Moreover, the revenue constraint in eq 6.4 is quadratic in the decision variables. Hence, the mathematical form of the optimization model is 0-1 mixed integer quadratic, which is non-linear and requires the use of branching and bounding. In total, 731 constraints were generated to solve the programming in this model.



The optimization model was solved using the commercial software “What’s Best®”. The optimal price was found to be USD 1.25 per vaccination, and the optimal number of locations was found to be 14. At the optimal solution, about 87% of people living in Daxu Township would be vaccinated (47,000), and total cost and revenue would be exactly the same (about USD 58,000). The locations of the 14 vaccination outposts are shown in Figure 6.1, which also indicates how many people would be vaccinated at each outpost.

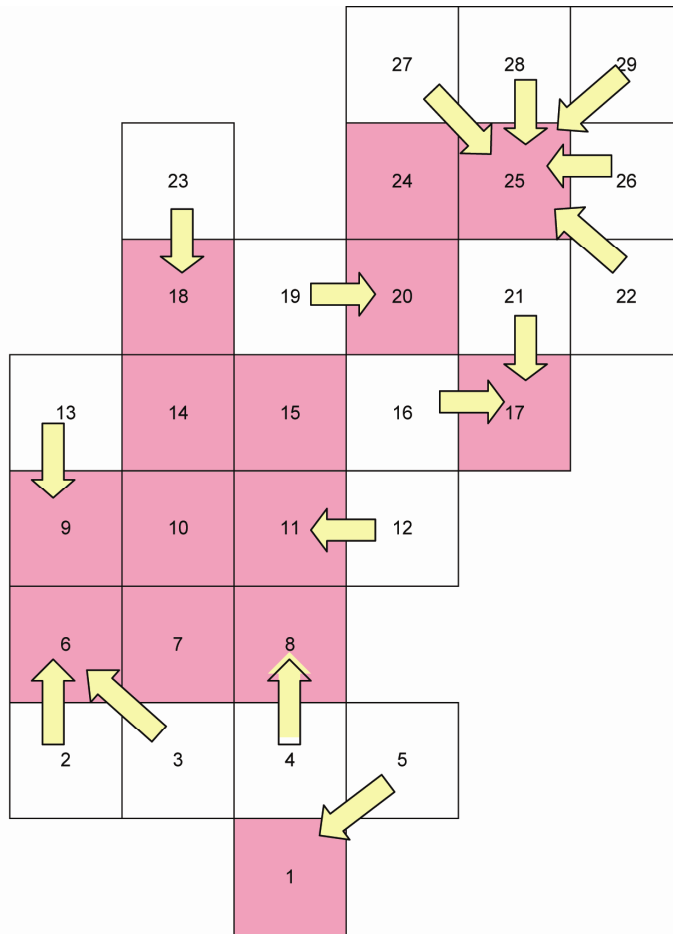
Figure 6.1. Locations of 14 vaccination outposts in “globally optimal” solution



Since only 14 cells are selected as outpost locations, people in the other 15 cells have to travel to an outpost to be vaccinated. Figure 6.2 shows which cells are served by each of

the 14 selected cells shaded. It shows that the outpost located in five cells (#7, #10, #14, #15, and #24) would serve only the people living within them, while the other 10 cells would serve people from neighboring cells as well as people living inside the cells with outposts. For instance, cell #6 serves people traveling from cells #2 and #3 as well as people in cell #6. Assuming that travel distance of people in cell #6 is negligible (we can assume it is zero), only people in cells #2 and #3 have to travel to be vaccinated.

Figure 6.2. Travel pattern to 14 outposts in “globally optimal” solution



\* The optimal cells are shaded.  
 \*\*\* Arrows show how cells assign to outposts.

Using this assumption, Table 6.1 breaks down the total number of vaccinations into (1) the number demanded by people living at the outpost cell and (2) the number demanded by people who have to travel to the outpost. It also presents average travel distance of all people vaccinated at each outpost plus the people who have to travel for vaccinations to the outpost. Overall, about 20% of the vaccinees (9,900 out of 47,000) travel about 6.6 km on average roundtrip (one-way distance is 3.3 km) to get vaccinated at the outpost in a neighboring cell. The other 80% would have an outpost in the cell where they live.

Table 6.1. Number of vaccinations and travel distance to 14 outposts in “globally optimal” solution

Outpost ID	No of vaccinations demanded by people living at the outpost cell	No of vaccinations demanded by people who travel to the outpost	Average one-way distance of those who have to travel (km)	Average one-way distance traveled by everyone to be vaccinated (km)
1	2,285	268	3.1	0.3
6	2,235	1,486	3.0	0.7
7	4,323	0	-	0
8	4,151	885	3.8	0.7
9	2,538	1,016	3.3	0.9
10	1,228	0	-	0
11	2,737	854	4.5	1.1
14	2,198	0	-	0
15	3,819	0	-	0
17	1,028	2,461	2.3	1.6
18	1,664	809	3.7	1.2
20	4,145	346	3.0	0.2
24	2,725	0	-	0
25	1,890	1,775	3.8	1.9
Overall	SUM= 36,967	SUM= 9,900	Average = 3.3 Standard deviation = 0.7	Average= 0.7 Standard deviation = 0.6

As noted in Chapter 4, while Table 6.1 is based on the assumption that people living in a cell with an outpost travel a distance of zero, in fact they have to travel about 0.7 km one-way on average (1.4 km roundtrip). There exists a certain variation in average travel

distance across the outposts. For instance, people traveling to cell #11, who live in the cell #12, have to travel about 4.5 km (9 km roundtrip), while those who travel to the cell #17, who live in the cells #16 and #21, have to travel only 2.3 km on average (4.6 km roundtrip). The total amount of roundtrip travel necessary to vaccinate all people in the township who are willing to pay for vaccinations was about 65,000 km, or about 1.4 km per vaccinee.

#### 6.4. Sensitivity analysis

##### 6.4.1. Number of outposts

Is the “globally optimal” solution with 14 outposts truly best for Daxu Township? Planners may prefer fewer outposts because it may be difficult or even infeasible to employ 14 vaccination outposts, perhaps due to limited labor or other resources. Furthermore, the set covering and  $p$ -median models in Chapter 4 showed that there are diminishing marginal vaccination sales when the number of outposts increases, which raises the question of whether it is truly worth employing as many as 14 outposts to maximize sales even if the budget constraint can be met. Also note that this model is deterministic without considering any uncertainty issue associated with the solution, and thus there is no guarantee that the predicted number of vaccinations from the model will materialize in practice. Considering all of these, it might be judicious to keep the number of outposts low so the price charged can be low. Thus, a sensitivity analysis is conducted to examine how much the model output would change if the specified number of outposts ( $K$ ) were fewer than 14, by adding the fifth

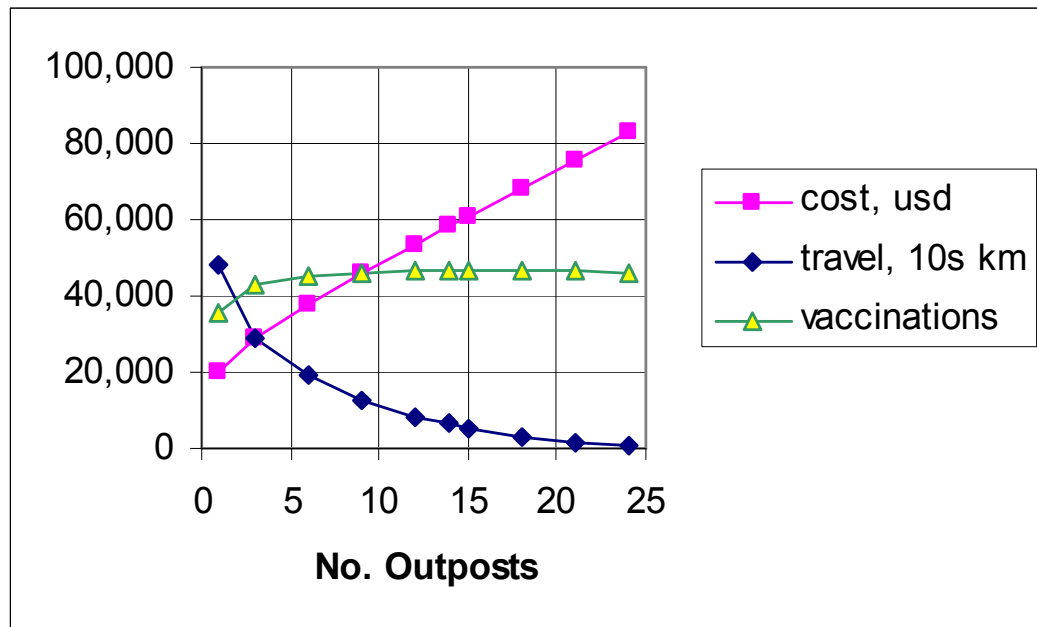
constraint in eq. 6.6. Table 6.2 summarizes the results for  $K = 1, 3, 6, 9, 12, 15, 18, 21,$  and 24. Figure 6.3 shows three curves with key results from this analysis.

Table 6.2. Vaccination program outputs vs. number of outposts

Number of outposts specified ( $K$ )	Optimal price ( $p^*$ ) (USD)	Number of vaccinations ( $Q^*$ )	Total Cost (USD)	Total roundtrip travel distance (person-km)	Percentage of vaccinees who travel	Average one-way distance by travelers (km)
1	0.6	35,456	20,228	484,873	96	7.1
3	0.7	42,883	28,942	286,243	77	4.4
6	0.8	45,150	37,575	190,091	60	3.5
9	1.0	46,296	45,648	125,233	44	3.1
12	1.1	46,762	53,381	84,186	29	3.1
14	1.25	46,867	58,433	65,538	21	3.3
15	1.3	46,852	60,926	56,291	18	3.2
18	1.5	46,714	68,357	31,398	12	2.9
21	1.6	46,393	75,696	18,510	6	2.8
24	1.8	45,798	82,899	8,383	3	2.7

\* "Globally optimal" solution is shaded.

Figure 6.3. Results of sensitivity analysis

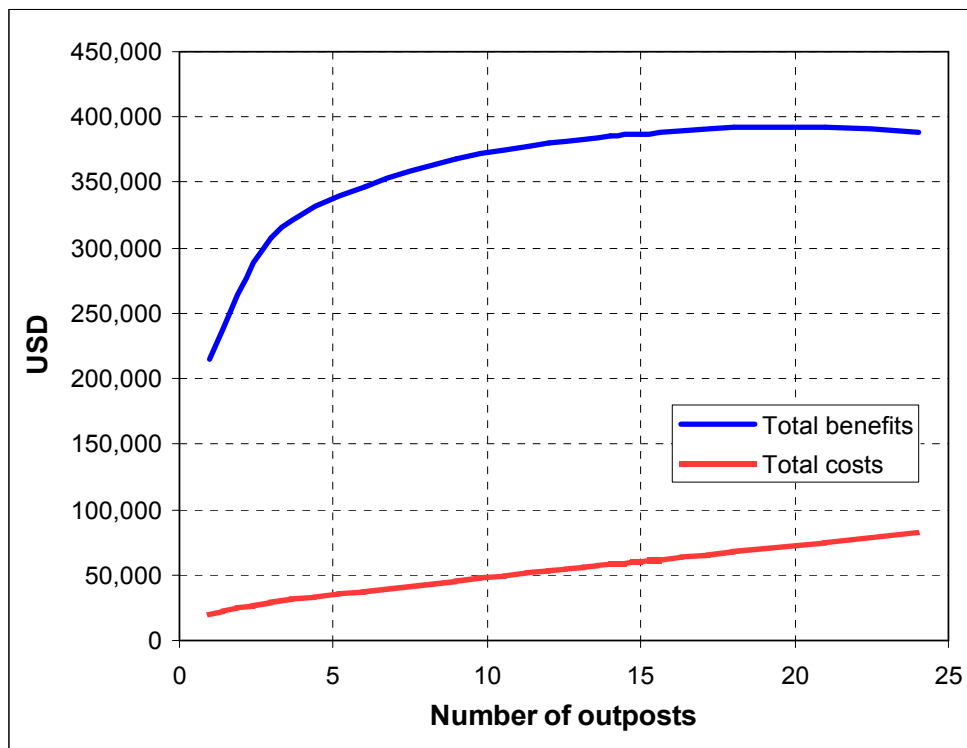


Several findings are interesting from this analysis. First, the total number of vaccinations does not change much for about 6 or more outposts. Substantial marginal increases in the number of vaccinations are found only when the number of outposts increases from 1 to 6 (the largest increase is from 1 to 3). In other words, there is very little payoff in terms of additional vaccinations by having more than about 6 outposts, which in turn implies that there is little gain in the private benefits, which is the implicit objective of this optimization model. Increasing the number of outposts from 6 to 14 would only increase the number of vaccinations by less than 2,000. This indicates that the optimization model can fully capture the maximum number of vaccinations only by having more and more outposts that make fewer and fewer sales. For example, Table 6.2 shows that the average number of sales per outpost with 6 outposts is about 7,500, but average sales with 14 outposts are only 3,300, less than half as many. While the objective of maximizing the number of vaccinations is impressive and seems reasonable, planners may not do so at any cost since decreasing marginal returns cannot be ignored.

Recall that the private benefits of vaccinations per household depend on travel distance; USD 39 if average travel distance were 0 km (i.e. at each village) while USD 27 if it were 6.8 km (i.e. at the CDC). Following the same logic of calculating the total private benefits presented in Chapter 4, the total private benefits were calculated for all other cases with different numbers of outposts associated with different average travel distances, using the number of households in Table 6.2. Figure 6.4 shows the total costs and benefits as a function of the number of outposts. It shows that the total private benefits due to vaccinations are maximized with around 18 outposts, but that is obviously not the optimal solution from an economic efficiency perspective. It is shown that marginal benefits are roughly equal to

marginal costs in the range of about 9 to 10 outposts. Considering the issue of uncertainty associated with these numbers, a judicious decision would be to locate a little less than 9-10 outposts in this township to keep the number of outposts low so the price charged can be low (i.e. 6-8 outposts). More importantly, this marginal analysis strongly confirms that having a single or fewer sites in this township might not be the best for society, an argument which has already been made in the previous chapters of this dissertation.

Figure 6.4. Total benefits and costs vs. number of outposts



Note also in Figure 6.3 that total cost increases almost linearly for more than about 5-6 outposts, which indicates that the increase in cost is due mostly to fixed (USD 2,500 per outpost) rather than variable cost because the number of vaccinations does not change much for more than 5-6 outposts. The slope of the cost curve in Figure 6.3 is approximately USD 2,500.

Table 6.2 shows that the price that would have to be charged increases with the number of outposts because cost increases but the number of vaccinees remains about the same. Price is about USD 0.8 for 6 outposts, but it increases to USD 1.3 for 15 outposts. Figure 6.5 shows the association between the required user price and the number of outposts.

Figure 6.5. Association between the required price and the number of outposts

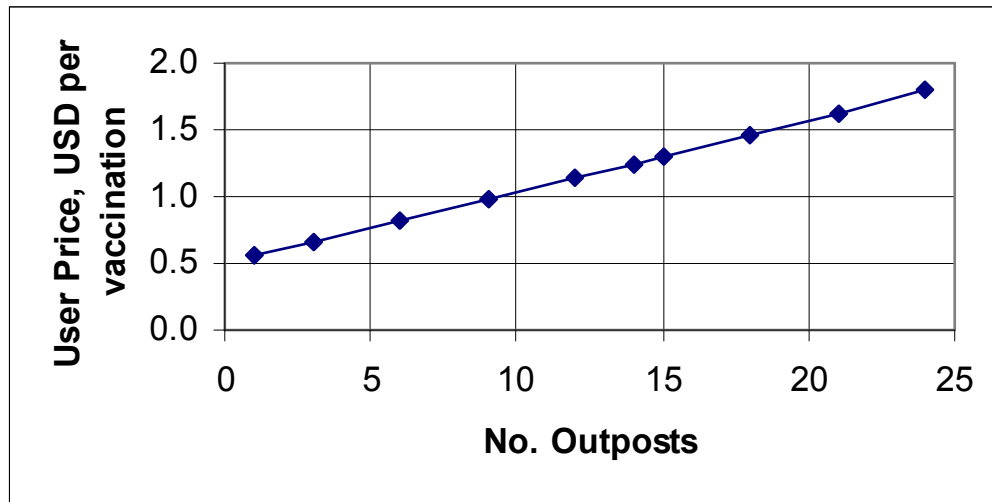
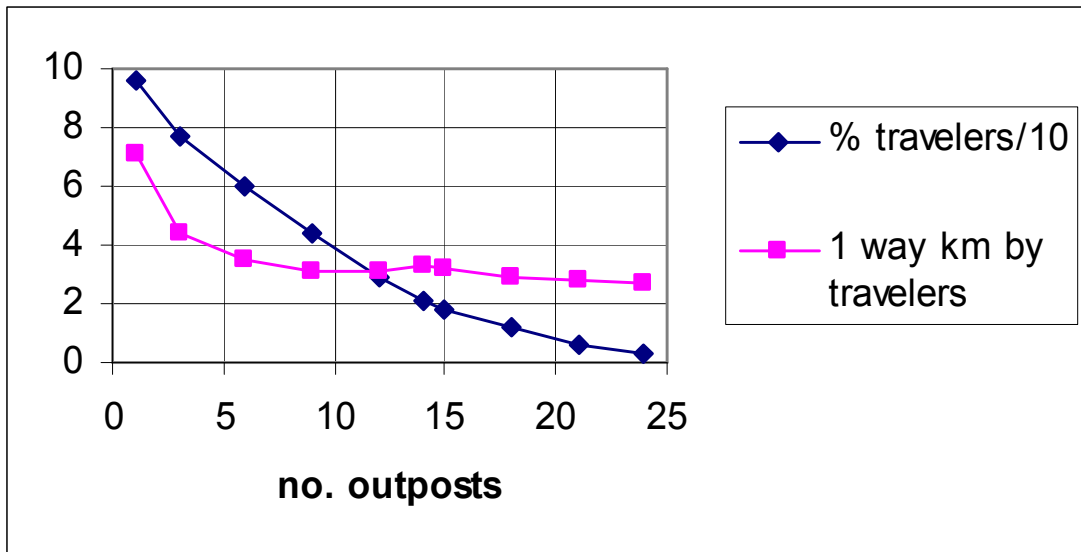


Figure 6.3 also shows that the total travel distance required to vaccination sites decreases sharply with more outposts, although the number of vaccinations changes little. The total roundtrip distance for mass vaccination would be almost 200,000 person-km with 6 outposts, while it would be only 65,000 person-km with 14 outposts. This decrease in distance is not because the average roundtrip distance for travelers decreases but rather because the number of travelers decreases. The last two columns in Table 6.2 were used to analyze how villagers' travel patterns change as the number of outposts increases. Figure 6.6 shows that the percentage of travelers decreases constantly with increase in outposts, while average travel distance by travelers drops quickly with the increase of outposts from 1 to 5, and then stops decreasing when the number of outposts is greater than about 5.



Figure 6.6. Percentage of travelers and travel distance by travelers vs. the number of outposts



Most vaccinees would have to travel if there were only a single outpost (e.g. at the township CDC), while almost none would travel if the number of outposts were 25. If 6 outposts were provided, 60% of the vaccinees would have to travel, but only 20% would have to travel with 14 outposts.<sup>30</sup> However, the average roundtrip distance for those who would have to travel would remain the same at around 3 km one-way (6 km roundtrip) for any number of outposts greater than about 5. This analysis shows that the actual benefit of installing more than about five outposts does not reduce travel distance of those who have to travel, but rather it reduces the number of users who have to travel.

The information in Table 6.2 can be used to impute a monetary value to the effort involved in traveling to get vaccinated. Suppose that the vaccination planners in Daxu Township, after reviewing the information in Table 6.2 and Figure 6.3, decide that having 5 outposts is definitely worthwhile. However, after consideration, they think that maybe having

<sup>30</sup> A loglinear regression function (R-square = 0.97) was fitted to show the relationship between the percentage of travelers and the number of outposts: percentage of travelers =  $139 * \exp(-0.14 * Z)$ . It indicates that there is a 14% decrease in the percentage of travelers per additional outpost.

6 outposts would be even better. The marginal cost of adding one more outpost to the 5 which they definitely want is about USD 2,500. Six outposts would reduce total roundtrip travel from about 220,000 km to about 200,000 km, but would increase the number of vaccinations only marginally. Hence, if it is decided to have 6 outposts instead of 5, the planners would implicitly assign a benefit of about USD 0.125 per km of travel ( $=2500/(220,000-200,000)$ ). If the average roundtrip distance for travelers is about 6.5 km, then the implicit benefit assigned to the reduction in traveling is about USD 0.8 per vaccination.

In order to observe which cells are given most priority, Table 6.3 summarizes which cell was dropped at each of the solutions as the number of outposts decreases from the “globally optimal” solution. For  $K=13$ , all the locations from the “globally optimal” solution remain except for the outpost in cell #7 which makes people in cell #7 now have to travel to the outpost in cell #10. However, average travel distance of travelers and the number of vaccinations remains about the same. For  $K=12$ , the outpost in cell #17 was dropped, and people in that cell are assigned to the outpost in cell #20, without any substantial change in the total number of vaccinations. Following such steps, Table 6.3 summarizes which cell was eliminated at each step. Note that all included outposts remain unchanged as  $K$  decreases stepwise.

Table 6.3. Order of the outposts dropped out of “globally optimal” solution

$K$	14	13	12	11	10	9	8	7	6	5	4	3	2	1
ID of the outposts dropped for each $K$	“Globally optimal” solution	#7	#17	#9	#24	#18	#11	#6	#14	#25	#1	#15	#8	#20

#### 6.4.2. Parameters in cost and demand functions

How is the optimal solution sensitive to different parameters in the model? Sensitivity analyses were conducted to understand how much the optimal solutions change based on different assumptions in the model. The demand function in Chapter 3 and cost function in Chapter 5 play key roles in the optimization model, but the parameters in those functions are uncertain.

Table 6.4. Sensitivity analysis by parameters in demand function

Assumptions		Optimal price, USD ( $p^*$ )	Optimal number of outposts ( $Z^*$ )	Maximum Number of vaccination ( $Q^*$ )	Cost (=Revenue) (USD)
Price coefficient ( $\beta_p$ )	Distance coefficient ( $\beta_d$ )				
-0.10	-0.02	0.86	7	48,248	41,624
-0.10	-0.05	1.25	14	46,867	58,433
-0.10	-0.10	1.59	20	45,698	72,849
-0.05	-0.02	1.14	13	50,807	57,904
-0.05	-0.05	1.50	20	50,208	75,104
-0.05	-0.10	1.60	22	49,801	79,900

Table 6.4 summarizes the results of sensitivity analysis for the demand function. The price coefficient in the demand function based on the contingent valuation survey was about -0.1, and the distance coefficient was -0.05 (shaded; baseline). If the distance coefficient is assumed to be -0.02 instead of -0.05, both the optimal price and the optimal number of outposts are lowered while more people would get vaccinated. If the distance coefficient is assumed to be the same as the price coefficient (-0.1), higher price and more outposts would be required to ensure the maximum number of vaccinations although the vaccination coverage is lower than the baseline case. If the price coefficient is cut in half (-0.05), the optimal price and number of outposts increase, but the size of change is larger if the distance

coefficient is small. Note that the optimal solutions do not change much in spite of the change in price coefficient when the distance coefficient is -0.1.

Table 6.5 summarizes the results of sensitivity analysis for the two parameters of the cost function in eq. 5.1, which are approximately  $a = 2,500$  and  $b = 0.5$  (shaded; baseline case). First, if no cost is associated with the number of outposts (i.e. no setup cost) ( $a=0$ ), vaccinations should be delivered at all candidate locations and the optimal price should be the same as cost per vaccination ( $b$ ). The larger parameter  $a$  is, the higher the optimal price becomes while the optimal number of outposts decreases. However, a higher parameter  $b$  (variable cost per vaccination) makes the optimal price higher but does not much affect the optimal number of outposts.

Table 6.5. Sensitivity analysis by parameters in cost function

Assumptions		Optimal price, USD ( $p^*$ )	Optimal number of outposts ( $Z^*$ )	Maximum Number of vaccination ( $Q^*$ )	Cost (=Revenue) (USD)
Cost per outpost, USD ( $a$ )	Cost per vaccination, USD ( $b$ )				
0	0.5	0.50	25	51,938	25,969
0	1.0	1.00	25	49,521	49,521
1,500	0.5	1.12	20	48,638	54,319
1,500	1.0	1.65	20	46,232	76,232
2,500	0.5	1.25	14	46,867	58,433
2,500	1.0	1.73	13	44,528	77,028
3,500	0.5	1.42	12	45,526	64,763
3,500	1.0	1.89	11	43,205	81,705

To better understand the effect of the four parameters in cost and demand functions, the results in Table 6.4 and 6.5 are combined and analyzed by regression analysis. The regression function ( $F=25.4$ ;  $R^2=0.93$ ) for the optimal price is:

$$p^* = 0.03 + 0.0003*a + 1.0*b + 3.3*\beta_p - 7.1*\beta_d \quad \text{eq. 6.9}$$

All parameters are highly significant (at the 1% level) except for the price coefficient in the demand function, which is significant at the 10% level. Intercept is not statistically significant. The optimal price is more sensitive to cost and distance parameters than price coefficient. In other words, the optimal price increases linearly with cost of a vaccination, but has a weak association with price coefficient itself. If  $b$  increases by 1.0 (from 0.5 to 1.5), for instance, then the optimal price would increase by almost 1.0 to cover the extra cost due to larger  $b$ .

The next regression was for the optimal number of outposts using the same four parameters ( $F=21.7$ ;  $R^2=0.92$ ):

$$Z^* = 24.6 - 0.004*a + 0.9*b + 66.9*\beta_p - 127.6*\beta_d \quad \text{eq. 6.10}$$

Both price and distance coefficients are statistically significant at the 5% level, but cost per vaccination ( $b$ ) is no longer significant ( $p=0.7$ ). It indicates that the optimal number of outposts does not depend on the variable cost, and thus the total cost increases almost linearly with the number of outposts regardless of the variable cost per vaccination. The stronger the price effect is, the fewer outposts would be optimal due to decrease in vaccination coverage. However, the stronger the distance effect is, the more outposts would be optimal in order to minimize the negative distance effect on vaccination coverage by bringing the outposts closer to cells. The intercept is highly significant and its size is about the same as the number of all candidate outposts (25).

Third, the number of vaccinations at the optimum ( $Q^*$ ) was regressed against the four parameters ( $F=134.8$ ;  $R^2=0.98$ ) and the result is:

$$Q^* = 61755 - 1.8*a - 4801*b + 65724*\beta_p + 21713*\beta_d \quad \text{eq. 6.11}$$

All parameters including intercept are statistically significant. If the variable cost increases by USD 0.1, about 500 vaccinees would be dropped. The stronger effect price and distance has, the fewer people would be vaccinated. Note that price effect is about three times as strong as distance effect, given the units assumed for price (USD) and distance (km). For instance, if the price coefficient ( $\beta_p$ ) changes from -0.05 to -0.1, about 3,000 vaccinations would be dropped. If the distance coefficient ( $\beta_d$ ) changes from -0.05 to -0.1, about 1,000 vaccinations would be dropped.

Fourth, the total vaccination cost ( $TC$ ) was regressed against the four parameters as follows ( $F=19.9$ ;  $R^2=0.91$ ):

$$TC = 20424 + 9.7*a + 42413*b + 257542*\beta_p - 316895*\beta_d \quad \text{eq. 6.12}$$

A positive sign for  $a$  and  $b$  implies that total costs would be higher with higher setup cost or variable cost. While total cost decreases when price effect becomes stronger, it increases when distance effect is stronger. For instance, if price coefficient changes from -0.05 to -0.1, total cost would decrease by approximately USD 13,000 because fewer number of people would be vaccinated due to the stronger price effect. If the distance coefficient

changes from -0.05 to -0.1, total cost would increase by approximately USD 16,000 in order to install more outposts to minimize the distance effect.

#### 6.4.3. Non-zero vaccine purchase cost

So far, all of the analyses are based on the assumption that vaccines would be obtained free of charge and thus only delivery cost is covered by user fee. However, it is possible that users have to pay not only for delivery but also for the vaccine. We assume that vaccine price is in the range of USD 0.5-2.0 per dose. If it were USD 1.0, then it simply changes the cost function:  $TC = 2500*Z + 1.5*Q$ . Without any constraint on the number of outposts ( $Z=K$ ), the optimal price was USD 2.3 and the optimal number of outposts was found to be 13. Compared to the “globally optimal” solution with zero cost of vaccine purchase (see Section 6.3), the optimal locations of outposts are the same except that the outpost in #7 was excluded. This finding suggests that the optimal number and location of outposts is not affected much by the variable cost of vaccinations, which is consistent to the finding from the regression in eq. 6.10 that  $b$  is not significant. However, users would have to pay more in order to cover the larger costs, and the increase in user fee is almost as large as the amount of vaccine purchase cost (in this case, USD 1). The higher fee would reduce vaccination coverage about 10% (from 47,000 to 42,000) which in turn would increase the total cost by almost USD 40,000 (from USD 58,000 to 96,000), compared to the case of zero vaccine purchase cost.

A series of optimization analyses were also run to solve the model with non-zero vaccine purchase cost for different numbers of outposts. Table 6.6 shows the results of the

models with the vaccine purchase cost of USD 1, in comparison with those of the models with zero cost of vaccine purchase.

Table 6.6. Sensitivity analysis by number of outposts: zero vs. non-zero cost of vaccine purchase

Assumptions		User price (USD)	Total Cost (USD)	Number of vaccinations
Cost of vaccine (USD)	Number of outposts			
0	1	0.6	20,228	35,456
	2	0.6	25,846	41,692
	3	0.7	28,942	42,883
	4	0.7	31,932	43,864
	5	0.8	34,764	44,527
	6	0.8	37,575	45,150
1	1	1.6	50,816	32,211
	2	1.6	61,786	37,857
	3	1.7	65,878	38,919
	4	1.8	69,681	39,787
	5	1.8	73,051	40,367
	6	1.9	76,366	40,910

For the cases of 1 to 6 outposts, the models with non-zero vaccine purchase cost produce larger optimal price and cost but fewer vaccinations than the model with zero purchase cost. However, the same set of cells always turns up as optimal in each solution, regardless of vaccination purchase cost. No feasible solution was found in the model with the number of outposts greater than 6 if vaccine purchase cost were USD 1.

Recall that, in Section 6.4.1, the implicit benefit assigned to the reduction in traveling was calculated as about USD 0.8 per vaccination when the vaccine purchase cost were zero. If the vaccine cost USD 1.0, the imputed benefit would decrease to USD 0.6 per vaccination.<sup>31</sup> This indicates that the benefits from reduced travel become smaller because

---

<sup>31</sup> Calculations are as follows. Compared to 5 outposts, 6 outposts would reduce total roundtrip travel from about 199,000 km to about 172,000 km; in both cases the number of vaccinations is about the same. Hence, if it is decided to have 6 outposts instead of 5, planners are implicitly assigning a benefit of about USD 0.093 per



fewer people would be vaccinated due to price increase resulting from the non-zero vaccine cost.

#### 6.5. Maximizing cases avoided

The optimization models in the previous sections aim to maximize vaccination coverage or sales (“coverage-maximization model” hereafter). However, policy-makers might want to maximize the number of typhoid cases avoided due to a vaccination program, which would put stronger emphasis on health (“cases-avoided-maximization model” hereafter). Compared to the previous coverage-maximization model, the objective of this case-avoided-maximization model has a primary concern of maximizing not only private benefits but also health effects. Thus, this model takes account of spatial variation in disease incidences in the target area, and gives priority to where the disease is most intense and where people are most at risk.

The number of cases avoided due to vaccination is calculated by subtracting the number of cases with a vaccination program from the number of cases without the program. The total number of cases that occur without a program in a 3-year period is (Lauria et al., 2005):

$$\text{No. of cases without vaccination} = \sum_{i=1}^N 3 \cdot I_i \cdot T_i \quad \text{eq. 6.13}$$

where  $I_i$  is incidence, the probability of contracting typhoid per year in cell  $i$  and  $T_i$  is the total number of candidate vaccinees in the cell.

---

km of travel (=2500/(199,000-172,000)). If the average roundtrip distance for travelers is about 6.5 km, then the implicit benefit assigned to traveling is about USD 0.6 per vaccination.

On the other hand, let  $Q_i$  be the total number of people vaccinated in cell  $i$ . Recall that in the previous section  $Q_{ij}$  was defined as the number of people in cell  $i$  who would be vaccinated at the outpost in cell  $j$  and  $x_{ij}=1$  if people in cell  $i$  are served by a vaccination outpost at cell  $j$  and 0 otherwise,  $Q_i$  can be expressed as  $\sum_{j=1}^M Q_{ij} \cdot x_{ij}$ . Given the assumption that the vaccine is 70% effective for 3 years, the number of cases that occur with a vaccination program in a 3-year period is the sum of the number of people who contract typhoid fever because they are not vaccinated ( $\sum_{i=1}^N 3 \cdot I_i \cdot (T_i - Q_i)$ ) and the number of cases among people who have been vaccinated but the vaccinations were not effective ( $\sum_{i=1}^N 3 \cdot I_i \cdot (1 - 0.7) \cdot Q_i$ ):

$$\text{No. of cases with vaccination} = \sum_{i=1}^N 3 \cdot I_i \cdot (T_i - Q_i) + \sum_{i=1}^N 3 \cdot I_i \cdot (1 - 0.7) \cdot Q_i \quad \text{eq. 6.14}$$

Subtracting eq.6.14 from eq.6.13, the total number of cases avoided in 3 years due to the vaccination program is expressed as follows:

$$\text{Maximize: } 2.1 \cdot \sum_{i=1}^N I_i \cdot Q_i = 2.1 \cdot \sum_{i=1}^N \sum_{j=1}^M I_i \cdot Q_{ij} \cdot x_{ij} \quad \text{eq. 6.15}$$

This is the objective function of the alternative optimization model of maximizing cases avoided. Note that the coefficient (2.1) has no effect on the optimal solution of this model, although it does affect the optimal value of the objective function. This objective function contains the product of candidate population and incidence, which is the expected

number of disease cases per year. It seems counterintuitive to want to maximize this quantity, but this objective is in fact to maximize the number of vaccinations of candidate population weighted by incidence, which is exogenous in the model. By using incidence as a weighting factor, this model gives priority to the cells with higher incidence in locating outposts. The main constraints of this model remain unchanged from the previous coverage-maximization model.

Unfortunately, it is not possible to have much confidence in these data because they are based on reported cases of illness compiled by the health authorities in Daxu Township during the period 2000 to 2004. However, they are the only data available, and I use them for illustrative purposes. These data are aggregated for adults and children because there is no significant difference in typhoid incidence between these two groups in this area. Figure 6.7 shows typhoid incidences vary substantially from one cell to another.

Figure 6.7. Typhoid incidence in Daxu Township

			34	0	46
	32		263	79	17
	177	64	81	76	238
398	697	145	0	59	
97	557	233	163		
133	295	190			
172	39	328	1565		
		361			

\* Numbers in the cells are cases per 100,000 inhabitants; annual average for years 2000-2004

While the model of this section uses the incidence of each cell, an alternative approach could be to divide the cells into two groups, one with high incidence, say more than 100 cases per year per 100,000 persons, and the other with low incidences below this level. In Figure 6.6, the cells whose incidences are in yellow (gray for a black-and-white copy) are high, and the other cells have low incidence. By this measure, there are 13 cells with low incidence that are mostly clustered in the northeastern part of the township, and their average incidence is 48 cases per year per 100,000 persons, and the standard deviation is 31, which is obviously high. The other 16 cells with high incidence have an average of 370 cases per year per 100,000 persons and standard deviation of 354.

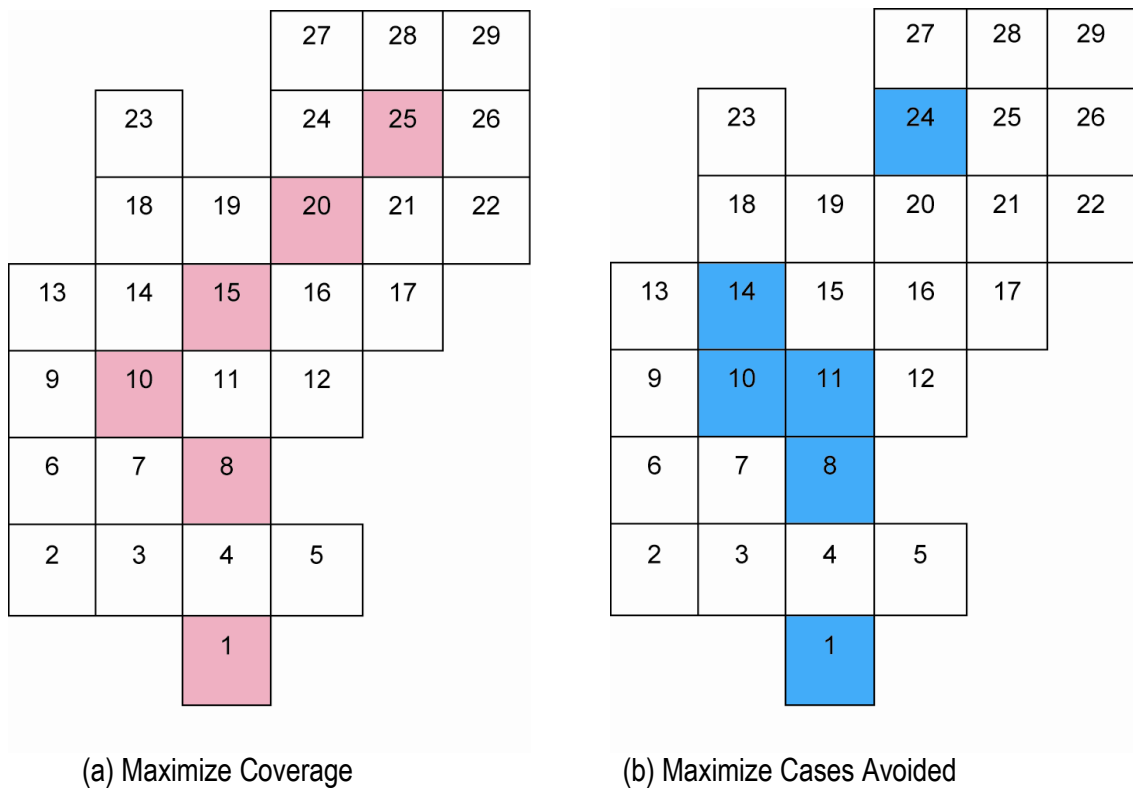
In the previous section, I found that the expected number of vaccinations does not increase much for 6 or more outposts; there is little payoff by using more than 6. Thus, here the solutions from the coverage-maximization model are compared with those from the cases-avoided-maximization model of this section first when the number of outposts is set to be 6 ( $K=6$ ) and then when  $K=3$ . Table 6.7, which compares the results of the two models for  $K=6$ , shows that the optimal price, number of vaccinations, and total cost differ only slightly. However, the solution from the alternative model would vaccinate slightly fewer people but avoid a few more typhoid cases and require slightly longer travel.

Table 6.7. Output of two optimization models with different objectives (If  $K=6$ )

	Maximize coverage	Maximize cases avoided
Optimal price, USD	0.83	0.84
Number of vaccinations at the optimal solution ( $Q^*$ )	45,150	44,671
Total costs (revenues), USD	37,575	37,335
Cases avoided	202	210
Average one-way travel distance, km	2.1	2.3

Although many of the outputs from the two models are similar, Figure 6.8 shows that the best locations for vaccination outposts are somewhat different. Since deciding where to locate outposts is a key element in the design of a vaccination program, this difference is an important finding. Three of the 6 cells are common to both models, but three cells (#15, #20 and #25) in the coverage-maximization model were replaced by other three cells (#11, #14, and #24) in the cases-avoided-maximization model.

Figure 6.8. Optimal locations from two optimization models



\* Numbers in the cells are cell identification numbers.  
 \* The optimal cells are shaded.

The explanation for this change derives from two considerations. First, the cells that were replaced had lower incidences than the new cells that replaced them. Since incidence is

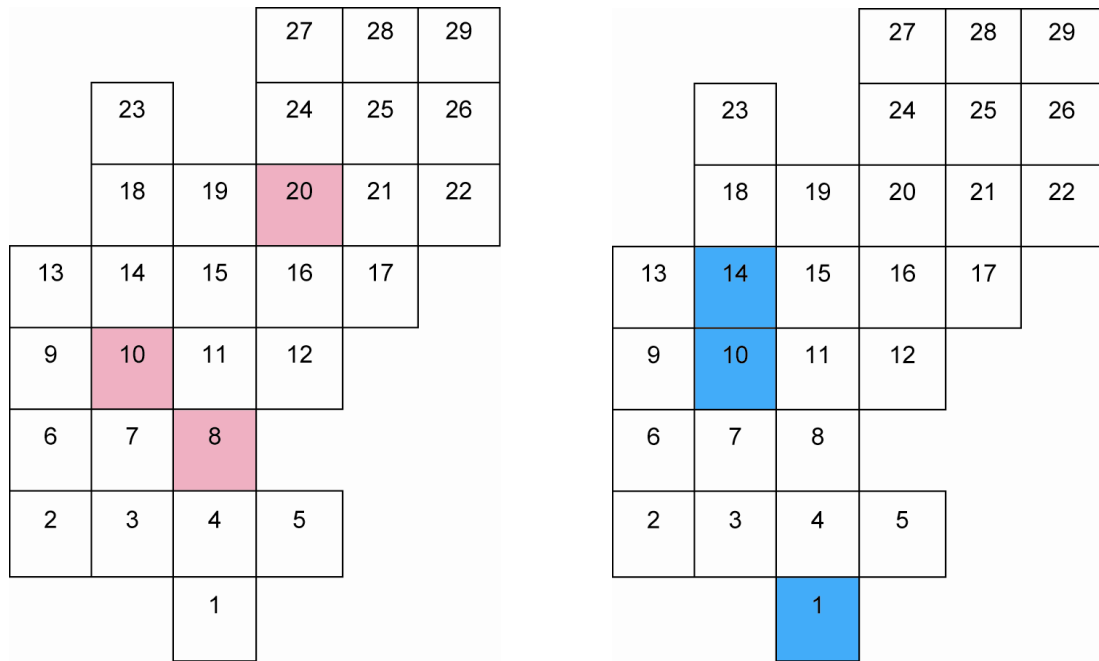
a weighting factor in the objective function of the model in this section, this change is not surprising. But the substitution depends not only on higher incidences but also on distance; the new cells that entered the solution are all in the neighborhoods of the old cells that were replaced. For example, cell #11 with incidence of 233 came into the solution, but cell #7 with higher incidence of 295 did not. Thus, the model of this section does not simply locate outposts in cells with higher incidences but in fact takes travel distance into account in order to maximize the number of cases avoided.

Table 6.8 presents the outputs from two optimization models where only three outposts are allowed (two in addition to the township CDC). The required prices are similar, but vaccination coverage from the cases-avoided-maximization model decreases by more than 3,000 compared to the coverage-maximization model, and average travel distance increases. The decrease in vaccinations is undoubtedly due to the increase in average travel distance. Although the alternative model delivers fewer vaccinations, it avoids a few more cases, but the increase is insignificant. This implies that the ‘optimal solution’ is largely an artifact of arithmetic. Thus, in this case, it would be hard to argue that the case-avoided model is preferable to the coverage-maximization model, even if the objective is to avoid cases, mainly because the price that would have to be charged is higher, the number of vaccinated persons is lower, distance is longer, but cases avoided are about the same. It therefore follows that judgment must be exercised in the use of these models. They are aids to judgment and must be used judiciously. As shown in Figure 6.9, the locations for the two selected outposts are fairly different between the two models.

Table 6.8. Output of the two optimization models with different objectives (If  $K = 3$ )

	Maximizing coverage	Maximizing cases avoided
Optimal price ( $p^*$ )	0.67	0.69
Number of vaccinations at the optimal solution ( $Q^*$ )	42,883	39,608
Total costs/revenues	28,942	27,304
Cases avoided	190	195
Average one-way travel distance	3.4	4.7

Figure 6.9. Optimal locations from two optimization models (If  $K = 3$ )



(a) Maximize Coverage

(b) Maximize Cases Avoided

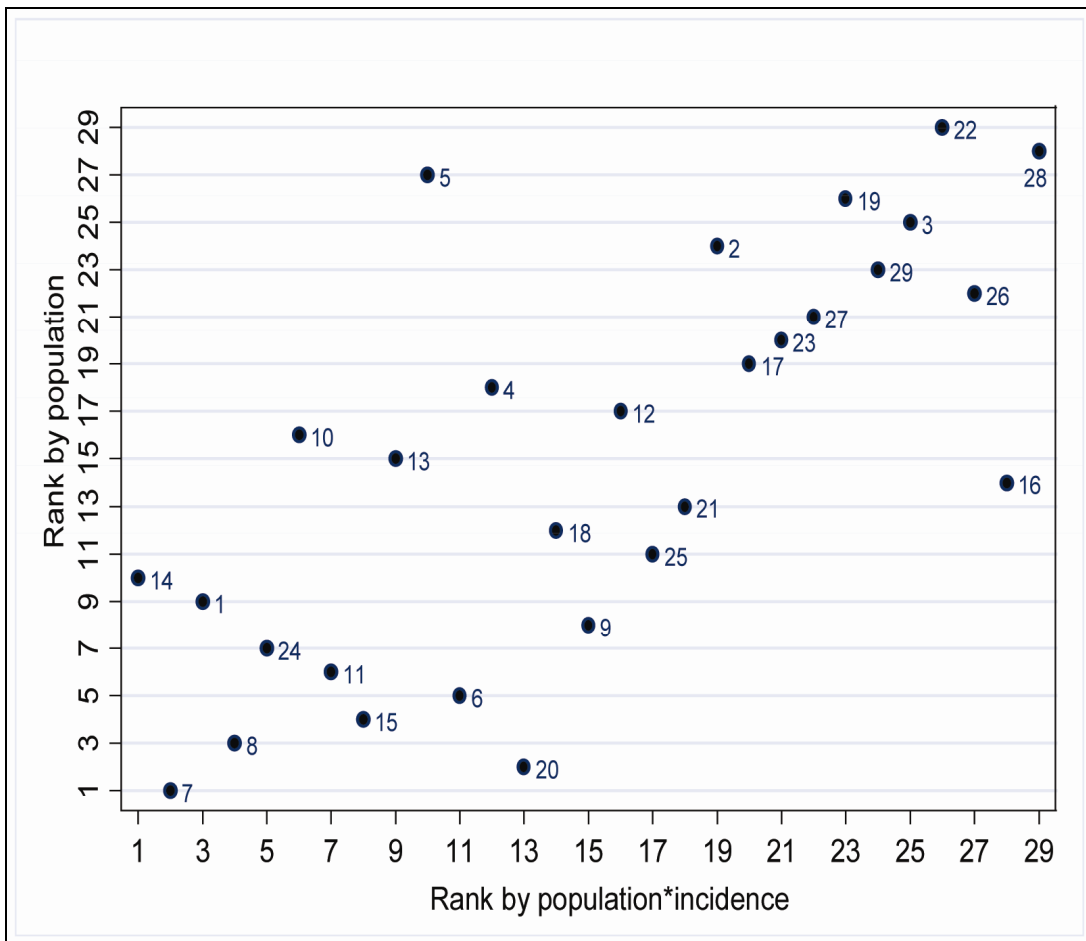
\* Numbers in the cells are cell identification numbers.

\* The optimal cells are shaded.

To better understand why the optimal locations of outposts are different between the two models, the cells were ranked by population and also by the product of population and incidence, as plotted in Figure 6.10. Note that cells #14 and #1 rank about 10<sup>th</sup> by population but much higher (second and third) by population times incidence. This explains why those

two cells were not chosen by the coverage-maximization model with  $K=3$  but appear in the cases-avoided-maximization model with  $K=3$ . On the other hand, cell #20 ranks second by population and thus was selected as optimal by the coverage-maximization model with  $K=3$ , but it ranks only 13<sup>th</sup> when weighted by incidence and thus was dropped from the cases-avoided-maximization model with  $K=3$ . Cell #8 ranks high for both models, but was not chosen by the cases-avoided-maximization model with  $K=3$  since its weighted population is not as large as other cells in its neighborhood.

Figure 6.10. Ranks of cells by population size vs. population weighted by incidence





In summary, it is evident that weights using incidence can play an important role in determining where to locate outposts, but neither model automatically produces the best solution, at least for Daxu Township. They are aids to judgment. Nor is it possible to know without using the models how the best locations of outposts differ if different objectives are adopted for planning, e.g. either maximizing vaccinations or maximizing cases avoided. This chapter shows that higher incidence is a driving force for determining outpost locations if the objective is to avoid cases of illness, but it is not the only consideration. Travel distance also has a role to play, thus requiring use of these optimization models rather than a simpler approach based, for example, on heuristic rules.

Figure 6.11(a) shows the population of each cell, and Figure 6.11(b) shows population multiplied by incidence in each cell. Comparing these figures suggests how the factors – population, distance, and incidence – influence the locations of outposts and gives a clue about why some cells are dropped out of the solution from the coverage-maximization model and new cells entered in the cases-avoided-maximization model. For instance, the cells with larger population are scattered around the center of the township (highlighted in green in Figure 6.11(a)), while the cells with higher incidence times population are clustered toward the west side of the township (highlighted in pink in Figure 6.11(b)). In other words, the green cells take priority if the objective is to vaccinate as many people as possible, but the pink cells have priority in order to avoid as many cases as possible. If minimizing total population-weighted travel distance is the main objective of the program, the outposts should be located as close as possible to the cells with large population.

Figure 6.11. Population size and population  $\times$  incidence in each cell

			848	180	615
	1097		2938	2097	674
	1904	443	4669	1568	85
1417	2443	4397	1523	1143	
2801	1377	2951	1230		
3164	4884	4496			
604	517	1193	348		
		2541			

(a) Population size in each cell

			0.03	0.00	0.03
	0.04		0.77	0.17	0.01
	0.34	0.03	0.38	0.12	0.02
0.56	1.70	0.64	0.00	0.07	
0.27	0.77	0.69	0.20		
0.42	1.44	0.86			
0.10	0.02	0.40	0.55		
		0.92			

(b) Population times incidence in each cell

## Chapter 7

### Use of optimization tools in vaccination planning processes

The previous chapters of this dissertation develop a decision-analytic tool for vaccination planning based on optimization models integrated with a variety of quantitative techniques such as the contingent valuation method, location models, cost estimation, simulation, and sensitivity analysis. This optimization-based tool is now available for health planners in developing countries to use for choosing the locations of vaccination outposts along with the level of user fee. However, it is widely reported that planners who have actually used optimization tools<sup>32</sup> usually faced many obstacles to successful application which often overshadowed the benefits of the tools (Ravn and Vidal, 1986). Due to such obstacles, there has been no widespread adoption or implementation of optimization tools in the health planning process despite the increasing number of academic publications dealing with optimization research for health problems (Wilson, 1981; Fone et al., 2003; Brailsford, 2005). As Carter et al. (1973) pointed out, the implementation problem is even more critical when applied to the contexts of developing countries.

This concluding chapter discusses how the tool developed in this dissertation for determining the Optimal Price and Locations of Vaccination (“OPLV tool”, hereafter) can best be used in the actual vaccination planning processes in developing countries such as China. The first section of this chapter reviews the key literature in the field to examine how

---

<sup>32</sup> In this chapter, the term “optimization tools” is used in a broad sense which covers operational research (OR), OR-type mathematical tools, location models, and systems analysis (Rogers and Fiering, 1986).

optimization tools have been used in a variety of different planning practices in developing countries, such as economic development planning (Ackoff, 1977; Fisher and Rushton, 1979; Clayson, 1980), water resources planning (Yeh, 1985; Rogers and Fiering, 1986; Cai et al., 2002), and health care planning (Wilson, 1981; Hassam et al., 1986; Durrheim et al., 2002; Harper and Pitt, 2004). This literature review summarizes the potential obstacles to adopting and implementing optimization tools and the recommendations for overcoming such obstacles. Based on the literature review, the second section discusses how to put the OPLV tool into practice in vaccination planning processes in China. In particular, it highlights how to present the potential contributions of the OPLV tool to vaccination policy-makers in China for the design of vaccination strategies which would be best for the entire society. It is hoped that these efforts help facilitate the successful adoption and utilization of this tool in the national vaccination planning process in China and in other developing countries.

#### 7.1. Use of optimization tools in planning contexts: Obstacles and resolutions

A number of studies argue that the systematic selection of locations for health services is one of the main keys to improving the results of such services in developing countries (Hassam et al., 1986; Rushton, 1988; Rahman and Smith, 1999). The literature has demonstrated that location decisions based upon optimization tools may provide better results than conventional decisions in the absence of any formal analysis (Rahman and Smith, 2000). In spite of many academic authors praising the virtues of optimization tools, however, they have often gone neglected as locations for health services frequently have been determined politically or pragmatically without a systematic approach (Fisher and Rushton,

1979; Rahman and Smith, 1996; Nyongator and Kutzin 1999).

Since the 1960s, optimization tools have been applied to a wide range of public problems. The potential contributions of optimization tools are now widely recognized among researchers, but the issue at hand is how to ensure their utilization (Lee and Olson, 1980). While a majority of the academic literature has been dedicated to developing more sophisticated optimization models, few researchers discussed how they have been put into practice in the planning process. Furthermore, most of the literature reported significant problems in implementation. Among others, Ackoff (1960) examined a number of published reports dealing with optimization research, and found that only a few adopted or implemented the results from such findings in actual planning practices. Rogers (1980) reviewed 22 case studies of applications of optimization tools to water resources planning, and found only 7 of them reported that the tools were eventually adopted by decision-makers on water planning and management. Fone et al. (2003) in their review of the literature on computer simulation modeling in health care delivery from 1980 to 1999, found that the outcomes of the models were used in only a few cases. Brailsford (2005) discussed why the enormous success of optimization tools in industry is not the case in the health care field. He grouped potential barriers to implementation of optimization tools in the health field into five categories: unique culture of resistance to changes, cost of data cleaning and analysis, poor quality of data, different agenda between academic modelers and their clients, and the need for case-specific models.

From the 1970s on, optimization tools have been transferred to developing countries. Similar to cases of transferring industrial technologies to developing countries, the lessons learned from using the optimization tools developed in industrialized nations were expected

to provide assistance to developing countries by identifying pitfalls and sharing examples of success (Ravn and Vidal, 1986). Upon successful implementation, the impact of optimization research should be even more remarkable in developing countries since the problems peculiar to most developing nations reflect the fact they have insufficient human and financial resources which are also often misallocated (Sagasti, 1972; Lee and Olson, 1980; Rogers and Fiering, 1986).<sup>33</sup> However, there are unique problems faced in adopting and implementing optimization tools in developing countries, which were reported by a number of researchers. Lee and Olson (1980) and Kembal-Cook and Wright (1981) reviewed the OR literature applied to developing countries and found that optimization tools were successfully adopted and implemented in developing countries only when optimization researchers effectively dealt with several unique factors affecting decision problems in developing nations, such as centralized planning systems, political factors, uncertainty in the planning environment, and shortage of skilled supervisors and management. Rogers and Fiering (1986) argued that decision-makers in developing countries are suspicious of the direct transfer of optimization tools developed in industrial nations to their own planning process since they do not perceive similarities in social and governmental situations.

Interestingly, several barriers to implementation are found consistently in the literature over the past 30 years regardless of areas of planning. Below, I classify them into five major types of barriers; (1) unawareness or distrust of the benefits of optimization tools, (2) complexity of political aspects with competing objectives, (3) lack of adequate communication and interaction, (4) shortage of expertise and resources, and (5) uncertainty due to limited or unreliable data. These factors should be taken into account when the

---

<sup>33</sup> Two selected examples of successful implementation of optimization tools in developing countries are found in Hassam et al. (1986) and Durrheim et al. (2002).

optimization-based tool developed in this dissertation is adopted and implemented in developing countries such as China. Potential resolutions to each of the barriers suggested by the literature are also summarized in this section.

#### 7.1.1. Unawareness or distrust of the benefits of optimization tools

First of all, optimization tools are unlikely to be adopted in the planning process when policy-makers do not fully appreciate the problems of the current approach and/or the potential contribution of the tools. They cannot justify the use of optimization tools when they do not see the value of the alternative approach. Even if they agree to change their current planning strategy, decision-makers often distrust the results from the tools since the optimization approach based on sophisticated mathematical models is unfamiliar to them (Roger and Fiering, 1986). According to the literature, the likelihood of optimization tools being adopted may be improved by (1) ensuring that clear and important problems are addressed, and (2) providing decision-makers with clear evidence of the benefits brought about by the tools. These are discussed below in more detail.

Kemball-Cook and Wright (1981) argued that optimization tools tend to be hardly used in the planning process unless they are applied to the problems that are high priority and urgent on the national or local agenda and there is sufficient need of resolving problems of the current approach (Brailsford, 2005). Therefore, those who intend to apply an optimization tool to a planning problem should ensure that decision-makers are fully aware of the problems of the current strategy and have strong motivation to change based on the evidence provided by a systematic tool. Note that, however, the application in my

dissertation research did not ensure decision-makers' full awareness of the current problems and motivation to change.

Once an important problem is identified, decision-makers should be persuaded by clear evidence of the potential contribution of the proposed tool in the planning process (Harper and Pitt, 2004). The literature argues that the additional costs of applying optimization tools such as hiring professional expertise or purchasing computational resources can be justified only if the alternative approach suggested by the tools would bring larger benefits than their conventional approach (Clayson, 1980; Rogers and Fiering, 1986). However, when the potential contribution of optimization tools is presented to decision-makers, they should not be misguided about the tools as a panacea that always guarantees the superior optimal solution to a problem. Rogers and Fiering (1986) proposed that optimization tools should be used only to identify the "negotiation frontier" in the vicinity of the optimal solution.

#### 7.1.2. Complexity of political aspects with competing objectives

The second challenge to effective adoption of optimization tools in planning process is the political environment surrounding the planning process itself (Ackoff, 1971). The importance of taking into account political factors in the optimization process is highlighted in identifying the objective of the planning problems. Lee and Olson (1980) and Ravn and Vidal (1986) argued that the most difficult challenge for optimization planners is how to reach agreement on their ultimate objective which satisfies the competing agendas of those involved. Optimization tools tend to guarantee implicitly that the recommended solution



would be in the best interest of all stakeholders, but it is in fact very difficult to have all stakeholders agree on the model objectives and constraints (Rogers and Fiering, 1986). Multi-objective planning (Cohon and Marks, 1975; Harewood, 2002) is one of the potential approaches to address all the objectives considered not only by policy-makers but also those who are affected by the policy.

The economics and public policy literature suggests that public programs should be evaluated in terms of the benefits and costs from a society's perspective, including all parties affected by the program (Layard and Glaister, 1994). However, decision-makers in governments tend to see the benefits only from their perspective ignoring the full private benefits that accrue to all beneficiaries of the program. For instance, vaccination decision-makers may simply consider maximizing coverage or cases avoided without fully understanding the benefits from the user's perspective such as the peace of mind due to vaccinations or user's convenience in receiving vaccinations. In such a case, the government's conventional vaccination strategy may be improved by the optimization-based alternative producing larger private benefits. Therefore, a key task for successful adoption of optimization tools in the planning process is to present policy-makers with evidence that society might be substantially better off in terms of economic efficiency when optimization-based planning is implemented.

### 7.1.3. Lack of adequate communication and interaction

The implementation of the results of optimization research often calls for some innovations within the affected organization, but decision-makers and their staff are often

culturally resistant to change their existing approach, particularly in the health field (Lee and Olson, 1980; Brailsford, 2005). They may tend to have psychological resistance to adopting solutions from computer-based methods and an inclination to trust their experience when making decisions on routine tasks. Furthermore, decision-makers tend to pay little attention to research-based tools for their decisions for their project unless they have had enough involvement with them to trust the results (Rogers and Fiering, 1986). In order to overcome any resistance or disinterest from the affected organization and facilitate the adoption of optimization tools, optimization researchers should maintain dynamic interaction and constant communication with decision-makers (Huysmans, 1970; Innvaer et al., 2002), which is often limited in developing countries.

The optimization researchers should communicate closely with decision-makers at every stage of implementing an optimization tool. The optimization modeling process is often bounded by existing internal factors such as overall government policies and currently used or proposed strategies (Lee and Olson, 1980), most of which can be ascertained by communicating with high-ranking decision-making officials in developing countries (Rahman and Smith, 1999). Policy-makers also play a critical role in identifying problems and determining whether or not and to what extent the findings from optimization tools will be implemented in the planning process (Kemball-Cook and Wright, 1981). Active communication with decision-makers enables planners to understand the political context of the problems and prevent misuse of optimization tools by policy-makers. Besides, close interaction with decision-makers enhances the validity and credibility of optimization tools and promotes their confidence in the results of the tools (Harper and Pitt, 2004).

A well-structured organizational setting of engaging optimization staff in the planning process may facilitate communication and narrow the conceptual gap between decision-makers and optimization researchers (Rahman and Smith, 1999). As Lee and Olson (1980) pointed out, instead of being isolated in an organization, optimization researchers should be spread throughout an organization so that they can help the needed parts more effectively. In this way, optimization researchers can interact with policy-makers and their subgroups and support them in a more functional way.

#### 7.1.4. Shortage of expertise and resources

Another unique challenge to applying optimization tools in the planning process in developing countries is the overall weakness of planning and management systems in these nations (Garner et al., 2001). They often include a shortage of skilled manpower (McCarthy, 1978; Lee and Olson, 1980), a lack of practical experience (Ravn and Vidal, 1986), a lack of access to research (Garner et al., 2001), and a shortage of financial resources (Brailsford, 2005). Although the literature has long emphasized the importance of capacity building in developing countries, there is still great need to train, develop, and motivate personnel in optimization-based planning techniques. The use of optimization tools can provide good opportunities for transfer of advanced technology to local governments in developing countries because it requires a multidisciplinary approach including economics, operations research, computer science, mathematics, systems analysis, and management (McCarthy, 1978). However, technology transfer cannot be the blind acquisition of ready-made technical tools from advanced countries. Without serious reflection on implementation and its impact

to the system in the unique context of developing countries, such transfer of technology might result in undesirable outcomes. In other words, technology should not only be transferred, but should also be adapted to the needs of the developing country considering the political, social and cultural context (Ravn and Vidal, 1986).

A dearth of financial resources in developing countries might make building expertise more difficult. It might be costly to bring in outside experts or train in-house personnel, and to maintain high-quality data management staff and system (Brailsford, 2005), all of which may delay successful and expeditious implementation of optimization tools in the planning and problem-solving process. Lee and Olson (1980) suggested that cooperation with universities and professional organizations in developed countries could help lead to the collection of existing data and information on the optimization technique at a reasonable cost. They also emphasized the effectiveness of on-the-job training for indigenous optimization specialists in actual planning processes in developing countries.

The application of optimization tools based on simple models might be helpful to overcome the lack of expertise and resources in developing countries by building up capacity. In many cases, complex models developed by academic researchers might be unnecessary because the planning process often does not allow the time to do complex modeling (McCarthy, 1978; Rogers and Fiering, 1986). According to Lee and Olson (1980), in order to avoid the negative impact of overly complex models, optimization models should be simple and cost-effective in developing countries. Complex models have been preferred mostly by academic researchers who perceive little advantage in publishing the applications of a well-known algorithm in a given project, but their publishing objectives tend to conflict with successful implementation (Rogers and Fiering, 1986). Therefore, when seeking the optimal

solution from complicated models is not practical, it is worth considering less sophisticated but still acceptable models which handle the implementation problems in developing countries.

Simulation-based approaches might function well as a complement or even substitute for complex optimization models (Kemball-Cook and Wright, 1981; Fone et al., 2003). A simulation model incorporates the relationships among variables and estimates the planning outcomes based on numerous runs of the model under a given set of input parameters and conditions. The simulated output illustrates the responses of the model to variations of many input parameters, by which optimal or near-optimal solutions can be sought (Rogers and Fiering, 1986). Simulation models are usually more readily understood and more flexible to be used by decision-makers since they present the simulated results of alternative strategies along with different assumptions rather than one single solution. This approach may be simple enough for use by internal analysts within a local planning system in developing countries, thus helping to avoid the substantial implementation costs of hiring highly-trained analysts from outside. Such an approach will not only compensate for shortages of resources and skilled manpower but also facilitate capacity building in developing countries in the long run.

#### 7.1.5. Uncertainty due to limited or unreliable data

Users of optimization tools often face greater uncertainties in the decision environments of developing countries than in developed countries (Lee and Olson, 1980). One of the major sources of uncertainty is that data used in the models are often limited or

unreliable. Although the technique is precise, if data are subject to substantial limitations such as missing values and erroneous information, optimization programming is rarely used (Rogers and Fiering, 1986). In particular, healthcare data are notoriously of poor quality because many health care systems still use old and incompatible computer systems at best or paper-based systems at worst, and their staff are relatively less computer-literate than those in other fields, and thus extreme care must be exercised when using health data (Harper and Pitt, 2004; Brailsford, 2005). In addition, Rogers and Fiering (1986) argued that social and economic data often have poor quality in the sense of duration, coverage, precision, and accuracy.

However, Oppong and Hodgson (1994) insisted that data limitations should not preclude the use of optimization models to support decision-making in developing countries. A few suggestions are found in the literature to address data uncertainty. Wilson (1981) argued that a detailed description of data collection would be critical to ensure the reliability of the data. Kemball-Cook and Wright (1981) argued that the shortage of reliable data can be compensated for by the tools employed if the tools are developed enough to tackle many complex and uncertain problems facing developing countries. Stochastic programming techniques would be one useful approach to address uncertainty embedded in planning problems (Yeh, 1985), such as Monte Carlo simulation and sensitivity analysis of model solutions. Rogers and Fiering (1986) suggested that planners should develop optimization tools to improve decision-making in spite of poor-quality data, arguing that benefits from using optimization tools with less reliable data could be greater than those from using conventional approaches. Therefore, although reliable data might be unavailable,

optimization researchers should look for a range of alternatives that maximize the probability of achieving “satisfactory” outcomes, within their levels of uncertainty.

## 7.2. Implementation guide for the optimization tool in vaccination planning in China

This section discusses how the OPLV tool can be adopted and implemented successfully in the vaccination planning process in China. Most of the barriers discussed in the previous section are pertinent to the case of vaccination planning in China. This section proposes a plan to address the barriers reported in the literature using examples from the case study for Daxu Township. It is intended to serve as a potential guide for a consultant who intends to apply the OPLV tool to determine the optimal price and outpost locations of vaccinations in China (“the OPLV consultant” hereafter). Although the proposed implementation guide in this section uses examples from China, it should be useful for vaccination planning in other developing countries as well.

Figure 7.1 shows a flowchart laying out the planning process to emphasize what kinds of tasks and decisions need to be made in each step of the adoption and implementation process. During this process, the OPLV consultant must interact closely with government health officials (i.e. CDC officials) to help them to make the best decisions on their vaccination program design. This flowchart provides a general framework that can be applied to any vaccination campaign in developing countries, with the understanding that modifications should be made to account for country-specific conditions of each vaccination program.

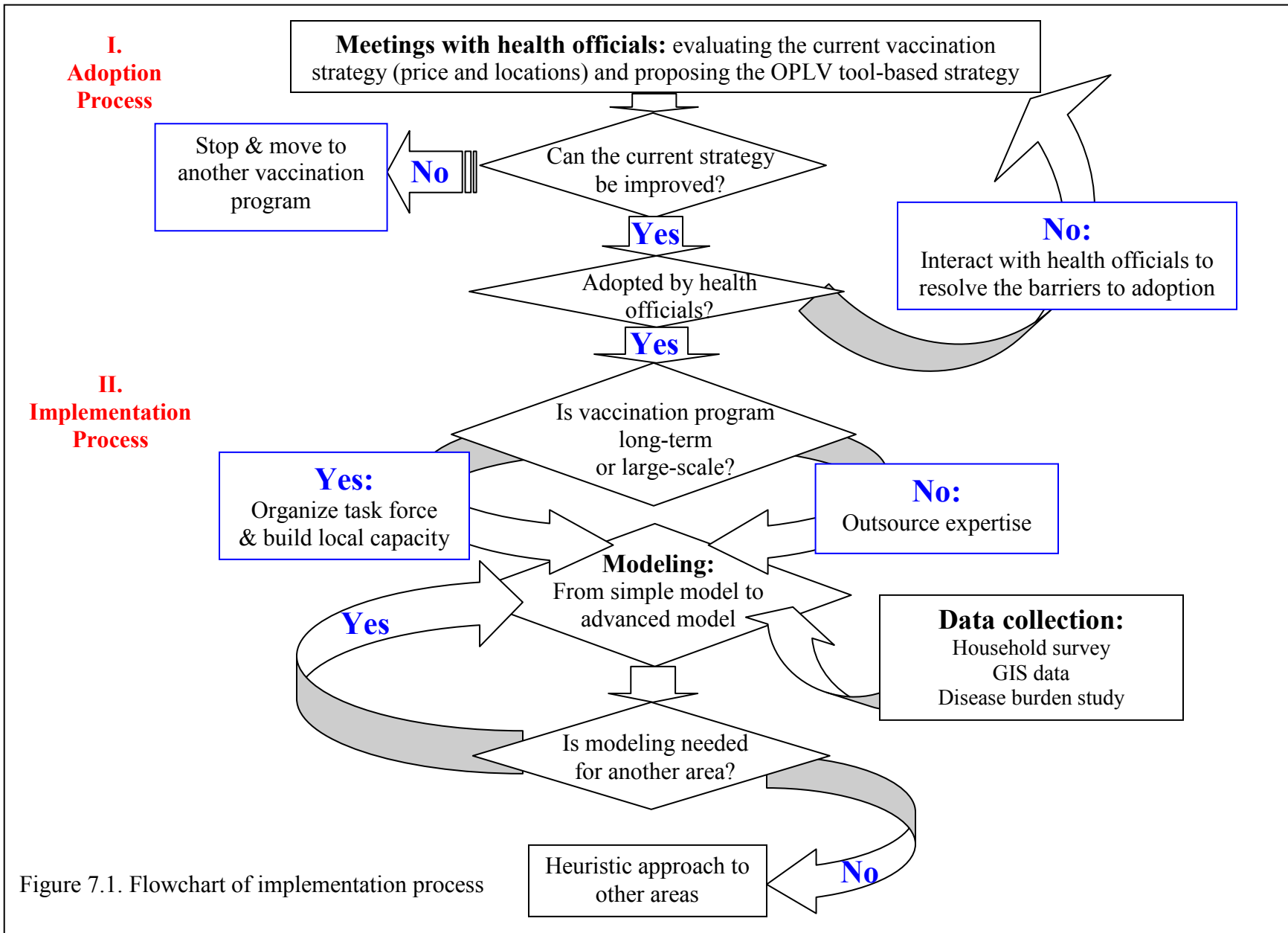


Figure 7.1. Flowchart of implementation process



### 7.2.1. Adoption process: Justification of the tool

Before the OPLV tool can be adopted, government health officials must be convinced of the need to consider a new approach. The first section of the guide discusses this process using examples from the case study in Daxu Township, China. To initiate the process, the OPLV consultant should meet with decision-makers to identify whether their current strategy of determining price and locations of vaccinations can be improved, and if so, present health officials with clear evidence that the tool-based alternative strategy outperforms the current approach. This section first proposes a progressive approach when presenting the potential contribution of the OPLV tool to health officials, depending on their reaction, starting from simple analyses without any modeling and progressing to comprehensive modeling with benefit and cost data. It then discusses that the tool may be adopted differently depending on the nature of vaccination planning approach in the target area, such as supply-based or demand-based.

#### *Progressive approach*

The OPLV consultant should first identify the appropriate planning agency that makes decisions on price and locations of vaccinations for the target area. In China, since 1985 the immunization system has been decentralized and local public health agencies are responsible for managing and financing vaccination programs and designing vaccination delivery strategies (IVI, 2001). Thus, the provincial-level or county-level CDC officials are the appropriate local counterparts with whom to discuss the adoption of the OPLV tool since

they direct planning for vaccination programs in the area. By communicating with them, the consultant would be able to obtain the information on their current vaccination strategy. In Daxu Township, the government provides typhoid vaccinations only at a single mega-site (i.e. the CDC), and the users must pay for them. There is no external funding to subsidize the typhoid vaccination campaign in the township.

Given that the government maintains their current vaccination delivery strategy (i.e. mega-site vaccination at the CDC) for their vaccination campaign in the township, the consultant may first evaluate the appropriateness of the current location of the CDC. The consultant can run a simple p-median model to find out the optimal location for a vaccination outpost when only one is built in the township. As presented in Chapter 4, the p-median model reveals that the current location of the CDC is indeed the optimal location for Daxu Township, but this might not be the case for other townships. The consultant should then present outcomes of the current vaccination strategy and compare them with those of the other extreme alternative of delivering vaccinations at all villages. Outcomes include the number of vaccinations, the number of cases avoided, travel distance, revenue, and private benefits, all of which could be used as criteria for decision-making.

In most cases, the government officials who are designing vaccination strategies care mostly about health-related payoffs such as maximizing cases avoided. Recollecting the case of Daxu Township described in Chapter 4, if the price users have to pay is USD 1, then the number of typhoid cases avoided with only one outpost at the CDC is 163 over 3 years; however, if the government provides vaccinations at outposts in each cell (about 25 outposts) in the township, the cases avoided would only increase by fewer than 60. However, having 25 outposts instead of one would save people about 14 km (roundtrip) of travel time on

average for vaccinations, which would produce additional private benefits of about USD 150,000 for all people who would be vaccinated, which seems quite substantial.

The consultant could then make initial runs of the simplest models or work with health officials to make initial runs. A simple p-median model or set covering model might be suitable for the initial screening of the candidate locations. As shown in Chapter 4, these models provide some guidance on how many vaccination outposts there should be and where to locate them although they are simple and do not require demand and cost information. However, their suggestions from the models without demand and cost data are limited to be used for the optimal vaccination designs in terms of economic efficiency. The consultant could do these initial analyses for free of charge, hoping to get a future contract.

If health officials agree to reconsider their current vaccination strategy and sign a contract with the consultant for further advice on how many outposts are needed and where they should be located based on actual demand and cost data, the consultant can now begin actual data collection and modeling tasks. The consultant may develop more comprehensive models, such as the coverage-maximization or case-avoided-maximization models developed in Chapter 6. If the data are not available or hard to collect, the consultant communicates with local health officials to obtain their best estimate of the parameters so as to incorporate the most reliable assumptions in the model. Using these models, the consultant can identify not only the “globally optimal” price and locations of outposts, but also how much the vaccination outcomes change with different number of outposts. These models may take account of cost and benefit from a society’s perspective (including private benefits), identifying the optimal solution in terms of economic efficiency. The consultant may conduct

sensitivity analyses to show how vaccination outcomes change with different assumptions and constraints.

Since government health officials may not be able to understand these modeling techniques and analytic tools, the consultant should use as plain language as possible to describe the theoretical concepts and practical examples of the tools to them. A PowerPoint presentation may be an effective way of describing the tools, and the presentation should be easy and clear to decision-makers in a non-technical language. A prototype model interface presenting the sensitivity of the results to different assumptions may help the consultant to be more responsive to inquiries of health officials. Using this approach, the consultant would be able to change the models in response to health officials' input on the objectives and constraints of vaccination program alternatives.

#### *Supply-based vs. demand-based vaccination planning*

The adoption process for the OPLV tool could differ depending on the nature of the vaccination planning system. Vaccination planning has long been conducted through a top-down approach, especially in developing countries. Decisions about price and outpost locations of vaccinations tend to be dominated by supply side considerations, with little input or feedback from households themselves. In a top-down approach, running a simple p-median or set covering model might be sufficient to seek out the optimal number and locations of the outposts given a certain price. Without full consideration of costs and private benefits of the vaccination program, the OPLV tool employing a simple model can assist

decision-makers who want to make decisions in terms of health payoff, such as maximizing cases avoided while also ensuring that the vaccination program is financially self-sufficient.

According to the previous chapters in this dissertation, health payoff from vaccinations (e.g. cases avoided) in Daxu Township appears to be relatively modest compared to private benefits of vaccination which turn out to be substantial. However, private benefits count mainly in democracies, not necessarily in socialized economies such as China. In the case of China, which has long operated with a socialized, centrally planned-and-directed, top-down system, most of vaccination policy decisions have been made by government health officials using a supply-based approach without fully considering the household preferences. Although immunization programs are financed by user fees in China, vaccination programs are not demand driven. Therefore, vaccination decision-makers in China might not be willing to spend money and efforts on employing more outposts for only a little marginal health payoff if substantial private benefits are not considered under a supply-based approach.

However, lessons learned from water-sector planning may shed light on the importance of a demand-based approach in vaccination planning. One of the key lessons summarized by the U.S. Agency for International Development (USAID) is that participation of the users in managing water supply systems is critical to long-term sustainability and the government should provide the necessary environment for their participation (Hopkins et al., 2004). Hopkins et al. (2004) thus proposed two tools for strengthening demand-based planning of rural water systems in developing countries: (1) contingent valuation (CV) surveys to measure the private demand for improved water supply, and (2) mathematical models built around CV survey results to identify policy alternatives to meet the demands of

the private sectors. “Participatory” water-supply planning based on household demand surveys is also suggested by Davis and Whittington (1998). This lesson can be directly applied to vaccination planning, at least for non-essential vaccines. Both water supply and vaccinations have long been treated as public goods and have been managed solely by the public sector in developing countries. However, recently there is an increasing need to charge consumers most or all of the costs of these services to make the programs sustainable. The previous chapters in this dissertation demonstrate that a CV-based optimization tool can be applied well to typhoid vaccination planning in developing countries.

China is experiencing rapid transition toward a market-oriented economy and a democratic society. A change to a demand-based approach would require the Chinese government to design their planning systems so as to be more responsive to the private sector. Decision-makers in China may need to consider not only the health benefits of vaccinations but also private benefits in the design of vaccination strategies in order to improve economic efficiency and financial sustainability. If they agree to do so, the OPLV tool may be implemented by employing more comprehensive models considering the program costs and private benefit information. In such a case, the OPLV tool can play an even more important role in determining the optimal price and locations of vaccination so as to better serve society.

#### 7.2.2. Implementation process: Three issues

Once the OPLV tool is adopted by decision-makers for setting price and locations of vaccinations in China, the OPLV consultant and decision-makers should design a detailed

implementation plan together. Among a number of important issues to be considered for successful implementation, this section focuses on three major implementation questions: (1) Who should take what roles?, (2) What model is appropriate?, and (3) Should the model be developed for every area? This section discusses how to address each of these issues by using examples from the case study in Daxu Township.

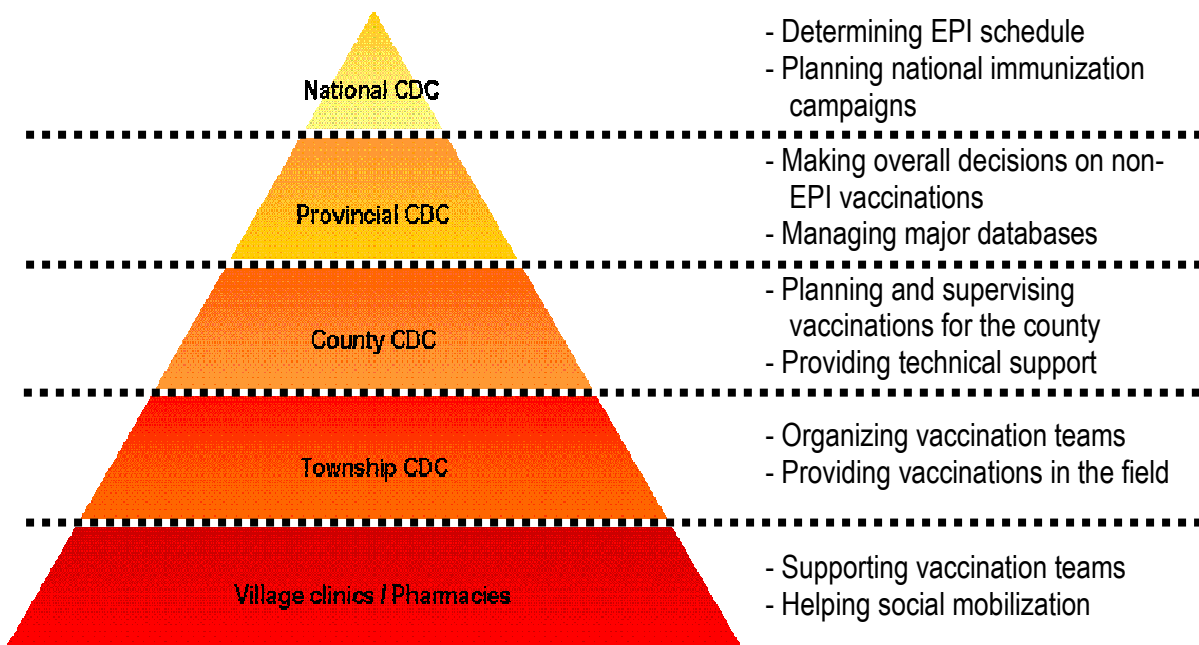
*Who should take what roles? – The optimization task force*

The first decision to be made is who should take the major roles in implementing the OPLV tool. Either outside experts should be hired or in-house personnel should be trained to build internal capacity for implementing the tool. The first option would be appropriate for the one-time or short-term project or for the local planning agency without sufficient human resources. With respect to the technical requirements of mathematical and statistical model building, and for small agencies with periodic needs, it might be more efficient for agencies to utilize external expertise. However, local staff training is usually critical to enhance local capabilities rather than relying solely on external consultants, especially for a project that requires continuous modeling. Because vaccination programs are conducted continuously in most cases, utilizing local permanent staff is generally advisable. Once the local staff are well trained for applying the tool to one vaccination program, they would be capable of determining price and locations for future vaccination programs on their own.

If the second option of using local staff is chosen, who should take the leading role of implementing the OPLV tool inside the organization? Understanding the multilevel hierarchical organizational structure of the CDC agencies in China provides some insight. As seen in Figure 7.2, multiple levels of CDC agencies are involved in vaccination planning in

China. The provincial and county level CDC officials usually take the role of making decisions that relate to overall planning of non-EPI vaccination programs, such as which non-EPI and optional vaccinations to offer, what price to charge, and how to deliver vaccinations (IVI, 2001). They also manage the databases that are imperative in the use of the tool, including incidence data, demographic and socioeconomic data, and geographic information systems. The township CDC staff usually take the lead in implementing tasks directly related to vaccinations such as operating vaccination teams and administering vaccinations to the users. The township CDC staff are sometimes responsible for defining and developing local health care plans due to the recent health sector reforms in China, but the county CDC staff still pass along national and provincial guidelines to them and provide technical support (Tang and Bloom, 2000).

Figure 7.2. Hierarchy of vaccination systems in China<sup>34</sup>

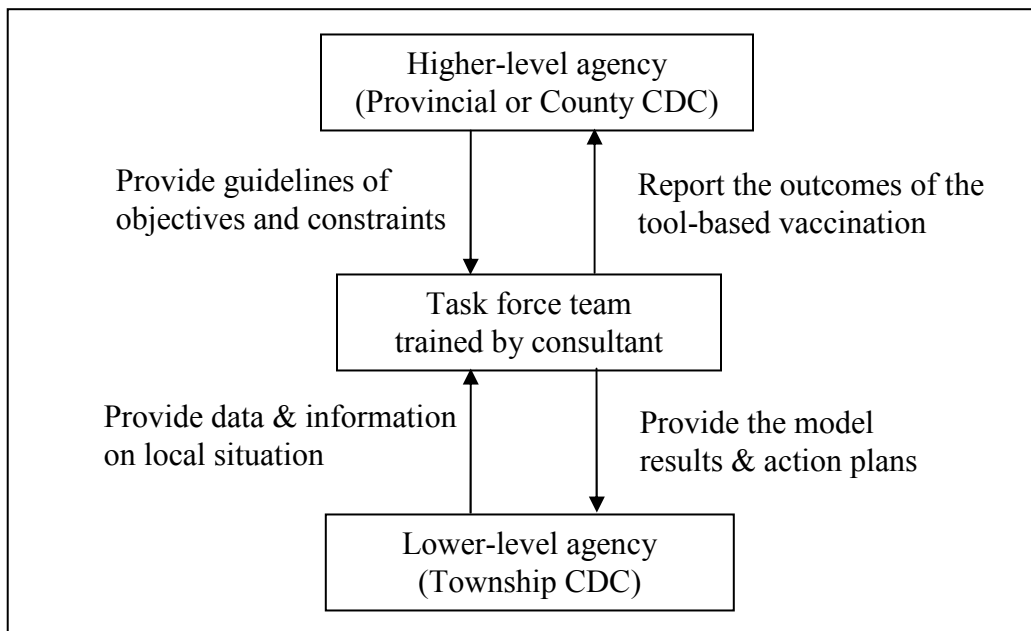


<sup>34</sup> Another mid-level CDC agency, called the municipal CDC, is excluded in this chart because it plays a similar role as the county CDC agency.



Lee and Olson (1980) suggested a team to coordinate the implementation process of optimization models involving different levels of agencies. To effectively coordinate multiple levels of vaccination planning systems in China, a task force team could be constructed including a key person from each level of the CDC agencies, along with external consultant(s). The task force team would take the leading roles in implementing the OPLV tool by communicating with all levels of CDC officials who are involved in the vaccination planning process. At each level, there should be a staff member who can help with the communication with the task force team. Figure 7.3 illustrates how the team interacts with higher-level and lower-level CDC staff in the implementation process.

Figure 7.3. Interaction process between task force team and each level of the CDC agencies



The task force team should build close contacts with higher-level CDC officials and inform them of the outcomes of vaccination planning based on the OPLV tool. The team can

also be informed of their program objectives and constraints by communicating with higher-level CDC officials. On the other hand, the team should interact with lower-level CDC staff to request the data or supporting information on the target areas for the modeling. In case data are unavailable or uncertain, the team may want to conduct primary data collection or data quality management by co-working with lower-level staff to reduce data uncertainty. Once the optimal solutions are determined, the team should provide the lower-level CDC staff with the results and actual guidelines for their tasks. Such a coordinating framework keeps all levels of CDC officials involved in the planning process, which improves the likelihood of successful implementation of the tool.

The well-designed training of team members is important when there is a lack of in-house expertise for implementing the OPLV tool in local health departments in China. The goal of staff training is that they can formulate, use, and interpret the model on their own. The consultant needs to prepare a detailed user guide for the tool and arrange training workshops or seminars. The consultant should work closely with local staff until they are fully able to use the tool on their own. A ready-to-use prototype program should be developed and brought in by consultants and left in local staff's hands for subsequent use.

#### *What model is appropriate? – The piecemeal approach*

Most of the literature suggests that optimization models need to be as simple as possible for successful implementation, in particular in developing countries. In cases where the objectives and constraints of the models become complex, the mathematical modeling also tends to be complex in order to incorporate all possible planning elements in model

formulation at once. For instance, the coverage-maximization model in Chapter 6 requires non-linear mixed integer programming to solve the optimal price and locations simultaneously for Daxu Township. This model is quite complex and requires many computational processes. One alternative in this case would be to use a “piecemeal” approach in order to avoid excessive complexity in the model and produce a simple version of the optimization model. Instead of seeking a simultaneous solution, a piecemeal approach employs a series of simple Linear Programming (LP) models stepwise to identify the optimal locations of vaccination outposts for a given price. Since these models treat price as an exogenous variable, they do not create any nonlinear variables. This approach is simple enough to be readily usable by local agencies, yet still provides valuable information. Figure 7.4 summarizes the results of the piecemeal approach of running a series of simple LP models given assumed prices.

Figure 7.4. Results of the piecemeal approach (LP models by assumed price (USD))

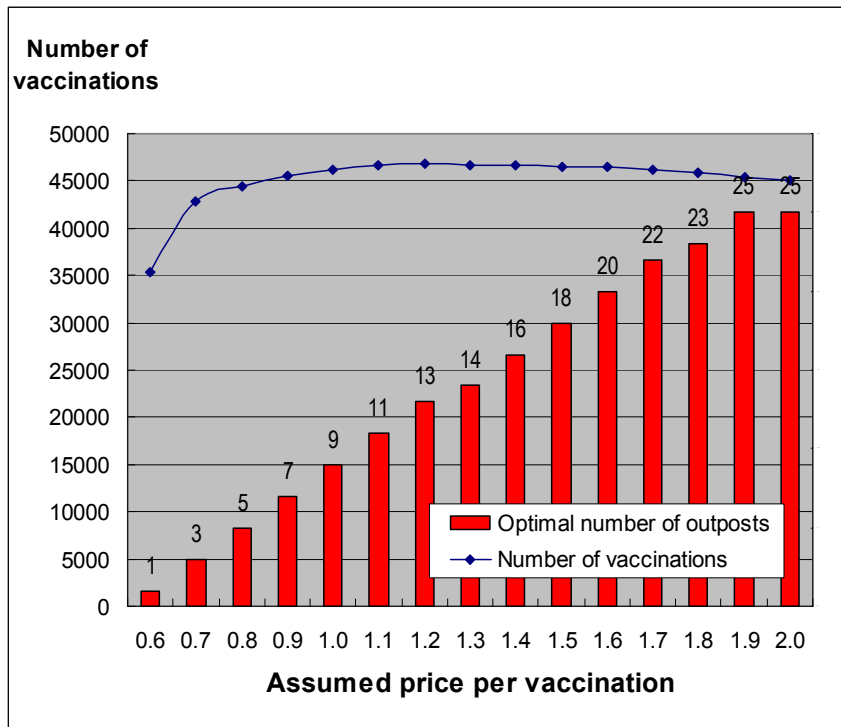


Figure 7.4 shows that the number of vaccinations reaches the maximum at price=USD 1.2, which is very similar to the “globally-optimal” price determined by simultaneous solutions in Chapter 6, and declines afterwards. Additionally, this piecemeal approach provides much helpful information to guide the planner’s decision on vaccination strategies. For instance, this approach demonstrates that price must be at least USD 0.6 to meet the constraint that program costs be covered only by revenue from private sales. This finding provides insight if the decision-maker’s goal is simply to minimize the price level under the cost-recovery constraint. It is also found from this approach that more outposts are needed as price increases, which indicates that extra revenue from price increases should be fully used to set up more outposts in order to maximize the number of vaccinations. The reduced number of vaccinations due to higher price would be made up for by additional vaccinations due to shorter travel distance with more outposts. It is also found that it is optimal to deliver vaccinations at all 25 candidate locations if price is set over USD 1.9. This approach provides a full range of results of the combination of price and locations, providing planners with the information they would need to make the final decision among the desirable sets of price and locations based on their local conditions (e.g. availability of external subsidy).

*Should the model be developed for every area? – Heuristic rules*

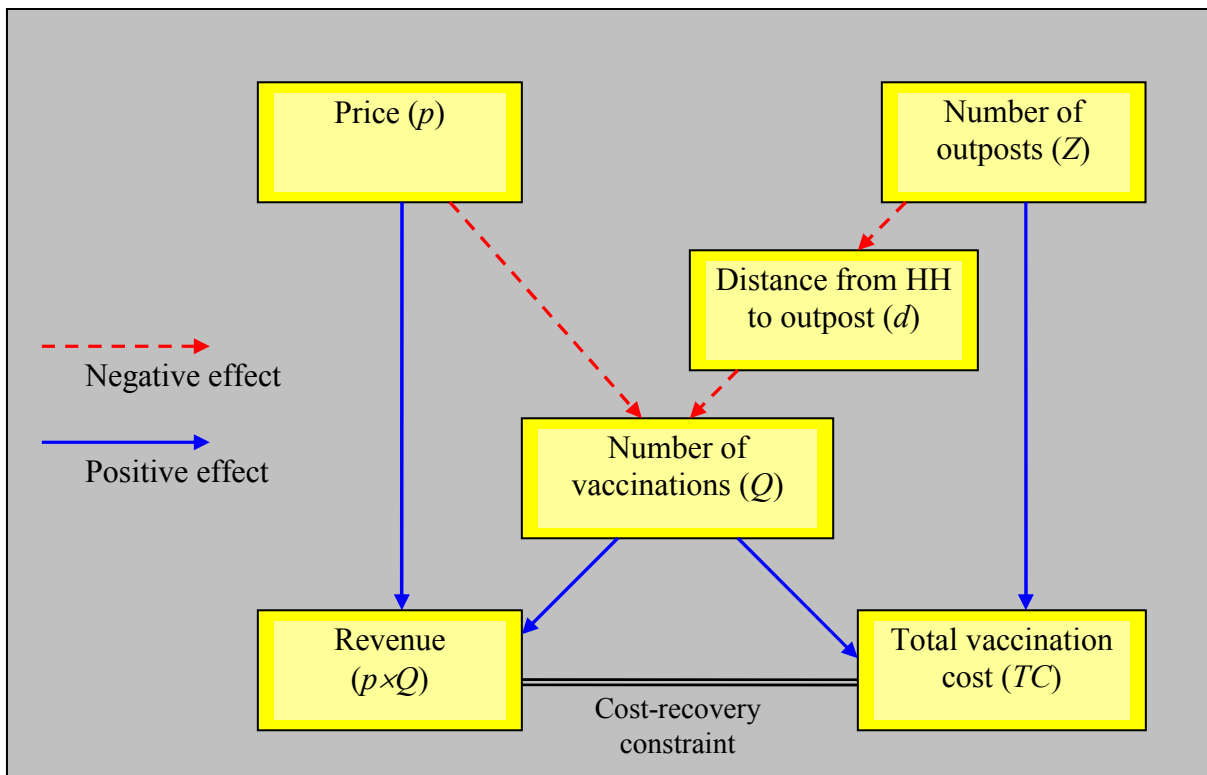
The OPLV tool is developed for determining the optimal price and locations of vaccination using the data from one rural township in China. In most cases, vaccination

campaigns take place in multiple townships throughout the county or province. Should the model be developed for every township by collecting all pertinent or required data from each township? Or can the model results from a few townships serve as heuristic guides for determining price and locations of vaccination for similar areas? Considering that a substantial amount of time and money would be spent collecting data and information required for the tool, developing a set of heuristic rules that can be generally applied to other townships is very important for successful, widespread implementation of the tool. Therefore, the model should be developed using the data from the smallest number of townships which are sufficient for developing satisfactory heuristic rules. The townships to be selected for data collection should cover all recognized existing different local situations such as rural vs. urban, high vs. low incidence, concentrated vs. dispersed population, and so on. Once the models are developed for the selected townships, the task force team should discern the heuristic rules to identify desirable sets of locations and prices for each township in the target area. The heuristic rules should be documented clearly in the form of a ready-to-use user guide, and shared with local CDC staff at a training workshop in each township. Below, one example of the heuristic rules developed from the case study for Daxu Township is discussed focusing on how the price and locations of vaccinations should be determined for other townships in China.

Figure 7.5 illustrates the underlying mechanism of the OPLV tool showing how the optimal price and number of outposts are determined in order to maximize the number of vaccinations given cost-recovery constraint. This diagram shows clearly two different routes of price effect on the number of vaccinations. Economic theory (i.e. the law of demand) suggests that price is negatively associated with the number of vaccinations (direct effect of

price), but at the same time, additional revenue by price increase covers costs of having additional outposts where more people would be vaccinated due to reduced travel distance (indirect effect of price; distance effect). If the direct effect of price is greater than the distance effect, price needs to be lowered to maximize the number of vaccinations. On the contrary, if the distance effect is larger than the direct price effect, more people would be vaccinated if vaccinations are delivered at more outposts in spite of increased price. Careful consideration of these effects would provide insight on how to determine price and locations heuristically for other areas.

Figure 7.5. Underlying mechanism in optimization process



Let us assume that the objective of the vaccination campaign in one township is to maximize vaccination coverage (i.e. number of vaccinations). In general, there might be four

different alternatives to be considered for the campaign, with regard to combinations of price and number of outposts, as presented in Table 7.1.

Table 7.1. Possible vaccination alternatives by price and number of outposts

Price \ Number of outposts	Many outposts	Few outposts
	<b>Alternative I</b>	<b>Alternative II</b>
Low price	<b>Alternative I</b>	<b>Alternative II</b>
High price	<b>Alternative III</b>	<b>Alternative IV</b>

**Alternative I** (low-price or free vaccinations at every village) would be the ideal alternative in most cases since it maximizes vaccination coverage in the case of no budget constraint. However, if costs are covered only by revenues from private vaccination sales, price would need to be increased to cover the costs of having more outposts in order to keep the program financially self-sufficient. **Alternative IV** appears to be the least preferable and should be used only in an exceptional case since it puts the burdens of both long travel distance and high price on households. Figure 7.4 indicates that, at the optimal condition, low price should be associated with few outposts (**Alternative II**) and high price be associated with many outposts (**Alternative III**). Therefore, the task force team would need to determine the most feasible and desirable strategy for each township between these two alternatives (**II and III**) based on the local situations.

Such decisions can be informed by careful consideration of three factors: (1) the cost of adding one more outpost ( $a$  in cost function; eq. 5.1), (2) the “direct” price effect on the number of vaccinations ( $\beta_p$  in demand function; eq. 3.2), and (3) the distance effect on the

number of vaccinations ( $\beta_d$  in demand function; eq. 3.2). The distance effect is also associated with the “indirect price effect,” as explained above. The first factor relates to the amount of setup costs<sup>35</sup>, while the second and third factors are associated with user’s demand for vaccination that depends on price and distance to the outpost. Table 7.2 presents the desirable alternatives for four different cases characterized by the three factors.

Table 7.2. Desirable vaccination alternatives for different situations

Demand side Cost side	Price effect > Distance effect on demand	Distance effect > Price effect on demand
Large setup cost (large $a$ )	<b>Alternative II</b> (Low price, Few outposts)	Higher price and fewer outposts than <b>Alternative III</b>
Small setup cost (small $a$ )	Lower price and more outposts than <b>Alternative II</b>	<b>Alternative III</b> (High price, Many outposts)

When the private demand for vaccination is expected to be more sensitive to price rather than distance, the best policy alternative would be dependent upon the magnitude of outpost setup costs. If setup costs are high, it might be reasonable to deliver vaccinations centrally at a few sites for low price because delivery costs would decrease and the reduction in vaccination sales due to the increase in travel distance would be minimal (**Alternative II**). However, if setup costs are relatively small, building more outposts would be beneficial. On the contrary, if the distance effect on private demand is relatively larger than price effect, many outposts would be needed to minimize the distance effect in spite of charging higher price (**Alternative III**). However, if setup costs are reasonably large, the number of outposts

<sup>35</sup> Chapter 6 shows that the cost of vaccinating one more person ( $b$  in cost function; eq. 5.1) has minor effect on the optimal solutions.



should be judiciously determined in order to ensure that the price does not become prohibitive.

These heuristic rules are mostly affected by different spatial distributions of population in the area. In rural and remote areas where population is widely distributed, distance effect tends to be larger than price effect. On the other hand, in urban areas where population is clustered, price effect might be more influential than distance effect. Therefore, credibility of the heuristic rules relies on proper understanding of the local situation. It would be very important to communicate with local CDC staff that have better access to the local data and better insight on local conditions. Involving local staff in the discerning process would also enhance the likelihood of the heuristic rules actually being used for designing their vaccination strategy. As Brill (1979) pointed out, by this heuristic approach, the OPLV tool serves as a catalyst for human creativity, while it does not provide definite solutions to be followed blindly. Ultimately, decision-makers would obtain insight from the tool on how to determine user fee and locations of vaccination for all other target areas.

### 7.3. Optimization-based vaccination planning as social learning

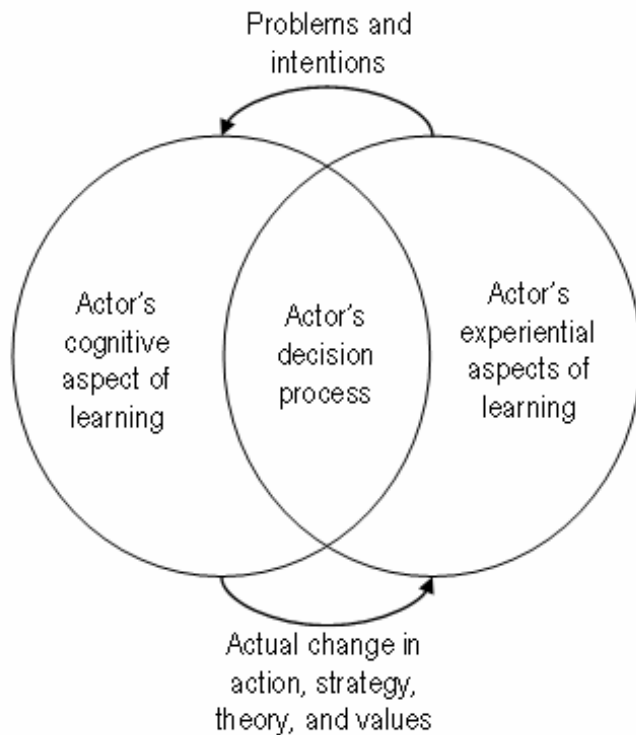
The preceding sections in this chapter argued that the successful adoption and implementation of optimization tools in an actual vaccination planning process require health officials to learn not only about a scientific technique, but also to experience both implicit and informal learning processes that causes various changes in their practical, daily activities. They would learn from a consultant or expert about how to use the tool and interpret the results, while learning from the communities about their demand and preference for

vaccination services, which is vital information to be incorporated into model development. They also would learn from their actual experience in using the tool, by which they would be able to refine the tool and develop heuristic rules. As a result, they would ultimately need to change their vaccination activities, and even their overall perspective on vaccination policy (i.e. supply-driven versus demand-driven approach).

In the regard that the task of designing vaccination programs using optimization tools involves constant and complex learning processes which change the actions of users of the tool (i.e. health officials), optimization-based vaccination planning could be viewed as “social learning” (Schon, 1971; Friedmann, 1987). This aspect of planning is often contrasted with planning as policy analysis. Policy analysis is a form of the cognitive decision-making process that uses technical tools to explore and evaluate possible courses of action, while social learning is a complex, time-dependent process that involves action, political strategy, theories of reality, and the values that inspire and direct the action (Friedmann, 1987).

As shown in Figure 7.6, in the social learning tradition, decisions are considered as a transitory moment in the course of continuing practices where actors (health officials, in this case) learn both cognitively and experientially from their own practice about all conflicting perspectives on the situation and their desirable changes (Schon, 1971). This figure also illustrates the double-loop learning process in planning (Friedmann, 1987). In vaccination planning, single-loop learning involves a simple change in the vaccination strategy to solve a given public health problem, while double-loop learning requires an adjustment of the norms governing the vaccination process and a change in the government’s cognitive restructuring of reality, values, and beliefs on vaccination. Such changes would affect the ultimate distribution of the costs and benefits of a vaccination program.

Figure 7.6. Planning as social learning



Source: Friedmann (1987)

This social learning process often involves a so-called “change agent” who encourages, guides, and assists actors in the process of changing reality. In optimization-based vaccination planning, the OPLV Consultant can play the role of “change agent”. This agent brings certain kinds of formal knowledge and technology to the ongoing social practice of government health officials who are involved in the vaccination process. As a matter of fact, for more effective implementation of the tool, both change agents and health officials should maintain a close mutual relationship where they learn from each other. The more they learn about the information generated and kept by health officials, the larger the role change agents would have in implementing the optimization tool.

As Forester (1987) pointed out, information is a source of power and misinformation can be a major source of obstacles to planning practice. Planners' actions could be manipulated by misinformation, and even planners themselves may produce misinformation since they work with limited data under time constraints (Forester, 1987). The impact of misinformation on planning practices would likely be even larger in the context of developing countries. Apparently, progressive planning practices based on a mutual learning process among all actors would minimize potential sources of misinformation, and as a result, would maximize the likelihood of successful adoption and implementation of the optimization tool in vaccination planning in developing countries.

## **Chapter 8**

### **Conclusion**

This dissertation research made the first attempt to determine the effect of both travel distance and user fee on the demand for vaccinations in a developing country incorporating stated preference data. It is also the first study to use location models from operations research for determining the required number, locations, and capacities of vaccination outposts. The optimization models applied in this research are simple tools that can be used by ministries of health in developing countries to design mass vaccination campaigns that maximize coverage and are financially self-sufficient.

This dissertation produced five primary findings that contribute to the growth of knowledge in this area of research. First, this research incorporated people's travel distance into the contingent valuation method, which is a classic private demand estimation tool that has been used to estimate demand for vaccinations for different levels of user fee. The previous private demand studies focused on the effect of user fee on demand for vaccination, but paid little attention to the effect of people's travel distance to vaccination site. This research is the first stated-preference private demand study showing that household demands are affected not only by user fee but also by travel distance, based on a case study in China. This implies that respondents considered not only the user fee that they would have to pay but also the burden of travel to the vaccination site, such as travel cost and opportunity cost of travel time, when they answered questions about their demand for vaccinations. This

research implies that the number and location of vaccination sites are equally important as the level of user fee in the design of a vaccination program.

Second, it demonstrated that vaccination brings substantial private benefits as measured by willingness-to-pay (WTP). These private benefits would be even larger if vaccinations are offered near to their residence location since it would save their travel costs and efforts to receive vaccinations. This finding implies that supply-based vaccination planning overlooking demand-side benefits may not serve society well, and having many sites might be the best for society due to the increase in private benefits resulting from travel costs saved.

Third, this research applied existing location models to vaccination program design, showing that the models have roles to play in locating vaccination sites. Furthermore, not only did it apply the existing models, but it also modified the models using the demand function estimated from data collected in a contingent valuation study. This modified location model based on household demands makes the solutions more reliable, and provides more valuable information on vaccination program design. This research illustrates that the existing location models are simple but powerful tools to assist planning decisions on how to locate vaccination sites, even without cost information.

Fourth and most importantly, this research formulated optimization models that take account of both user fee and locations. Using both demand and cost information obtained from the study site, this research formulated optimization models to determine simultaneous solutions for user fee and locations, with a specific objective of a vaccination program. In this dissertation, two kinds of optimization models were developed for the case study in China, such as one for maximizing vaccination coverage and the other for maximizing cases

avoided. These models can be easily reformulated to meet other planning objectives. The level of the user fee was treated endogenously in these models, and its optimal level was solved by the model given revenue-neutrality constraint that vaccination costs must be covered by revenue from user fees. Furthermore, with additional constraint on the required number of outposts, this model would provide more valuable information to be used for vaccination program design. For instance, total private benefits and costs of vaccination could be estimated for different numbers of outposts, which provide information on what is the optimal number of outposts from an economic efficiency perspective. The results from the case study show that the solution from optimization models would not be the best for society, which suggests that optimization tools should be used only as an aid to judgment, not as the definite answer to the problem. This finding also implies that the value of optimization models is not based on automatic solution, but on the use of the model in a simulation mode.

Lastly, this research developed an implementation guide for planning vaccination programs using an optimization-based tool based on the in-depth review of the literature concerning the obstacles to successful adoption and implementation of the tools in actual planning practices. Hopefully the implementation guide for the tool in this dissertation will make the tool more readily usable in vaccination planning processes in developing countries by overcoming many obstacles. In conclusion, all these models and tools developed in my dissertation research can provide important aids to planners' judgment on (1) where to locate outposts and (2) how to set the user fee level in order to meet a specific planning objective. Without this research, planners might not be clear about how to allocate their limited resources effectively.

Four major limitations of this dissertation deserve mention, along with direction of

further research. First, all models developed in this research assume a “hard” boundary of vaccination service within an administrative unit. The assumption that people in neighboring areas cannot receive vaccinations in the target area might be acceptable in China, but it is worthwhile to relax this assumption in further research to see how the results change with a “porous” boundary.

Second, these models considered only one-time vaccination. Yet there are a number of vaccinations including the typhoid vaccine that require booster doses or injections to keep immunized, and thus the target population might change in the follow-up vaccination. To account for such temporal factors, dynamic models would be necessary in further research.

Third, all models in this research aggregated adults and children because there was not a significant difference observed in demand and incidence in the study area. In some areas where demand or disease incidence is quite different according to age group, disaggregated models would be more reliable in general. Finally, if there is any evidence of herd immunity, it could be incorporated into the model in further research as well.



## APPENDIX 1:

### Variables and results of the household CV models in Poulos et al. (2006b)

Table A1.1 Variable definition and descriptive statistics in Poulos et al. (2006b)

Variable Name	Description	Mean	S.D.
<b>Demographic and Socioeconomic</b>			
Respondent's sex	1=if respondent is male; 0=otherwise	0.48	0.50
Respondent's age	Respondent's age (years)	39.7	7.6
Respondent's education	Years of school completed	7.0	3.7
	=1 if respondent completed primary school; 0 otherwise	0.3	0.5
	=1 if respondent completed middle school; 0 otherwise	0.4	0.5
	=1 if respondent completed high school; 0 otherwise	0.2	0.4
	=1 if respondent completed univ. and post-graduate; 0 otherwise	0.1	0.3
Household size	Number of household members (continuous)	4.2	1.2
	Number of members 0-1 years	0.09	0.28
	Number of members 2-5 years	0.19	0.40
	Number of members 6-14 years	0.61	0.64
	Number of members 15-19 years	0.61	0.75
	Number of members 20+ years	2.56	1.02
Income	Annual household income (continuous, USD)	1796	1809
	Natural log of annual household income	9.2	1.0
Rooms	Number of rooms in home	4.5	2.5
Phone	=1 if household has a telephone; 0 otherwise	0.53	0.50
Refrigerator	=1 if household owns a refrigerator; 0 otherwise	0.24	0.43
Television	=1 if household owns a color television; 0 otherwise	0.69	0.46
Motorbike	=1 if household owns a motorbike; 0 otherwise	0.24	0.42
<b>AVERTING AND MITIGATING BEHAVIOR</b>			
Distance to health facility	Distance to nearest health facility in meters	774	993
Health Insurance	=1 if respondent has health insurance; 0 otherwise	0.14	0.35
Wash hands before eating	=1 if Always; =2; =3 if Often if Sometimes; =4 if Never	3.0	0.8
Boil drinking water	=1 if Never; =2 if Sometimes; =3 if Often; =4 if Always	2.1	1.2
<b>RISK</b>			
Increasing risk	=1 typhoid is increasing in neighborhood; 0 otherwise	0.03	0.16
Outbreak	=1 if village had typhoid fever outbreak in last 3 years; 0 otherwise	0.23	0.42
Typhoid Common?	=1 if Never; =2 if Not Very Common; =3 if Common; =4 if Very Common	1.7	0.7
<b>KNOWLEDGE AND EXPERIENCE</b>			
Know typhoid	=1 respondent has heard about typhoid; 0 otherwise	0.75	0.43
Respondent had Vi vaccine	=1 if respondent had the Vi vaccine; 0 otherwise	0.07	0.25
Know someone having typhoid	=1 if respondent knows someone who has had typhoid; 0 otherwise	0.35	0.48
Household members had typhoid	=1 if a household member has ever had typhoid; 0 otherwise	0.11	0.31

Table A1.2 Poisson regression analysis of household demand for Vi vaccines in Poulos et al. (2006b)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Vaccine Price (USD)	-0.088 (0.000)**	-0.088 (0.000)**	-0.089 (0.000)**	-0.089 (0.000)**	-0.088 (0.000)**	-0.088 (0.000)**
Log of Household Income	0.065 (0.025)*	0.048 (0.104)++	0.078 (0.021)*	0.065 (0.055)+	0.087 (0.011)*	0.086 (0.011)*
Home Vaccination Option		0.022 (0.767)	0.020 (0.795)	0.016 (0.838)	0.025 (0.747)	0.025 (0.739)
Lives in Lingchuan County		0.026 (0.728)	0.069 (0.375)	-0.016 (0.847)	-0.033 (0.694)	-0.035 (0.671)
Typhoid WTP question follows cholera WTP question		-0.289 (0.001)**	-0.275 (0.001)**	-0.296 (0.000)**	-0.274 (0.001)**	-0.270 (0.001)**
Male respondent			-0.144 (0.013)*	-0.092 (0.135)++	-0.122 (0.049)*	-0.125 (0.043)*
Age of the respondent			-0.009 (0.028)*	-0.009 (0.024)*	-0.006 (0.203)	-0.006 (0.199)
Distance from home to the nearest health facility				0.000 (0.064)+	0.000 (0.110)++	0.000 (0.107)++
Village had an outbreak				0.126 (0.076)+	0.140 (0.047)*	0.143 (0.041)*
Respondent knows someone who had typhoid				0.001 (0.986)	-0.016 (0.812)	-0.017 (0.804)
Boils drinking water				-0.030 (0.293)	-0.037 (0.196)	-0.036 (0.186)
Washes hands before eating				0.100 (0.011)*	0.080 (0.042)*	0.080 (0.037)*
Respondent can read a newspaper					0.180 (0.037)*	0.177 (0.039)*
Number of children between 0 and 1 years old					0.146 (0.209)	0.147 (0.203)
Number of children between 2 and 5 years old					0.193 (0.032)*	0.192 (0.033)*
Number of children between 5 and 14					0.336 (0.000)**	0.338 (0.000)**
Number of young adults between 15 and 19					0.284 (0.000)**	0.285 (0.000)**
Number of adults above 20 years old					0.122 (0.000)**	0.120 (0.000)**
Constant	0.516 (0.057)+	0.714 (0.011)*	0.297 (0.375)	0.005 (0.990)	-0.492 (0.228)	-0.436 (0.242)
Has health insurance				-0.002 (0.987)	-0.011 (0.909)	
Respondent believes typhoid risk is high				0.000 (0.995)	-0.025 (0.712)	
Respondent believes child's typhoid risk is high				0.039 (0.540)	0.044 (0.484)	
Number of household members with poor or very poor health				-0.040 (0.294)	-0.007 (0.860)	
Respondent Completed Middle School			0.064 (0.345)	0.036 (0.604)		
Respondent Completed High School			-0.020 (0.814)	-0.048 (0.582)		
Respondent Completed University or postgraduate school			0.053 (0.679)	-0.050 (0.689)		
Number of household members			0.121 (0.000)**	0.141 (0.000)**		
Urban Area			-0.191 (0.135)++			

p values in parentheses ++ significant at 15%; + significant at 10%; \* significant at 5%; \*\* significant at 1%

## APPENDIX 2:

### Mathematical derivation of private benefits measured by household WTP

When price is zero, the respondent's total value in preventing typhoid fever for the entire family in household  $i$  ( $WTP_i$ ) is the area under the inverse household demand curve from the Poisson regression function. In general, this area can be calculated by integrating the Poisson demand function,  $\lambda(\bullet)$ , over prices from zero to infinity<sup>36</sup>:

$$WTP_i = \int_0^{\infty} \lambda(p_i, d_i, I_i, H_i) dp \quad \text{eq. A2.1}$$

$$= \int_0^{\infty} \exp(\alpha + \beta_p \cdot p_i + \beta_d \cdot d_i + \beta_I \cdot \ln(I_i) + \beta_H \cdot H_i) dp \quad \text{eq. A2.2}$$

Thus, if price were zero, the household WTP for the entire family is:

$$WTP_i = -\frac{1}{\beta_p} [\exp(\alpha + \beta_d \cdot d_i + \beta_I \cdot \ln(I_i) + \beta_H \cdot H_i)] \quad \text{eq. A2.3}$$

However, when non-zero price  $p^*$  is charged, the household WTP for the entire family is the sum of the expenditure on the vaccine and the remaining consumer's surplus, which is calculated as follows:

---

<sup>36</sup> Truncation of the demand function by household size (Cropper et al., 2004) is not considered in my model because no over-prediction of the demand was found in any observation in our data.

$$WTP_i = p^* \cdot \exp(\alpha + \beta_p \cdot p^* + \beta_d \cdot d_i + \beta_I \cdot \ln(I_i) + \beta_H \cdot H_i) + \int_{p^*}^{\infty} \exp(\alpha + \beta_p \cdot p^* + \beta_d \cdot d_i + \beta_I \cdot \ln(I_i) + \beta_H \cdot H_i) dp \quad \text{eq. A2.4}$$

$$= p^* \cdot \exp(\alpha + \beta_p \cdot p^* + \beta_d \cdot d_i + \beta_I \cdot \ln(I_i) + \beta_H \cdot H_i) - \frac{1}{\beta_p} [\exp(\alpha + \beta_p \cdot p^* + \beta_d \cdot d_i + \beta_I \cdot \ln(I_i) + \beta_H \cdot H_i)] \quad \text{eq. A2.5}$$

Eq. A2.5 indicates that the household WTP for the entire family is a function of all four explanatory variables, such as price, travel distance, natural log of household income, and household size.

Suppose the choke price is less than infinity  $c (< \infty)$ , the household WTP for the entire family in household  $i$  when price were  $p^*$  is:

$$WTP_i = p^* \cdot \exp(\alpha + \beta_p \cdot p^* + \beta_d \cdot d_i + \beta_I \cdot \ln(I_i) + \beta_H \cdot H_i) + \int_{p^*}^c \exp(\alpha + \beta_p \cdot p^* + \beta_d \cdot d_i + \beta_I \cdot \ln(I_i) + \beta_H \cdot H_i) dp \quad \text{eq. A2.6}$$

$$= p^* \cdot \exp(\alpha + \beta_p \cdot p^* + \beta_d \cdot d_i + \beta_I \cdot \ln(I_i) + \beta_H \cdot H_i) + \frac{1}{\beta_p} [\exp(\alpha + \beta_p \cdot c + \beta_d \cdot d_i + \beta_I \cdot \ln(I_i) + \beta_H \cdot H_i)] - \frac{1}{\beta_p} [\exp(\alpha + \beta_p \cdot p^* + \beta_d \cdot d_i + \beta_I \cdot \ln(I_i) + \beta_H \cdot H_i)] \quad \text{eq. A2.7}$$

If price were zero, the household WTP for the entire family is:

$$\begin{aligned} &= \frac{1}{\beta_p} [\exp(\alpha + \beta_p \cdot c + \beta_d \cdot d_i + \beta_I \cdot \ln(I_i) + \beta_H \cdot H_i)] \\ &\quad - \frac{1}{\beta_p} [\exp(\alpha + \beta_d \cdot d_i + \beta_I \cdot \ln(I_i) + \beta_H \cdot H_i)] \end{aligned} \quad \text{eq. A2.8}$$

The first term of eq. A2.8 makes modifications on the right tail of the demand function. If the choke price  $c$  is close to infinity, the term is close to be zero and thus eq. A2.8 equals A2.3. However, if  $c$  becomes smaller, the household WTP will be substantially modified.

## APPENDIX 3:

### Description of the BME method used to predict income for unsampled villages

The Bayesian Maximum Entropy (BME) method was used to predict average household income in unsampled villages based on spatial dependency pattern of the existing data from sampled villages. Before presenting the results, the spatial interpolation technique is briefly described.

#### A3.1. Bayesian Maximum Entropy (BME): Brief description

A high degree of spatial dependence in household incomes in sampled areas may justify use of spatial interpolation procedures to predict those in unsampled areas. Unlike *ad hoc* and deterministic methods of interpolation or smoothing such as inverse distance methods, triangulation (Cressie, 1993), and simple moving average (Ali et al., 2002), the geostatistical tradition involves spatial interpolation using spatial “weights” based on the structure of spatial dependence determined in an initial exploratory data analysis.

The data to be used for spatial interpolation are often scarce and thus indirect measurement or uncertain observation is frequently used to overcome this lack of information, providing generally fewer measurements of the target variables. Researchers have attempted to simply combine all these available data sources in order to satisfy the highest possible accuracy requirement. The BME approach appears to be a potential candidate for achieving this task. It is especially designed for simultaneously managing data of various natures and quality. In other words, the BME method of spatial analysis and

mapping provides definite rules for incorporating prior information, “hard” (exact observation) and “soft” (uncertain or probabilistic) data into the mapping process. It relies on a two-step procedure that first involves an objective way of obtaining a *prior* distribution in accordance with the general knowledge at hand, and then a Bayesian conditionalization step that updates this *prior* probability distribution function (pdf) with respect to the data collected in the target area.

The BME method adopts a stochastic representation of the data distribution across space in terms of the random field model,  $X(\mathbf{s})$ , where the spatial location vector  $\mathbf{s}$  defines a point in the 2-dimensional spatial domain<sup>37</sup>. The uncertainty of the distribution appears as an ensemble of realizations  $\{\chi\}$  of the possible  $X(\mathbf{s})$  values, and the spatial random field assigns a probability depending on  $\mathbf{s}$  to each of these realizations (Serre et al., 2003). The mean function  $m_x(\mathbf{s})$  of the spatial random field characterizes trends and systematic structures in space, and the covariance function  $c_x(\mathbf{s}, \mathbf{s}')$  expresses spatial correlations and dependencies (Choi et al., 2003);

$$m_x(\mathbf{s}) = \overline{X(\mathbf{s})}, \quad c_x(\mathbf{s}, \mathbf{s}') = \overline{[X(\mathbf{s}) - \overline{X(\mathbf{s})}][X(\mathbf{s}') - \overline{X(\mathbf{s}')}]}$$
 eq. A3.1

where the over-bar denotes stochastic expectation. The realization vector  $\chi_{data} = (\chi_1, \dots, \chi_m)$  denotes the data values available at points  $\mathbf{s}_i$  ( $i = 1, \dots, m$ ).

The BME spatial estimation is generally concerned with the prediction of the values of the relevant fields at unmeasured (unsampled) locations  $\mathbf{s}_k$  ( $k \neq i$ ) given all knowledge bases

---

<sup>37</sup> The BME method can account for time dimension as well as spatial dimension, but time factor was not considered in the income interpolation in this research.

available. Socioeconomic data, such as household income, are often collected over sampling regions or administrative areas of fixed size and location and thus the observed values are available at arbitrary discrete locations instead of a continuous space domain. The BME method resolves this issue by generating interval “soft” data from uncertain measurements and secondary information, which are then used to construct spatial maps of income estimates for the entire target area. These maps provide a continuous posterior pdf ( $f_{\kappa}$ ) in space of the field values obtained at the measurement scale by integrating general knowledge and site-specific knowledge. This posterior pdf offers a complete description of the field of relevant data (here, household income) at the prediction points such as predictors (mean, median or mode of  $f_{\kappa}$ ) or prediction error variance (variance of the density  $f_{\kappa}$ ) (Choi et al., 2003).

Kriging, one of the traditional spatial mapping techniques, is a special case of the BME approach, under restrictive assumptions regarding the prior information and the data available. The BME method combines “soft” data with “hard” data along with prior information to compensate for the limited amount of measurements available, while kriging considers only “hard” data (Christakos and Li, 1998). In that aspect, the BME method is an extension of kriging, which allows the spatial interpolation to consider additional knowledge bases such as “soft” data. Therefore, in the limited case when a general knowledge consisting of only the mean and covariance and site-specific knowledge consisting only of “hard” data are considered, then the BME method reduces to kriging.



### A3.2. Estimating average household income for all villages in Daxu Township

In my income estimation presented here, the income data were used only as “hard”, and therefore the BME method reduces to kriging. Estimating average household income for all unsampled villages by spatial interpolation using the BME technique (same as kriging, here) would be feasible only if there is significant evidence of any spatial dependence pattern among income data from the DOMI surveys at 30 villages in Daxu Township. According to the marker plot in Figure A3.1, it appears that there exists a significant spatial clustering in average household incomes aggregated by village. Covariance plot, shown in Figure A3.2, shows a clear evidence of spatial clustering of income data.

Figure A3.1. Marker plot of average household income for sampled villages

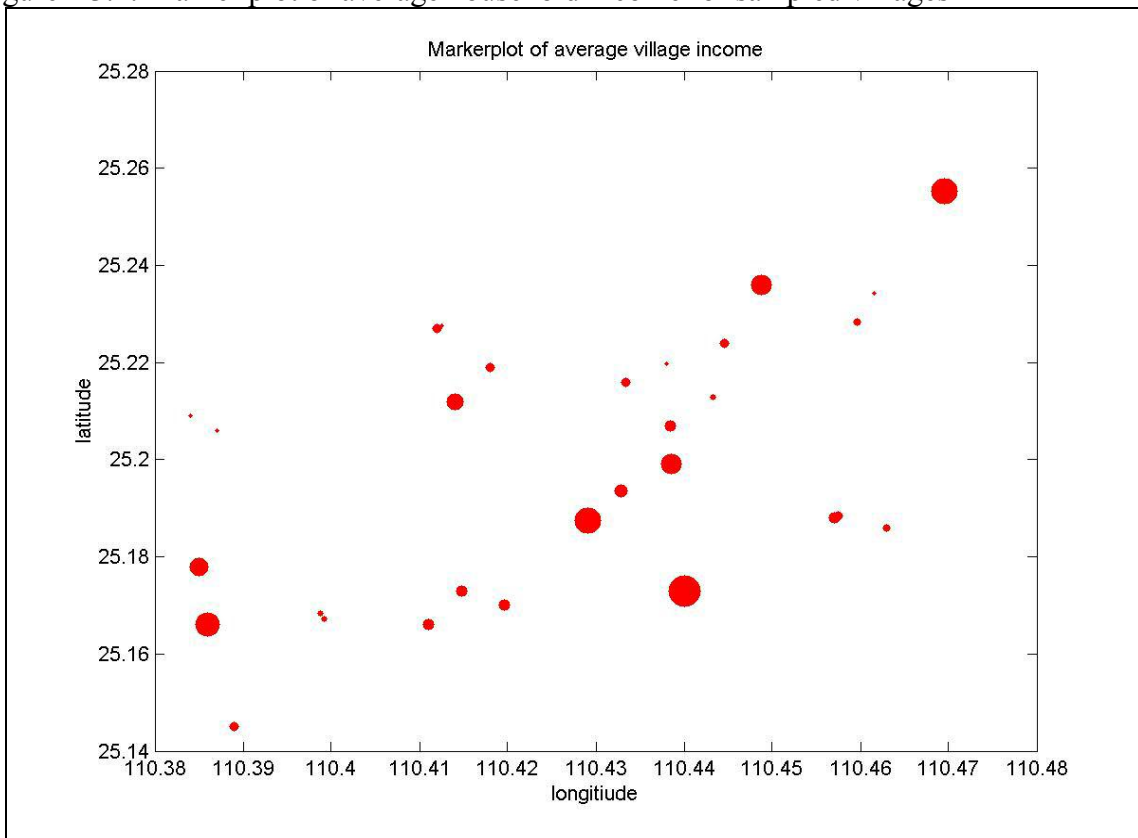
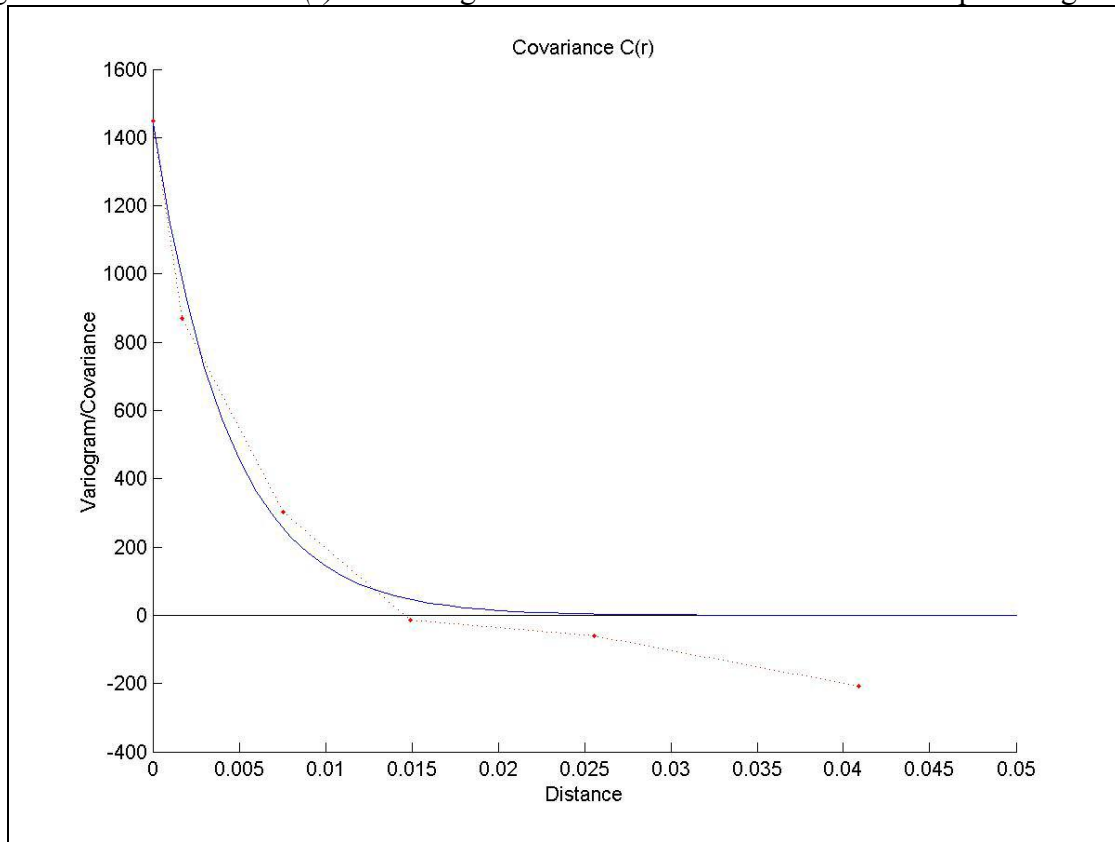


Figure A3.2. Covariance  $c(r)$  for average household income as a function of spatial lag  $r$



Using the findings from covariance analysis, the theoretical covariance model was constructed to account for village-level factors that make village incomes spatially correlated as follows:

$$c(r) = c \exp(-3 r/a_r) \quad \text{eq. A3.2}$$

where  $c=1448$ ,  $a_r=0.013$  degrees (approximately 1.5 km). By applying the parameters of the covariance model to the entire surface of the township, the BME map of village income and its error variance map were created as follows:

Figure A3.3. BME map of the predicted household income in Daxu Township

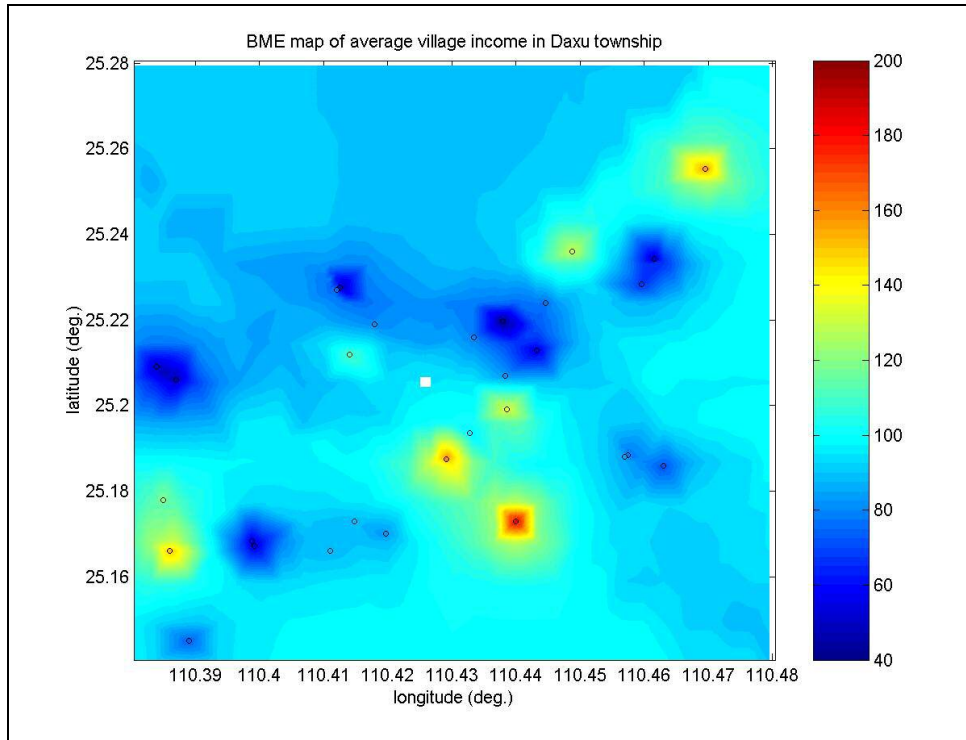
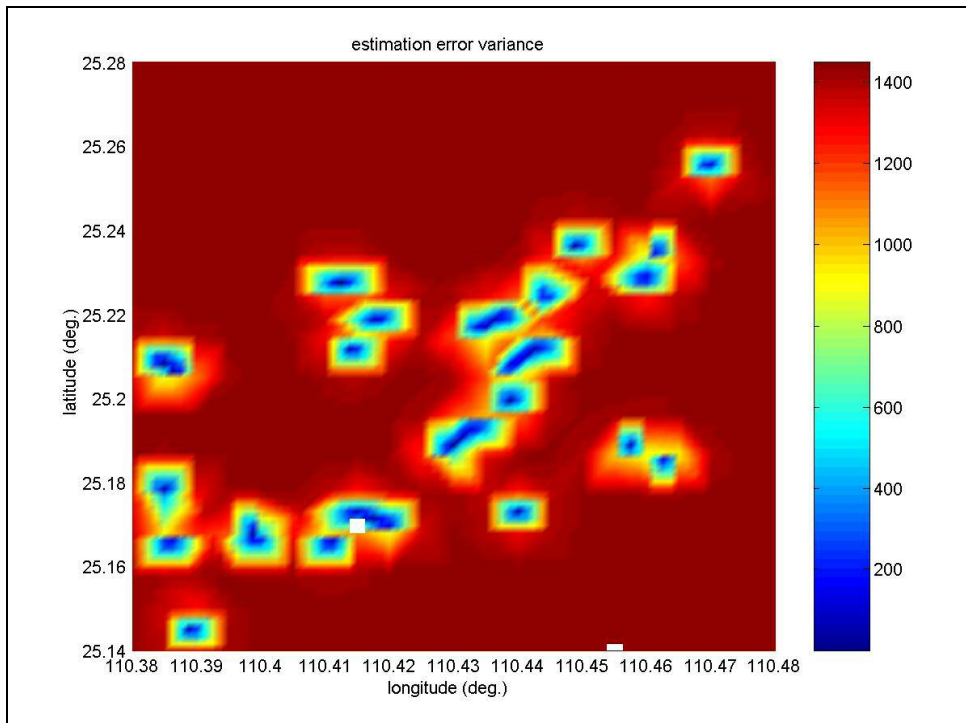
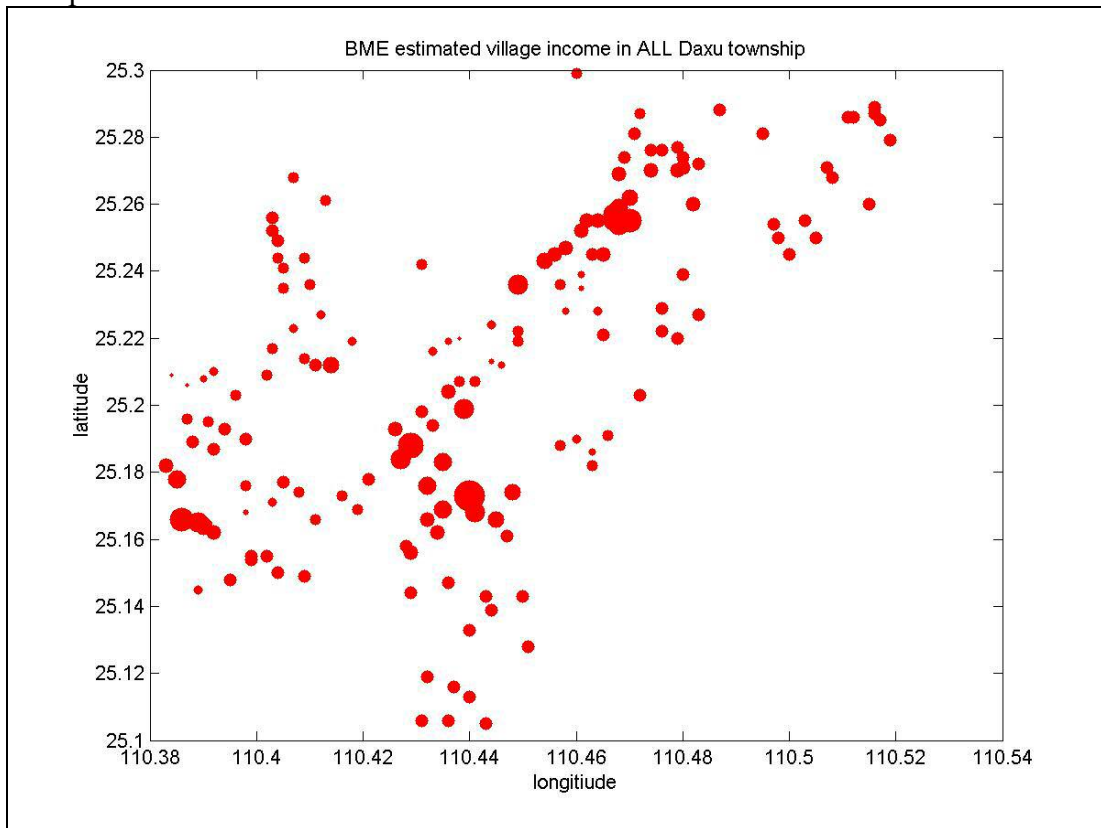


Figure A3.4. BME map of error variance associated with the predicted household income



Using the BME surface of the predicted household income in Figure A3.3, the BME estimates of average household income for all villages in Daxu Township were obtained as plotted in Figure A3.5, and were used as input data for the demand function to estimate the number of vaccinations at all villages and cells in the township.

Figure A3.5. BME estimates of average household income in all 141 villages in Daxu Township

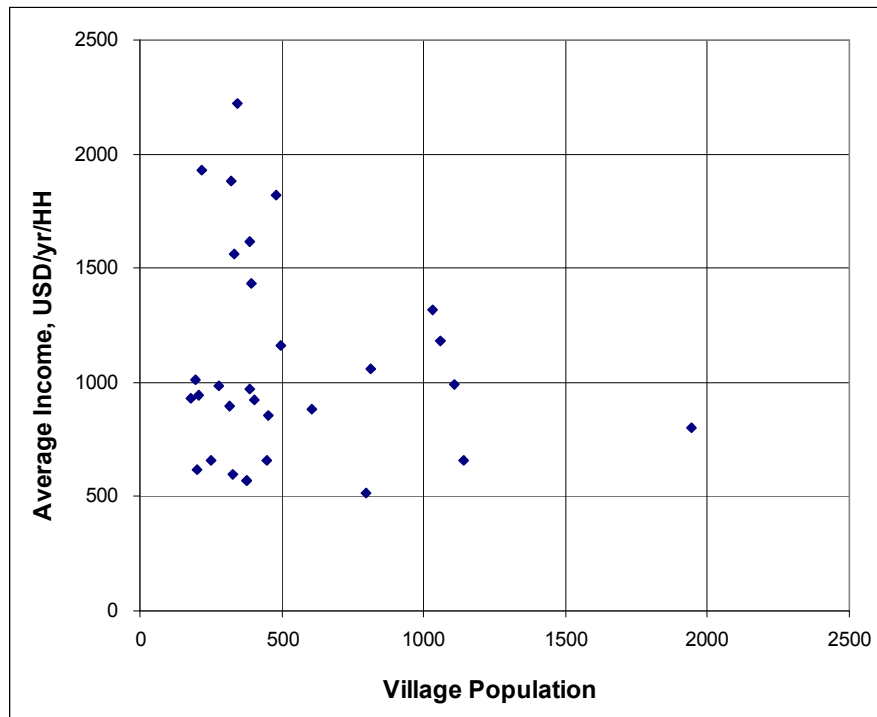


### A3.3. Validating the predicted income data

As a matter of fact, the method used here to predict the household income for unsampled villages is subject to a few limitations. First, although the sampled villages are well scattered throughout the township (as shown in Figure A3.1), the data available only at

30 sampled villages might not be sufficient for the spatial interpolation to all 141 villages in Daxu Township. Such lack of data may increase the uncertainty level of the predicted incomes, especially in the border areas (see Figure A3.3). However, I have not found any better way to obtain the income data for all villages given the data available. Second, the estimates from the BME-based spatial interpolation without taking the size of village population into account might be biased if any association exists between average household income and village population for the sampled villages. Fortunately, no association was found between average income and village population, as shown in Figure A3.6. The regression coefficient is not statistically significant when average income was regressed against village population.

Figure A3.6. Scatter plot of average household income in sampled villages vs. village population



Another limitation of this income prediction approach would be that the income data were considered as “hard” assuming no uncertainty, but there are various sources of uncertainty in the data. The BME framework would allow the interpolation to account for uncertainty in the data by considering it as “soft”. In the future, the BME approach considering the data as “soft” would be useful to account for sampling error in the data, as well as for the change of scale between individual household income and village aggregated household income.

One way of validating the use of income data based on the BME prediction would be to compare the distribution of observed income with that of predicted income, which is discussed in the main text (see Figure 4.4). Another way of validating the results of the models using the predicted income data from the BME method would be to conduct sensitivity analyses on the parameter of income variable. In Chapter 6, it is confirmed that the final results are not sensitive to the income parameter, which indicates that the potential bias or uncertainty in the predicted household income data at unsampled villages are minimal.

## REFERENCES

- Abdu Z, Mohammed Z, Bashier I, Eriksson B, The impact of user fee exemption on service utilization and treatment seeking behaviour: the case of malaria in Sudan, *International Journal of Health Planning and Management* 2004, 19(S1):S95-S106.
- Abernathy WJ and Hershey JC, A spatial-allocation model for regional health-services planning, *Operations Research* 1972, 19:629-642.
- Ackoff RL, Unsuccessful case studies and why, *Operations Research* 1960, 8: 259.
- Ackoff RL, National development planning revisited, *Operations Research* 1977, 25:207-218.
- Acosta CJ, Hong-Hui Y, Ning W, Qion G, Qun D, Xiaolei M, Baode Z, Liu W, Danovaro-Holliday CM, Ochiai RL, Wang XY, Kim DR, Zhi-Yi X, Bai-Qing D, Galindo CM, Clemens JD, Efficacy of a locally produced, Chinese Vi polysaccharide typhoid fever vaccine during six years of follow-up, *Vaccine* 2005; 23(48-49): 5618-23.
- Acton JP, Nonmonetary factors in the demand for medical services: Some empirical evidence, *The Journal of Political Economy* 1975, 83(3):595-614.
- Adamowicz W, Boxall P, Williams M, Louviere J, Stated preference approaches for measuring passive use values: Choice experiments versus contingent valuation, *American Journal of Agricultural Economics* 1998, 80: 64-75.
- Addis Ababa Consensus on Principles on Cost Sharing in Education and Health 1997, United Nations Economic Commission for Africa (UNECA), UNICEF, and World Bank. Brochure printed by UNICEF, June 1998, New York.
- Ali M, Emch M, Donnay JP, Spatial filtering using a raster geographic information system: methods for scaling health and environmental data, *Health and Place* 2002, 8(2):85-92.
- Anselin L, Spatial externalities, spatial multipliers, and spatial econometrics, *International Regional Science Review* 2003, 26(2):153-166.

- Anson O and Shifang S, *Health Care in Rural China: Lessons from HeBei Province*, Ashgate Publishing, Ltd., 2005.
- Bahl R, Sinha A, Poulos C, Whittington D, Sazawal S, Kumar, Costs of illness due to typhoid fever in Indian urban slum community: implications for vaccination policy, *Journal of Health, Population and Nutrition* 2004, 22:304-10.
- Bates AS, Fitzgerald JF, Dittus RS, Wolinsky FD, Risk factors for under-immunization in poor urban infants, *Journal of American Medical Association* 1994, 272:1105–10.
- Birkin M and Clarke M, The generation of individual and household incomes at the small area level using synthesis, *Regional Studies* 1989, 23(6):535-548.
- Blas E, Limbambala M, User-payment, decentralization and health service utilization in Zambia. *Health Policy and Planning* 2001, 16(Suppl. 2): 19–28.
- Booth D, Milimo J, Bond G, *Coping with Cost Recovery: A Study of the Social Impact of and Response to Cost Recovery in Basic Services (Health and Education) in Poor Communities in Zambia*, Report to SIDA, commissioned through the Development Studies Unit, Department of Social Anthropology, Stockholm University, 1995.
- Bos A., *The role of engineers in the demand responsive approach: A case study from South Africa*, MSc, Loughborough University, Leicestershire, 2001.
- Boxall PC, Adamowicz WL, Swait J, Williams M, Louviere J, A comparison of stated preference methods for environmental valuation, *Ecological Economics* 1996,18: 243-253.
- Brailsford S, Overcoming the barriers to implementation of operations research simulation models in healthcare, *Clinical and Investigative Medicine* 2005, 28(6):312-315.
- Brenzel L, Claquin P. Immunization programs and their costs, *Social Science and Medicine* 1994, 39:527-536.
- Brill Jr. ED, The use of optimization models in public-sector planning, *Management Science* 1979, 25(5):413-422.



- Cai X, McKinney DC, Lasdon LS, A framework for sustainability analysis in water resources management and application to the Syr Darya Basin, *Water Resources Research* 2002, 38(6):1085-1098.
- Canh DG, Whittington D, Thoa LTK, Utomo N, Hoa NT, Poulos C, Thuy DTD, Kim D, Nyamete A, and Acosta C, Household Demand for Typhoid Fever Vaccines in Hue, Vietnam, *Health Policy and Planning* 2006, 21(3):241-255.
- Carter RD, Hamilton JG, Willams PJ, Corporate planning in developing countries, *Long Range Planning* 1973, 6:79-85.
- Chen R, and Handler GY, The conditional  $P$ -center problem in the plane, *Naval Research Logistics* 1993, 40:117-127.
- Chena X, Stanton B, Wang X, Nyamette A, Pach A, Kaljee L, Pack R, Seidlein L, Clemens J, Gonge Y, Mao R, Differences in perception of dysentery and enteric fever and willingness to receive vaccines among rural residents in China, *Vaccine* 2006, 24(5):561-571.
- Choi K, Serre ML, Christakos G, Efficient mapping of California mortality fields at different spatial scales, *Journal of Exposure Analysis and Environmental Epidemiology* 2003, 13(2):120-133.
- Christakos G and Li X, Bayesian maximum entropy analysis and mapping: A farewell to kriging estimators?, *Mathematical Geology* 1998, 30(4):435-462.
- Clarke PM, Cost-benefit analysis and mammographic screening: a travel cost approach, *Journal of Health Economics* 1998, 17:767-787.
- Clarke PM, Testing the convergent validity of the contingent valuation and travel cost methods in valuing the benefits of health care, *Health Economics* 2002, 11:117-127.
- Clayson JE, How relevant is operational research to development? The case of Kenyan industry, *Journal of Operational Research Society* 1980, 31:293-299.

- Cohon JL and Marks DH, A review and evaluation of multiobjective programming techniques, *Water Resources Research* 1975, 11(2):208-220.
- Collins C, Green A, Decentralisation and primary health care: some negative implications in developing countries, *International Journal of Health Services* 1994, 24:459-475.
- Cook J, Whittington D, Cahn DG, Johnson FR, and Nyamete A, Reliability of stated preferences for cholera and typhoid vaccines with time to think in Hue, Vietnam, *Economic Inquiry* 2007, 45(1):100-114.
- Creese AL, Cost-effectiveness of alternative strategies for poliomyelitis immunization in Brazil, *Review of Infectious Diseases* 1984, 6(Suppl. 2):S404-S407.
- Creese AL, User charges for health care: a review of recent experience, *Health Policy and Planning* 1991, 6(4):309-319.
- Cressie NA, *Statistics for Spatial Data*, New York: John Wiley & Sons, 1993.
- Cropper ML, Haile M, Lampietti J, Poulos C, Whittington D, The demand for a malaria vaccine: evidence from Ethiopia, *Journal of Development Economics* 2004, 75: 303-318.
- Crump JA, Luby SP, Mintz ED, The global burden of typhoid fever, *Bulletin of the World Health Organization* 2004, 82(5):346-353.
- Davis J and Whittington D, "Participatory" research for development projects: A comparison of the community meeting and household survey techniques, *Economic Development and Cultural Change* 1998, 47(1):73-94.
- DeRoeck D, Clemens JD, Nyamete A, Mahoney RT, Policymakers' views regarding the introduction of new-generation vaccines against typhoid fever, shigellosis and cholera in Asia, *Vaccine* 2005; 23(21): 2762-74.
- Drezner Z, *Facility Location: A Survey of Applications and Methods*, New York: Springer, 1995.

- Drezner Z, A note on the location of medical facilities. *Journal of Regional Science* 1990, 30: 281-286.
- Durrheim DN, Speare R, Harries AD, Research that influences policy and practice – characteristics of operational research to improve malaria control in Mpumalanga Province, South Africa, *Malaria Journal* 2002, 1:9.
- Farhan B, and Murry AT, Distance decay and coverage in facility location planning, *Annals of Regional Science* 2006, 40:279-295.
- Fauci AS, Infectious diseases: considerations for the 21<sup>st</sup> century, *Clinical Infectious Diseases* 2001; 32: 675-685.
- Field KS, and Briggs DJ, Socioeconomic and locational determinants of accessibility and utilization of primary health care, *Health and Social Care in the Community* 2001, 9(5):294-308.
- Fielding JE, Cumberland WG, Pettitt L, Immunization status of children of employees in a large corporation, *Journal of American Medical Association* 1994, 271: 525–30.
- Fisher HB and Rushton G, Spatial efficiency of service locations and the regional development process, *Papers in Regional Science Association* 1979, 42:83-97.
- Flowerdew R, Green M, Kehris E, Using areal interpolation methods in geographic information systems, *Papers in Regional Science* 1991, 70(3):303-315.
- Fone D, Hollinghurst S, Temple M, Round A, Lester N, Weightman A, Roberts K, Coyle E, Bevan G, and Palmer S, Systematic review of the use and value of computer simulation modeling in population health and health care delivery, *Journal of Public Health Medicine* 2003, 25(4):325-335.
- Forester J, Planning in the face of power, *Journal of the American Planning Association* 1982, 49:67-80
- Foster V and Mourato S, Elicitation format and sensitivity to scope, *Environmental and Resource Economics* 2003, 24: 141-160.

- Friedmann J, *Planning in the Public Domain: From Knowledge to Action*, Princeton: Princeton University Press, 1987.
- Garner P, Smith H, Kale R, Dickson R, Dans T, Salinas R, Implementing research findings in developing countries, In: Hanes A, Donald A, (ed.) *Getting research findings into practice*, 2<sup>nd</sup> ed, London: BMJ Publishing Group, 2001.
- Global Alliance for Vaccines and Information, Annual deaths in 2002 from vaccine-preventable diseases WHO Estimates, January 2005, *GAVI Background Materials*, found at:  
[http://www.vaccinealliance.org/Media\\_Center/Background\\_Materials/press\\_disease.php](http://www.vaccinealliance.org/Media_Center/Background_Materials/press_disease.php)
- Gore P, Madhavan S, Curry D, McClung G, Castiglia M, Rosenbluth SA, Predictors of childhood immunization completion in a rural population. *Social Science and Medicine* 1999, 48:1011–27.
- Gusein-Zade SM, Comments on A note on the location of medical facilities, by Z. Drezner, *Journal of Regional Science* 1992, 32:229-231.
- Gwatkin DR and Deveshwar-Bahl G, Immunization coverage inequalities: An overview of socio-economic and gender differentials in developing countries, *unpublished draft*, 2001.
- Hall J, Kenny P, King M, Louviere J, Viney R, and Yeoh A, Using stated preference discrete choice modeling to evaluate the introduction of varicella vaccination, *Health Economics* 2002, 11:457-465.
- Harewood SI, Emergency ambulance deployment in Barbados: A multi-objective approach, *Journal of the Operational Research Society* 2002, 53:185-192.
- Harper PR and Pitt MA, On the challenge of healthcare modeling and a proposed project life cycle for successful implementation, *Journal of the Operational Research Society* 2004, 55:657-661.
- Hassam B, Akhtar R, Askew ID, Applying operations research to health planning: locating health centers in Zambia, *Health Policy and Planning* 1986, 1(4):326-334.

- Hessel L, Debois H, Fletcher M, Dumas R, Experience with *Salmonella typhi* Vi capsular polysaccharide vaccine, *European Journal of Clinical Microbiology Infectious Disease* 1999, 18:609-20.
- Hopkins OS, *Planning rural water supply systems in developing countries: The case of Rwanda*, PhD dissertation, University of North Carolina at Chapel Hill, 2004.
- Hopkins OS, Lauria DT, Kolb A, Demand-based planning of rural water systems in developing countries, *Journal of Water Resources Planning and Management* 2004, 130(1):44-52.
- Houtrouw SM, Carlson KL, The relationship between maternal characteristics, maternal vulnerability beliefs, and immunization compliance, *Issues on Comprehensive Pediatrics and Nursing* 1993, 16:41–50.
- Huysmans JH, *The Implementation of Operations Research; An Approach to the Joint Consideration of Social and Technical Aspects*, Wiley-Interscience, New York, 1970.
- International Vaccine Institute (IVI), Policy analysis regarding DOMI-targeted disease and vaccines: China, *Unpublished Draft*, 2001.
- International Vaccine Institute (IVI), Typhoid fever, May 2007, found at: [http://www.ivi.org/program/tr\\_domi\\_typhoid.html](http://www.ivi.org/program/tr_domi_typhoid.html)
- Innvaer S, Vist G, Trommald M, Oxman A., Health policy-makers' perceptions of their use of evidence: a systematic review, *Journal of Health Services Research and Policy* 2002, 7:239-244.
- Ivanoff B, Levine MM, and Lambert PH, Vaccination against typhoid fever: present status, *Bulletin of World Health Organization* 1994, 72:957-71.
- Jacobson SH, Sewell EC, Deuson R, Weniger BG, An integer programming model for vaccine procurement and delivery for childhood immunization: a pilot study, *Health Care Management Science* 1999, 2(1):1-9.

- Jeuland M, Lucas M, Clemens J, and Whittington D, Estimating the private benefits of vaccination against cholera in Beira, Mozambique: a travel cost approach, *Unpublished draft*, 2007.
- Jia H, Ordonez F, and Dessouky M, *A modelling framework for facility location of medical services for large-scale emergencies*, CREATE Report, University of Southern California, April 2005.
- Jing F, Health sector reform and reproductive health services in poor rural China, *Health Policy and Planning* 2004, 19(Suppl.1): 40-49.
- Johnson RM and Orme BK, *How Many Questions Should You Ask In Choice-Based Conjoint Studies?*, Sawtooth Software, Inc., ART Forum, Beaver Creek, 1996.
- Johnson FR, Mathews KE, and Bingham MF, Evaluating welfare-theoretic consistency in multiple-response, stated-preference surveys, TER Technical Working Paper No. T-0003. Durham, NC, Triangle Economic Research, 2000.
- Kemball-Cook D and Wright DJ, The search for appropriate O.R.: A review of operational research in developing countries, *The Journal of the Operational Research Society* 1981, 32(11):1021-1037.
- Kennedy P, *A Guide to Econometrics* (3<sup>rd</sup> ed.), MIT Press: Boston, 1992.
- Khan MM, Khan SH, Walker D, Fox-Rushby J, Cutts F, Akramuzzaman SM, Cost of delivering child immunization services in urban Bangladesh: A study based on facility-level surveys, *Journal of Health, Population and Nutrition* 2004, 22(4):404-412.
- Khan MM, Ali D, Ferdousy Z, and Al-Mamun A, A cost-minimization approach to planning the geographical distribution of health facilities, *Health Policy and Planning* 2001, 16(3):264-272.
- Kilmartin MR, Woodward DR, Leigh Blizzard C, Turner K, Immunisation of babies: The mothers' perspective. *Australian Family Physician* 1998, 27(Suppl 1):S11-4.

- Kim D, Canh DG, Poulos C, Thoa LTK, Cook J, Hoa NT, Nyamete A, Thuy DTD, Deen J, Son ND, Clemens J, Thiem VD, Anh DD, and Whittington D, Private demand for cholera vaccines in Hue, Vietnam. *Value in Health*, forthcoming.
- Lauria DT *et al.*, Use of the Vi polysaccharide vaccine to prevent typhoid: The case of Vietnam, *Unpublished draft*, 2005.
- Layard R and Glaister S, *Cost Benefit Analysis*, 2<sup>nd</sup> ed., Cambridge; New York: Cambridge University Press, 1994.
- Lee SM and Olson D, The challenge of operations research in the developing country, *Journal of Technology Transfer* 1980, 4(2):37-45.
- Lin FC, Vo AH, Phan VB, Nguyen TT, Bryla D, Tran CT, Ha BK, Dang DT, Robbins JB, The epidemiology of typhoid fever in the Dong Thap Province, Mekong Delta region of Vietnam, *American Journal of Tropical Medicine and Hygiene* 2000, 62(5): 644–8.
- Linkins RW, Mansour E, Wassif O, Hassan MH, and Patriarca PA, Evaluation of house-to-house versus fixed-site oral poliovirus vaccine delivery strategies in a mass immunization campaign in Egypt, *Bulletin of the World Health Organization* 1995, 73(5):589-594.
- Logan BI, A micro-level approach to rural development planning: the case of piped water in Sierra Leone, *Applied Geography* 1987, 7: 29-40.
- Longley PA and Tobon C, Spatial dependence and heterogeneity in patterns of hardship: An intra-urban analysis, *Annals of the Association of American Geographers* 2004, 94(3):503-519.
- McCarthy SJ, Potential applications of OR in developing countries – A generalization from Botswana, *Journal of Operational Research Society* 1978, 29:167-170.
- McIntosh E and Ryan M, Using discrete choice experiments to derive welfare estimates for the provision of elective surgery: Implications of discontinuous preferences, *Journal of Economic Psychology* 2002, 23:367-382.

- McLafferty S, and Broe D, Patient outcomes and regional planning of coronary care services: a location-allocation approach, *Social Science and Medicine* 1990, 30:297-304.
- McPake B, Hanson K, and Mills A, Community financing of health care in Africa: An evaluation of the Bamako Initiative. *Social Science & Medicine* 1993, 36(11): 1,383–1,395.
- Mills E, Montori VM, Ross CP, Shea B, Wilson K, and Guyatt GH, Systematically reviewing qualitative studies complements survey design: An exploratory study of barriers to pediatric immunization, *Journal of Clinical Epidemiology* 2005, 58:1101-1108.
- Milteer RM, Jonna S, Parental reasons for delayed immunizations in children hospitalized in a Washington, DC, public hospital. *Journal of National Medical Association* 1996, 88:433–6.
- Moller-Jensen L and Kofie RY, Exploiting available data sources: location/allocation modeling for health service planning in rural Ghana, *Danish Journal of Geography* 2001, 101:145-153.
- Muller I, Smith T, Mellor S, Rare L, and Genton B, The effect of distance from home on attendance at a small rural health center in Papua New Guinea, *International Journal of Epidemiology* 1998, 27:878-884.
- Noorali R, Luby S, and Rahbar MH, Does use of a government service depend on distance from the health facility?, *Health Policy and Planning* 1999, 14(2):191-197.
- Nyonator F and Kutzin J, Health for some? The effects of user fees in the Volta Region of Ghana, *Health Policy and Planning* 1999, 14(4):329-341.
- Ochiai RL, Wang X., Seidlein LV, Yang J., Bhutta ZA, Bhattacharya SK, Agtini M, Deen JL, Wain J, Kim D, Ali M, Acosta CJ, Jodar L, and Clemens JD, Salmonella paratyphi A rates, Asia. *Emerging Infection Diseases* 2005, 11(11):1764-6.
- Oppong JR, and Hodgson MJ, Spatial accessibility to health care facilities in Suhum District, Ghana. *The Professional Geographer* 1994, 46:199-209.



- Parker BR and Srinivasan V, A consumer preference approach to the planning of rural primary health care facilities, *Operations Research* 1976, 24:991-1029.
- Parry CM, Hien TT, Dougan G, White NJ, Farrar JJ, Typhoid fever, *New England Journal of Medicine* 2002, 347(22):1770-1782.
- Phonboon K, Shepard DS, Ramaboot S, Kunasol P, Preuksaraj S, The Thai expanded programme on immunization: role of immunization sessions and their cost-effectiveness, *Bulletin of the World Health Organization* 1989, 67(2):181-188.
- Pizzolato ND, and Silva Hbfd, The location of public schools: Evaluation of practical experiences, *International Transactions in Operational Research*, 1996, 4(1): 13-22.
- Poore P, Vaccination strategies in developing countries, *Vaccine* 1988, 6(5): 393-398.
- Poulos C *et al.*, Willingness-to-Pay for Typhoid Fever Vaccines for Adults and Children in Guilin, China, *Unpublished Draft*, 2006a.
- Poulos C *et al.*, Household Demand for Vi Polysaccharide Vaccines in Two Counties in Guangxi Zhuang Autonomous Region, China, *Unpublished Draft*, 2006b.
- Prislin R, Dyer JA, Blakely CH, Johnson CD, Immunization status and socio-demographic characteristics: the mediating role of beliefs, attitudes, and perceived control, *American Journal of Public Health* 1998, 88:1821-1826.
- Ragunathan TE, Lepkowski JM, Van Hoewyk J, Solenberger P, A multivariate technique for multiply imputing missing values using a sequence of regression models, *Survey Methodology* 2001, 27(1):85-95.
- Rahman MM, Aziz KMS, Munshi MH, Patwari Y, Rahman M, A diarrhea clinic in rural Bangladesh: Influence of distance, age, and sex on attendance and diarrheal mortality, *American Journal of Public Health* 1982, 72(10):1124-1128.
- Rahman MM, Islam MA and Mahalanabis D, Mothers' knowledge about vaccine preventable diseases and immunization coverage of a population with high rate of illiteracy, *Journal of Tropical Pediatrics* 1995, 41(6):376-378.

- Rahman S, and Smith DK, Use of location-allocation models in health service development planning in developing nations, *European Journal of Operational Research* 2000, 123(3):437-452.
- Rahman S and Smith DK, Deployment of rural health facilities in a developing country, *Journal of the Operational Research Society* 1999, 50(9): 892-902.
- Ravn HF and Vidal RVV, Operational research for developing countries – A case of transfer of technology, *The Journal of the Operational Research Society* 1986, 37(2):205-210.
- ReVelle CS and HA Eiselt, Location analysis: A synthesis and survey, *European Journal of Operational Research* 2005, 165(1):1-19.
- ReVelle C, and Swain RW, Central facilities location. *Geographical Analysis* 1970, 2:30-42.
- ReVelle CS, Church RL, and Schilling D, A note on the location model of Holmes, Williams and. Brown, *Geographical Analysis* 1975, 7: 457–459.
- Robertson RL, Davis JH, Jobe K, Service volume and other factors affecting the costs of immunizations in the Gambia, *Bulletin of the World Health Organization* 1984, 62(5):729-736.
- Rogers PP and Fiering MB, Use of systems analysis in water management, *Water Resources Research* 1986, 22(9):146S-158S.
- Routh S and Khuda B, An economic appraisal of alternative strategies for the delivery of MCH-FP services in urban Dhaka, Bangladesh, *International Journal of Health Planning and Management* 2000, 15:115-132.
- Rushton G, The Roepke lecture in economic geography: location theory, location-allocation models and spatial development planning in the Third world, *Economic Geography* 1988, 64:97-120.
- Russell S, Fox-Rushby J, Arhin D, Willingness and ability to pay for health care: a selection of methods and issues, *Health Policy and Planning* 1995, 10:94-101.

- Sagasti FR, Management sciences in an underdeveloped country: the case of operations research in Peru, *Management Science* 1972, 19(2).
- Schon DA, *Beyond the Stable State*, W. W. Norton & Company, 1971.
- Serre ML, Kolovos A, Christakos G, Modis K, An application of the holistochastic human exposure methodology to naturally occurring Arsenic in Bangladesh drinking water, *Risk Analysis* 2003, 23(3):515-528.
- Shepard DS, Robertson RL, Cameron III CSM, Saturno P, Pollack M, Manceau J, Martinez P, Meissner P, and Perrone J, Cost-effectiveness of routine and campaign vaccination strategies in Ecuador, *Bulletin of the World Health Organization* 1989, 67(6):649-962.
- Shepard DS, Sanoh L, Coffe E, *Cost effectiveness of EPI in the Ivory Coast: results from zones of Abidjan and Abengourou*, mimeo, 1982.
- Stevens T, Belkner R, Dennis D, Kittredge D, & Willis C, Comparison of contingent valuation and conjoint analysis in ecosystem management, *Ecological Economics* 2000, 32: 63-74.
- Stratfield S and Diamond M, Maternal education and child immunization, *Demography* 1990, 27(3): 447-455.
- Suraratdecha C, Ainsworth M, Tangcharoensathien V, and Whittington D, Private Demand for a HIV/AIDS Vaccine in Thailand, *Health Policy* 2005, 71: 271-287.
- Tang S, Bloom G, Decentralizing rural health services: a case study in China, *International Journal of Health Planning and Management* 2000, 15(3):189-200.
- Thomason J, Mulou N, and Bass C, User charges for rural health services in Papua New Guinea. *Social Science and Medicine*, 1994, 39(8): 1105–15.
- Toregas C, and ReVelle C, Binary Logic Solutions to a Class of Location Problem, *Geographical Analysis* 1973, 5:145–55.

- Verter V, and Lapierre S, Location of Preventive Health Care Facilities, *Annals of Operations Research* 2002, 110:123-132.
- Vollaard AM., Ali S, Asten H, Widjaja S, Visser L, Surjadi C, Dissel J, Risk factors for typhoid and paratyphoid fever in Jakarta, Indonesia, *Journal of American Medical Association* 2004, 291(21): 2607-2615.
- Vu DT, Hossain MM, Nguyen DS, Nguyen TH, Rao MR, Do GC, Naficy A, Nguyen TK, Acosta CJ, Deen JL, Clemens JD, Dang DT, Coverage and costs of mass immunization of an oral cholera vaccine in Vietnam, *Journal of Health, Population and Nutrition* 2003, 21(4):304-308.
- Walker D, Mosqueira NR, Penny ME, Lanata CF, Clark AD, Sanderson CFB and Fox-Rushby JA, Variation in the costs of delivering routine immunization services in Peru, *Bulletin of the World Health Organization* 2004, 82(9): 676-684.
- Whittington D, Matsui-Santana O, Freiburger JJ, Houtven GV, Pattanayak S. Private demand for a HIV/AIDS vaccine: Evidence from Guadalajara, Mexico. *Vaccine* 2002; 20: 2585-2591.
- Whittington D, Pinheiro AC, and Cropper M, The Economic Benefits of Malaria Prevention: A Contingent Valuation Study in Marracuene, Mozambique, *Journal of Health and Population in Developing Countries*, July 2003.
- Wilson JCT, Implementation of computer-simulation projects in health care, *Journal of the Operational Research Society* 1981, 32:825-32.
- World Health Organization, *The World Health Report*, World Health Organization, Geneva, 2003.
- World Health Organization, *Report on Ghana feasibility studies of immunization*, WHO document, EPI/GEN/79/5.
- World Health Organization, *Typhoid fever fact sheet*, 2000.

- Xie J and Dow WH, Longitudinal study of child immunization determinants in China, *Social Science & Medicine* 2005, 61: 601-611.
- Xinhua News Agency, *China's immunization scheme makes progress amid problems*, Xinhua's China Economic Information Service, June 8, 2005.
- Yang HH, Wu CG, Xie GZ, Gu QW, Wang BR, Wang LY, Wang HF, Ding ZS, Yang Y, Tan WS, Wang WY, Wang XC, Qin M, Wang JH, Tang HA, Jiang XM, Li YH, Wang ML, Zhang SL, and Li GL, Efficacy trial of Vi polysaccharide vaccine against typhoid fever in south-western China, *Bulletin of the World Health Organization* 2001, 79(7): 625-631.
- Yang J, Acosta CJ, Si G, Zeng J, Li C, Liang D, Ochiai RL, Page AL, Danovaro-Holliday MC, Zhang J, Zhou B, Liao H, Wang M, Tan D, Tang Z, Gong J, Park J, Ali M, Ivanoff B, Liang G, Yang H, Pang T, Xu Z, Donner A, Galindo CM, Dong B, Clemens JD, A mass vaccination campaign targeting adults and children to prevent typhoid fever in Hechi; Expanding the use of Vi polysaccharide vaccine in Southeast China: A cluster-randomized trial, *BMC Public Health* 2005, 5:49:1-9.
- Yeh WW, Reservoir management and operations models: A state-of-the-art review, *Water Resources Research* 1985, 21(12):1797-1818.
- Zeng X, Yang G, Liao S, Chen A, Tan J, Huang Z, and Li H, Survey of coverage, strategy and cost of hepatitis B vaccination in rural and urban areas of China, *World Journal of Gastroenterology* 1999, 5(4): 320-323.
- Zhang X, Wang L, Zhu X, Wang K, Knowledge, attitude and practice survey on immunization service delivery in Guangxi and Gansu, China, *Social Science and Medicine* 1999, 49:1125-1127.