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Three Essays in Environmental and Renewable Resource Economics

Sakai, Yutaro

UNIVERSITY OF CALGARY

Three Essays in Environmental and Renewable Resource Economics

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Yutaro Sakai

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Abstract

The environment and natural resources are fundamental to human life. Clean air is crucial for our health, fossil fuels are the base energy source for the modern economy, and fishery resources are the most important source of protein in many countries. Until the middle of the 20th century, the environment and natural resources were not the main subject of research, as human activities appeared to have negligible effects on them. Since then, however, the consequence of human activities started to manifest themselves. Environmental pollution, climate change, deforestation, and depletion of fishery resources are only a few examples. In effect, we live in an era where the careful management of environment and natural resources has never been more important.

A major challenge in environmental and resource management is their lack of property rights. For example, clean air is a public good, which is nonexcludable and nonrival. This means that one's pollution abatement effort benefits everyone in the population, while the cost of the abatement is borne by that individual. Consequently, everyone tries to free-ride on others' abatement efforts, and the resulting abatement effort level and air quality will be less than the socially optimal level. Similarly, many fishery resources are nonexcludable so that anyone can participate in a fishery. Because the cost of fishing increases as the size of the fish stock shrinks, an additional harvest by a new fisherman raises the cost of fishing for other fishermen. Thus, while the profit from harvests is enjoyed by each fisherman, the cost of harvest is shared by everyone in the industry. Consequently, the total harvest will be more than the socially optimal level. In both examples, an action of one individual affects others without market transactions (i.e. agreeing to incur the costs or benefits). This is the concept of externality. A positive externality exists if one's action benefits others—as in the case of abatement—, while a negative externality exists if one's action generates costs to others—as in the case of fishery.

In this thesis, I examine the management of fishery resources in Chapter 1 and the management of infectious diseases in Chapters 2 and 3. One may wonder why fishery resources and infectious pathogens are in the same thesis, but a closer look reveals that they share two key features. First, they are both renewable natural resources. Both are a part of the ecosystem, and one reproduces in lakes and oceans while the other reproduces in a host's body. The goal of a fishery resource manager is to maximize the rent from the fishery resource, while the goal of a pathogen resource manager (i.e. public health official) is to minimize the cost from the infectious pathogen.

Second, externalities are key in the management of both resources. Infectious diseases transmit from a host to another host without an accompanying market transaction. For many infectious diseases, vaccination exists that reduces the risk of infection. When a person vaccinates, this person bears the cost of vaccination such as money and pain, while everyone in the population benefits via the reduced risk of infection. Thus, everyone tries to free-ride on others vaccination decisions, and the vaccination rate will be lower than the social optimal level. This is a classic example of public goods. Therefore, the management of fishery resources and infectious pathogens both center around understanding the nature of externalities and finding the optimal level of resource stocks.

My analytical approach to these two types of resource management is also common. I first use reduced form econometrics to examine the overall relationship between key variables. I then use theory to explain the empirical results, and further explore other possible outcomes based on the theory. In the case of fishery resource in Chapter 1, theoretical models already exist in the literature, so I focus primarily on the empirical analysis. Alternatively, I show a new stylized fact about the relationship between income and vaccination rates in Chapter 2. As there is no theory in the literature that is consistent with this result, I construct a new theory in Chapter 3. The combination of theory and empirics is useful in examining the phenomenon of interest and discussing policy implications.

In Chapter 1, I investigate the impact of fishery subsidies on resource stocks in 23 OECD countries during 1996-2011. Subsidies are common tools to internalize externalities by aligning private and social costs. They are, however, also used for other political purposes. Thus, whether they have positive or negative consequences is an empirical question. My results show that the effect of subsidies depends on the type of subsidy and the management regime. Within this sample, cost reducing subsidies have no effect on stocks if management is individual quota-based but have negative effects if management uses traditional input/output restrictions. Subsidies for improving fishery management and infrastructure produce beneficial effects on stocks under traditional management, but no effect with individual quota-based management. These results suggest that global efforts to reform fishery subsidies should be carried out in a highly selective manner.

In Chapter 2, I present a new stylized fact about the relationship between income and childhood vaccination. It shows vaccination rates first rise but then fall as income increases. This pattern is observed in WHO country-level panel data, and in US county-level panel and individual-level repeated cross-section data. This data pattern suggests that both low and high-income parents are less likely to follow the standard vaccination schedule, and that such behaviour is reflected in the vaccination rate at the population level. I provide several alternative explanations as to why we observe this data pattern, including avoidance measures, medical care, and social segregation.

Finally, in Chapter 3, I develops a simple model of vaccination decisions in a population where agents differ in their exogenous income. Agents perceive the risk of infection as independent of their decisions, while it is endogenously determined by the population's vaccination rate. I show that while the monetary cost of vaccination prevents low-income agents from vaccinating, the opportunity cost of illness, interacted with the presence of a substitute for vaccination, can naturally generate non-vaccination at the high-income end. These vaccination decisions at the individual level may in turn generate a rise and fall in the vaccination rate as the population's income rises.

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Chapter 1

Subsidies, Fisheries Management and Stock Depletion

1.1 Introduction

The debate over possible new rules for fishery subsidies has not been settled in spite of a decade of discussion in the Doha Round of the World Trade Organization (WTO).[1] Complicating the debate is the common-property nature of the fishery resources since the state of regulation may be a key factor determining whether subsidies exacerbate or ameliorate the overexploitation of fish stocks. This is a real concern because annual fishery subsidies are large - with one estimate suggesting a figure of 34 US$ billion worldwide.[2] While subsidies lowering the costs of fishing are generally perceived as harmful, subsidies related to fishery management are more controversial. Given the overexploited state of many fishery resources, a resolution to this debate should not wait any longer.

As a step towards resolution, this paper uses a panel of data from 23 OECD countries for the 1996-2011 period to estimate the impact of subsidies on fish stocks. To do so, I match country level subsidy data with a resource stock index prepared by the Sea Around Us Project (SAUP).[3] Since the impact of subsidies is likely to vary by type, subsidies are grouped into three categories: income related Direct Payments, Cost Reducing Transfers, and subsidies to management and infrastructure investments that represent General Services.[4] Finally, as the debate has made clear the impact of subsidies is likely a function of existing fisheries management policies (UNEP 2004), I allow for two different management regimes: individual

[1] The WTO has no clear definition of fishery subsidies. A broad range of government spending is discussed as potential subsidies, including spending for research and management of the fishery.

[2] This amounts to more than one third of the world fishery production value. See Sumaila and Pauly (2006) and FAO (2009).

[3] See Pauly and Zeller (2015).

[4] Due to data limitation, management and infrastructure investments cannot be separated.

quota-based (e.g., IQ and ITQ) management and traditional input/output management. This distinction is likely to be important since individual quota-based management requires stricter monitoring and enforcement, and is expected to be more effective in protecting resource stocks than traditional input/output management (OECD 2006a; Munro et al. 2009).

There are a number of difficulties in identifying the effect of fishery subsidies on resource stocks. The first difficulty concerns data availability. Because stock assessment is available for only a limited number of fish stocks, we have to use harvests or harvest oriented indices for resource stocks. These measures, however, require special care with regard to when the effect will materialize. Subsidies could boost the harvest in the short-term, but decrease it in the longer-term through resource degradation (and vice versa). If we do not distinguish between these short- and long-term changes, we may mistakenly interpret the short-term increase in harvest as a resource recovery. To deal with this issue, the relationship is examined between current resource stocks and past subsidies using different lag structures. As the number of lags increases, the long-term effect of subsidies should emerge in the parameter estimate.

Second, subsidies and resource stocks may both be correlated with another variable. For example, economic fluctuations could affect both the budget for subsidies and the demand for fishery products (which affects resource stocks). To deal with this issue, the panel structure of the data is exploited and used to control for both country and year fixed effects. Even with these controls in place, it is possible that other unobservable country-specific time-varying factors may also play a role; for example, change in input or output prices may affect fishers' behaviour and also affect fishery policies. Therefore I include both import price of oil products and fishery products in the estimation to control for input and output price fluctuations.

Finally, there are potential issues with reverse causality that need to be considered. Fishery subsidies might cause resource decline, while at the same time resource decline might in turn call for government interventions such as subsidies.[5] Although one cannot entirely exclude the possibility of reverse causality, it seems less of a concern in the present work. Since the paper examines the relationship between past subsidies and current resource stocks, reverse causality means that current resource stocks affect past subsidies. This can happen when fishers demand subsidies based on the expectation of future resource stocks. As the number of lags becomes larger, however, the magnitude of uncertainty becomes larger and is likely to dominate the effect of expectations. Hence, reverse causality should produce minimal bias in the present context. The validity of this assumption is examined in Appendix A.

Overall, my results are consistent with the literature in that the impact of subsidies is conditional on the management regime in place, as well as dependent on the exact form the subsidy takes. Within the sample, my empirical results show that all three types of fishery subsidies have little effect in countries with individual quota-based management. However, in countries with traditional input/output management schemes, Cost Reducing Transfers today decrease the harvest of healthy stocks five years later,[6] while General Services today increase that of healthy stocks five years later. Direct Payments also decrease resources, but the effect is only marginally significant.

There is a large volume of literature addressing the issues of fishery subsidies. Some of this literature is descriptive in categorizing and estimating the value of fishery subsidies generally (Sumaila and Pauly 2006; Sumaila et al. 2010; Milazzo 1998), or providing estimates for specific countries (Sharp and Sumaila 2009; Mesnil 2008). Estimates of total subsidy values are upwards of 34 US$ billion. These papers typically assume open access fisheries and argue that cost-reducing subsidies decrease resources stocks.

[5]For example, after the collapse of Northern Atlantic Cod stocks in the late 1980s, the Canadian government established a number of programs including income maintenance to support the fishing industry (Schrank 2003).

[6]Healthy stocks refer to the stocks who are categorized as developing, exploited or rebuilding according to the SAUP criteria. The stated change in resource stocks occurs within a single year. The aggregate change in resource stocks over time will be larger, but that is beyond the scope of this paper.

The second strand of literature advances toward identifying the conditions under which subsidies affect resource stocks. This literature has developed using bio-economic models of the fishery evaluated using comparative statics (Munro and Sumaila 2002; Sumaila et al. 2008). The general conclusion here is that subsidies lead to overexploitation of resources in open access fisheries. However, fisheries with a proper level of harvest control can avoid overfishing. A corollary of this work is that the effect of subsidies depends on fisheries management programs in place. An interesting extension in international trade shows subsidies in one country may have spillover effects though the world price of fish (Brander and Taylor 1997; Jinji 2012; Bayramoglu et al. 2014).

The empirical work on subsidies is not extensive but the work by Yagi et al. (2008), Yagi et al. (2009) and Sumaila et al. (2013) are most closely related to the work at hand. Yagi et al. (2008) evaluate the empirical effects of subsidies on fishery production. A panel of 23 OECD countries, 1996-2002, is used to show that income subsidies increase harvest while management and infrastructure subsidies have the opposite effect. Yagi et al. (2009) use a similar analysis for Japanese time series data for the period 1971-2003 and find a positive effect of "Government other general services" on production value per fishers. Sumaila et al. (2013) use cross-section data of 37 island countries and examine the effect of subsidies on fish stocks. They find a negative relationship between "bad" subsidies and fish resources. Though suggestive, these studies either ignore the long-term effect of subsidies or ignore unobservable heterogeneity across countries. Moreover, none of them consider the potential role of fishery management.

1.2 Data

Subsidy data is available from a series of OECD Review of Fisheries publications.[7] The data set covers the period 1996-2011 and includes three types of fishery subsidies: Direct Payments, Cost Reducing Transfers and General Services.[8] Direct Payments are primarily directed at increasing the income of fishers, and thereby correspond to income subsidies. Examples include grants for new vessels and vessel decommissioning. This category also includes revenue enhancing subsidies such as market price support. Cost Reducing Transfers reduce fixed or variable costs of fishing. Interest subsidies and fuel-tax exemptions fall into this category. General Services corresponds to transfers for fisheries management and the development of infrastructure. Definitions and examples of each category are found in Table 1.

Because each country has a different size of fishing industry, the amount of fishery subsidies must be normalized to make it comparable across countries. As reliable data on the number of fishers in each country is not available, the output value of fishing industry in each country is used for the normalization. One concern is that the output value itself can be endogenous in the present context. For example, meteorological conditions on fishing grounds may affect both output values and resource stocks, thereby potentially inducing omitted variable bias in estimation. To minimize this concern, fishery subsidies are normalized by

[7]These reports contain data of government financial transfers, which are defined as "the monetary value of government interventions associated with fisheries policies." Because there is no internationally agreed definition on fishery subsidies, the government financial transfers are treated as subsidies in this paper, following two closely related studies (Yagi et al. 2008, 2009). Note, however, that Schrank and Keithly (1999) discuss the definition of fishery subsidies and propose that subsidies be defined as "Government action (or inaction) that modifies (by increasing or decreasing) the potential profits earned by the firm in the short-, medium-, or long-term." According to this definition, all the government financial transfers in the OECD database are regarded as subsidies.

[8]Missing observations are a serious problem with the subsidy data. For example, while 23 countries over 16-year period amounts to 368 observations, the number of observations for Cost Reducing Transfers is only 280 as shown in Table 3. Various OECD reports are used to obtain as complete a series as possible. The general survey section of a series of "Review of Fisheries in OECD Countries: Policies and Summary Statistic" is the main source of subsidy data, but it includes a lot of missing observations. To mitigate this issue, I read through the country note sections of these reports, because they sometimes include data that is not reported in the general survey section. Further, a series of "Review of Fisheries in OECD Countries: Country Statistics" and OECD (2006a, 2006b) are used to complement the data.

Table 1.1: Definitions and examples of fishery subsidies (OECD 2000)

Type	Definition	Examples
Direct Payment	Payments from government to fishers and are primarily directed at increasing the income of fishers.	Price support, Grants for new vessels, Grants for modernization, Grants for temporary withdrawal of fishing vessels, Vessel decommissioning, Income support, Unemployment insurance
Cost Reducing Transfer	Payments aimed at reducing the costs of fixed capital and variable inputs.	Subsidized loans for vessel construction/modernization, Interest subsidies, Fuel tax exemption, Government payments of access to other countries' water
General Service	Payments which are not necessarily received directly by fishers but nevertheless reduce the costs faced by fishers.	Management expenditure, Enforcement expenditure, Expenditure for information collection and analysis, Aid for restocking of fish resource, Support to build port facilities for commercial fisheries

the "average" output value over time in each country. The average output value is constant over time, so any factors that are correlated with them are controlled for by country fixed effects included in estimation.[9]

Measure for resource stocks

The measure of resource stocks[10] used in empirical work is based on the Fish Stock Over-exploited or Collapsed (FSOC) index developed by the SAUP and extended by Hsu et al. (2014). The index is defined for country i at year t and based on harvest in each country's

[9]Simple normalization using the output values gives qualitatively similar results.

[10]The SAUP defines the number of "stocks" as a time series of a given species, genus or family (higher and pooled groups have been excluded) for which the first and last reported landings are at least 10 years apart, for which there are at least 5 years of consecutive catches and for which the catch in a given area is at least 1000 tonnes.

Exclusive Economic Zone (EEZ). The FSOC index function[11] is written:

$$FSOC_{it} = \frac{\text{Harvest of stocks Overexploted or Collapsed in EEZ}_{it}}{\text{Total harvest of stocks in EEZ}_{it}} \tag{1.1}$$

Overexploited and Collapsed stocks are based on a five category stock classification used by the SAUP.[12] For ease of interpretation, this paper uses the following modified version of the FSOC (MFSOC) index:

$$MFSOC_{it} = (1 - FSOC_{it}) * 100 \tag{1.2}$$

Therefore, an increase in the MFSOC index corresponds to an increase in the harvest of developing, exploited, or rebuilding stocks, given the total harvest for country i at year t. The MFSOC has the advantage that an increase in the index corresponds to an increase in resource stocks.

Froese et al. (2012) argue that harvest-based resource indices perform reasonably well in capturing trends in biomass but respond to a decline in biomass in a delayed fashion. This means that short-term fluctuations in these indices do not necessarily reflect resource fluctuations. Fishery subsidies possibly boost harvests in the short-term but decrease them in the long-term through resource degradation (and vice versa). Short-term changes in the index should capture the effect on harvest, but not on resource stocks. Therefore, this paper focuses on the long-term changes in the MFSOC index.

The interpretation of the MFSOC index requires further caution because it changes both

[11] The index can be modified to examine the effect of catch share systems on resource stocks (Costello et al. 2008).

[12] The SAUP notes that stock-status categories are defined using the following criteria (all referring to the maximum catch [peak catch] or post-peak minimum in each series): Developing (catches $\leq$ 50% of peak and year is pre-peak, or year of peak is final year of the time series); Exploited (catches $\geq$ 50% of peak catches); Over-exploited (catches between 50% and 10% of peak and year is post-peak); Collapsed (catches $<$ 10% of peak and year is post-peak); and Rebuilding (catches between 10% and 50% of peak and year is after post-peak minimum).

at the intensive and extensive margins. At the intensive margin, harvest of stocks in each category (as defined by the SAUP) changes without re-categorizing these stocks. At the extensive margin, changes in harvest lead to re-categorizing of these stocks. For example, when the harvest of an overexploited stock increases, the MFSOC index first decreases (intensive margin), and when the harvest exceeds a certain threshold and the stock is re-categorized as "Rebuilding", the index increases (extensive margin). Detailed data is not available, however, to distinguish between the intensive and extensive margins. Hence, all changes in the index are presumed to be from the extensive margin. This may be reasonable given that the focus of this paper is the long-term effect of subsidies.

The 23 countries used in this study are divided into two groups; Quota countries, with fisheries management based on individual quota (IQ) or individual transferable quota (ITQ) systems, and Non-Quota countries with fisheries management based on traditional input/output restrictions. Quota based fisheries management typically allocates a fixed amount (or a proportion) of fishing quota to individual (or a group of) agents, with an intention to avoid the common-pool resource problem. Quota based systems require strict monitoring and enforcement of the total output restriction to avoid overfishing.[13] Country classification by management type is shown in Table 2.[14]

Summary statistics are provided in Table 3, where all prices are in 2009 US$. The MFSOC index shows that on average over all countries, 83% of fish stocks are at the developing, exploited, or rebuilding stage. The lowest value 75.91 is observed in the UK in 2008 while

[13] According to OECD (2006b), "The enforceability issue is indeed one of the salient challenges faced by IQs systems. It depends on Monitoring, Control and Surveillance (MCS) capacities...". Copeland and Taylor (2009) argue that the regulators enforcement power is a key to determine success in resource management. Munro et al. (2009) argue that quota-based management makes it easier to monitor harvests. Nevertheless, there are examples where quota-based management collapsed under an inability to monitor harvests (Cancino et al. 2007).

[14] The country classification is based on an overview of fisheries management by (OECD 2006b). It reports which country uses IQ or ITQ management systems, but does not report the extent to which a given system is used or how effective it is to manage fisheries in each country. It is also possible that countries that use quota systems are mistakenly reported as not using these systems. Hence, "quota countries" in this paper should be interpreted as countries that are using quota systems relatively more intensively, on average, than "non-quota countries". In the absence of a country level fisheries management database, this seems to be the best possible way to classify these countries.

Table 1.2: List of Quota and Non-Quota countries

15 Quota countries	8 Non-Quota countries
Australia, Canada, Denmark, France, Germany, Iceland, Italy, Netherlands, New Zealand, Norway, Poland, Portugal, Spain, UK, USA	Finland, Greece, Ireland, Japan, Korea, Mexico, Sweden, Turkey

the highest value 91.74 is observed in Greece in 1996. The total value of subsidies is on average 27% of the total landing value. The breakdown across subsidies from smallest share is 4% Cost Reducing, 5% Direct Payments and by far the largest at 18% is General Services. Also, General Services have the largest coefficient of variation 0.75, in contrast to 0.5 for the other two categories. Note the very large standard deviation for General Services is caused by Japan reporting more than 10 times the average value in the sample.[15] The import prices of fish products and oil products are used as control variables in the estimation.[16] Finally, the Quota-based management indicates that 67 percent of the sample countries are categorized as quota regulated countries.

Table 1.3: Summary statistics

Variable	N	Mean	SD	Min	Max
MFSOC index	368	83.32	2.19	75.91	91.74
Total subsidies / average revenue	267	0.27	0.33	0.00	2.26
Direct Payments / average revenue	314	0.05	0.10	0.00	1.31
Cost Reducing Transfers / average revenue	280	0.04	0.08	0.00	0.47
General Services / average revenue	349	0.18	0.24	0.00	1.79
Import price of fish products (USD/kg)	368	3.18	1.44	0.43	7.06
Import price of oil products (USD/kg)	368	1.43	1.07	0.04	6.55
Share of green party	368	1.59	2.75	0.00	11.60
Quota-based management	368	0.65	0.48	0.00	1.00

Notes: The sample covers the period 1996-2011, and consists of 23 OECD countries: Australia, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Korea, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Spain, Sweden, Turkey, UK and USA

[15] One potential reason is that the entire infrastructure-related budget is managed by the fishery agency in Japan, while some of the infrastructure-related budgets are managed by other agencies in other countries (Yagi 2008).

[16] The import price of fish products comes from the FAO Fish Stat Plus, while the that of oil products is constructed from the "value of oil imports" from the International Monetary Fund and the "volume of crude oil products" from the OECD.stat.

1.3 Estimation

1.3.1 Econometric model

This section examines the effect of three types of fishery subsidies on resource stocks. The equation of interest and the identification assumption are respectively given by:[17]

$$\begin{aligned} MFSOC_{it} &= \rho_{1k} DP_{it-k} * Quota_i + \rho'_{1k} DP_{it-k} * (1 - Quota_i) \\ &+ \rho_{2k} CRT_{it-k} * Quota_i + \rho'_{2k} CRT_{it-k} * (1 - Quota_i) \\ &+ \rho_{3k} GS_{it-k} * Quota_i + \rho'_{3k} GS_{it-k} * (1 - Quota_i) \\ &+ \gamma X_{it-k} + \alpha_i + \mu_t + u_{it} \quad \text{for} \quad k \in \{1, 2, ..\} \end{aligned} \tag{1.3}$$

$$E[u_{it} | \alpha_i, \mu_t, DP_{it-k}, CRT_{it-k}, GS_{it-k}, X_{it-k}] = 0 \quad \text{for} \quad k \in \{1, 2, ..\} \tag{1.4}$$

The outcome of interest is the MFSOC index for country i at year t. Three variables of interest, DP_{it-k}, CRT_{it-k}, and GS_{it-k} are respectively ln Direct Payments per output value, ln Cost Reducing Transfers per output value, and ln General Services per output value for country i at year t-k.[18] $Quota_i$ is an indicator variable that takes 1 if a country is categorized as a Quota country and 0 otherwise. X_{it-k} includes the import price of fish and oil products as proxies for input and output prices, α_i and μ_t are country and time fixed effects, respectively, and u_{it} is the unobserved error term. Since Japan is a clear outlier in terms of General Services, an interaction term of Japan Dummy and General Services is also included in the equation.[19]

I estimate the model using a different number of lags to examine the short- and long-term effects.[20] Due to the short time-dimension of the data, up to 6 lags are considered. One may

[17] An alternative specification is to estimate the equation separately for two groups of countries without the quota dummy variable. As shown in Appendix B, results are similar, but less precise when estimated separately due to the small sample.

[18] For observations that take 0, I added 1 before the ln transformation. This does not change the results qualitatively, but allows more precise inferences.

[19] Excluding Japan from the sample changes the results only marginally.

[20] Another approach for examining the timing of effects is to use the aggregated data over a different

question this specification in that subsidies in different time periods are not included together in the model; if subsidies have both short- and long-term effects, it is more appropriate to include subsidies at different time periods together in the model to separately identify these effects. This does not seem to be a serious issue in the present context, however, because serial correlations in subsidies are not so strong as to significantly affect results. Adding various lags at the same time does not change the conclusion of this paper. Further, subsidies with short time lags are more likely to be affected by reverse causality, so it is better not to include them to identify the effect of subsidies with longer time lags.

The equation includes country fixed effects so that a given country is compared to itself across years that have higher or lower amounts of subsidies. These fixed effects therefore eliminate sources of omitted variable bias generated by across-country differences that are constant over time and may be correlated with different amounts of subsidies. Difference in the productivity of fishing grounds and the public tolerance for subsidy are therefore controlled for in estimation.

The identification assumption means that subsidies are allocated as good as random after controlling for the fixed effects and other covariates. This assumption excludes the possibility of reverse causality. Because the independent variables are lagged, reverse causality means that fishers and fishery managers ask or allocate subsidies based on the expectation of the future resource. As the number of lags become larger, however, the magnitude of uncertainty becomes larger and likely dominate the effect of future expectation. Therefore, reverse causality is expected to produce minimal bias in the present context. The validity of this assumption is examined in Appendix A.

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number of years, while keeping the number of lags in the estimation as 1. See Acemoglu et al. (2008) as an example. Unfortunately, due to the short time dimension and the large number of missing observations, this approach is infeasible.

1.3.2 Results

The results are shown in Table 4. The first three rows correspond to Quota countries while the next three correspond to Non-Quota countries. As we move from left to right in the table, the lag of subsidies (k) increases from 1 to 6.

Table 4 exhibits a number of interesting features. First of all, fishery subsidies have significant effects only in Non-Quota countries. This is an indication of the heterogeneous effects of subsidies across management. In Quota countries, only Cost Reducing Transfers (CRTs) with a 4-year lag show a significant effect. CRTs with 3-year or 5-year lags, however, do not show any effects. Further, point estimates for these lags are notably different from that of the 4-year lag. Hence, this could be an artifact of the large missing observations in CRTs.

Second, in Non-Quota countries, Direct Payments (DPs) show a significant and negative association with resource stocks with 4 and 5-year lags. This seems reasonable since DPs include many effort-enhancing subsidies. DPs also include vessel buyback programs that are generally believed to be beneficial for resource conservation. As Clark et al. (2005) argue, however, these subsidies could be harmful if vessel buyback programs are anticipated by fishers and induced investment for the fishing capacity occurs. The result is in line with their argument.

Third, Cost Reducing Transfers (CRTs) show a strong negative effect with 3 - 5 year lags. It is worth pointing out that the point estimate with a 1-year lag is positive. This seems reasonable if CRTs boost harvest in the short-term but decrease it in the long-term through resource degradation. The MFSOC index increases first with the boost in harvest, but decreases later with resource degradation.

Finally, General Services (GSs) show the opposite of CRTs. It has a significant and negative effect with a 1-year lag, but a significant and positive effect with 4 - 6 year lags. This seems reasonable if GSs are spent on the stricter enforcement of fishery management.

This could reduce harvest in the short-term, but increase it in the long-term through resource recovery. The MFSOC index decreases with stricter management, but later increases with the resource recovery.

Table 1.4: Three subsidies in both groups of countries

	Dependent variable: MFSOC index					
	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
Quota:						
- DP	0.022	0.039	-0.104	-0.142	-0.108	0.021
	(0.065)	(0.069)	(0.093)	(0.104)	(0.168)	(0.163)
- CRT	0.010	0.031	0.078	0.272^{a}	0.138	-0.100
	(0.029)	(0.041)	(0.057)	(0.088)	(0.086)	(0.191)
- GS	0.168	0.099	-0.034	-0.205	0.010	0.021
	(0.169)	(0.182)	(0.188)	(0.163)	(0.242)	(0.167)
Non-Quota:						
- DP	-0.204	-0.247	-0.251	-0.339^{b}	-0.408^{c}	0.073
	(0.212)	(0.248)	(0.207)	(0.123)	(0.212)	(0.274)
- CRT	0.003	-0.030	-0.119^{a}	-0.128^{a}	-0.117^{a}	-0.061^{b}
	(0.077)	(0.064)	(0.035)	(0.026)	(0.026)	(0.022)
- GS	-0.088^{a}	-0.048	0.709^{c}	0.664^{c}	0.775^{a}	0.759^{a}
	(0.028)	(0.046)	(0.394)	(0.346)	(0.249)	(0.151)
- GS*Japan	0.048^{c}	0.016	-0.744^{c}	-0.714^{b}	-0.835^{a}	-5.651^{a}
	(0.024)	(0.045)	(0.385)	(0.343)	(0.253)	(0.946)
N	244	226	209	192	177	160
Countries	23	23	23	23	23	23
R2	0.377	0.356	0.375	0.325	0.272	0.212
RMSE	1.010	0.990	0.965	0.934	0.949	0.980

Notes: Standard errors are clustered at the country level. a, b, and c mean statistical significance at the 1 %, 5%, and 10% levels, respectively. All the specifications include country and year fixed effects, and input/output prices as control variables. DP: Direct Payments, CRT: Cost Reducing Transfers, GS: General Services.

1.3.3 Robustness and Magnitude

In this section, I check the robustness of the estimated impacts of fishery subsidies on resource stocks. I treat the main result with a 5-years lag as a base line, which is shown in Column 1 of Table 5. In Column 2, I include a 5-year lagged dependent variable as an additional control. If fishery managers decide the amount of subsidies in each period based on resource stocks in the respective period, the resource stocks in that period can be a source of omitted variable bias. The estimate is quite similar to the main result.

In Column 3, I re-categorize Japan and Korea as Quota countries. These two countries do not implement IQ or ITQ management, but they do implement community-based quota management (OECD 2006b). If communities can manage fishery well, these countries may have more effective output restrictions than the other Non-Quota countries. The result does not change qualitatively, though the point estimate for GSs is somewhat smaller.

In Column 4, I exclude Australia, France, Netherlands, the United Kingdom, and the United States from the estimation because they report "bad" harvest data for one or more EEZ (Hsu et al. 2014). As all of these countries are categorized as Quota-countries, the parameter estimates for Non-Quota countries changes little.

In Column 5, I use data only up to 2006 because the method used for constructing the FSOC (and MFSOC) index is different before and after 2006 (Hsu et al. 2014). Up to 2006, the index is calculated by the SAUP. It has, however, not published the index after 2006, so the EPI calculates the index using an "ad-hoc" method. This raises a concern for the consistency of the data. Using the data up to 2006 does not change the result qualitatively.

Finally, in Column 6, I use an alternative outcome variable for the estimation. The outcome variable here (MFSOC2 index) is the share of the "number" of fish stocks in an EEZ that are developing, exploited, or rebuilding. As discussed, the MFSOC index changes both at the intensive and extensive margins. This introduces some ambiguity in the interpretation of the results. The new index here has the advantage that it changes only at the extensive margin.[21] Therefore, if the result using this index is similar in terms of signs, it supports the presumption that the main results capture the changes at the extensive margin. The result is quite similar in terms of signs of parameter estimates.

Results are quite similar across the columns. Overall, the point estimates for CRTs and GSs are respectively about -0.1 and 0.7 for Non-Quota countries. Assuming that prices of the marginal stocks are equal to the average price of all stocks, these point estimates

[21] A drawback is that this index is available only up to 2006.

Table 1.5: Robustness check

	Dependent variable					
	MFSOC	MFSOC	MFSOC	MFSOC	MFSOC	MFSOC2
Quota:						
- DP	-0.108	-0.124	-0.158	0.350	0.033	-0.543
	(0.168)	(0.152)	(0.146)	(0.202)	(0.149)	(0.565)
- CRT	0.138	0.175^c	0.081	0.194^c	-0.064	0.522
	(0.086)	(0.097)	(0.093)	(0.102)	(0.120)	(1.091)
- GS	0.010	0.016	0.187	-0.413^b	0.260	1.792^b
	(0.242)	(0.227)	(0.258)	(0.179)	(0.155)	(0.822)
Non-Quota:						
- DP	-0.408^c	-0.426^c	-0.370	-0.398^c	-0.226	0.689
	(0.212)	(0.227)	(0.254)	(0.209)	(0.359)	(0.632)
- CRT	-0.117^a	-0.099^a	-0.102^a	-0.113^a	-0.290^a	-1.088^a
	(0.026)	(0.034)	(0.027)	(0.029)	(0.049)	(0.180)
- GS	0.775^a	0.729^b	0.604^b	0.722^b	0.798^b	0.098
	(0.249)	(0.270)	(0.261)	(0.262)	(0.310)	(0.965)
- GS*Japan	-0.835^a	-0.803^a		-0.769^b	-3.152^a	-5.769
	(0.253)	(0.270)		(0.266)	(0.971)	(5.022)
LagDep	NO	YES	NO	NO	NO	NO
N	177	177	177	143	93	93
Countries	23	23	23	18	20	20
R2	0.272	0.291	0.236	0.293	0.292	0.171
RMSE	0.949	0.940	0.973	0.966	0.969	4.427

Notes: Standard errors are clustered at the country level. a, b, and c mean statistical significance at the 1 %, 5%, and 10% levels, respectively. All the specifications include country and year fixed effects, and input/output prices as control variables. Subsidy variables are lagged by 5 years. DP: Direct Payments, CRT: Cost Reducing Transfers, GS: General Services. LagDep: Lagged dependent variable. MFSOC2 stands for the share of the "number" of fish stocks in an EEZ that are developing, exploited or rebuilding. Column 1 is the baseline model with 5-year lag. Column 2 includes the 5-year lagged dependent variables as an additional control. Column 3 recategorizes Japan and Korea as Quota countries. Column 4 excludes Australia, France, Netherlands, UK and USA from the sample. Column 5 uses data up to the year 2006. Column 6 uses MFSOC2 as an alternative resource index.

suggest that an additional 1 dollar for GSs today increases the harvest of healthy stocks by 0.2 kilograms five year later, which is worth 0.40 dollar in future value; and an additional 1 dollar for CRTs today decreases the harvest of healthy stocks by 0.6 kilograms five year later, which is worth 1.23 dollar in future value for an average country.[22]

[22]The mean value of GSs per output value is 0.17, and the mean value of GSs is 134.91 US$ million excluding Japan. This means that a 1 percent increase in GSs per output value amounts to 0.17 * 0.01* 134.91* 1000 = 229.347 US$ thousand. A (0.7/100) point increase in the MF-SOC index amounts to 770*0.83*(0.7/100)*0.01=44.737 ton, given the average output of 770 ton excluding Japan. The average price of fishery products is 2.09 US$/kg, so this amounts to

1.4 Discussion

The previous section suggests that in countries with individual quota-based management, subsidies have little effect on resource stocks. This seems a reasonable conclusion if individual quota-based management effectively limits the total harvest at a sustainable level. However, such a presumption is somewhat naive because a number of conditions are required in order for individual quota-based management to work effectively. For instance, Grafton (1996) notes that ITQ management maximizes the economic rent of a fishery only when in-season stock externalities and congestion externalities are absent. Further, he notes that without fishers' compliance with regulations, individual quota management can be detrimental to a fishery. Similarly, Bromley (2009) discusses, from various points of view, how the existence of an individual fishing quota system is neither a necessary nor a sufficient condition for successful management. This earlier research suggests that cost-reducing or capacity-enhancing subsidies could have a detrimental effect on resource stocks even under individual quota-based management.

Along similar lines, Munro and Sumaila (2002) discuss the consequence of a more extreme form of harvesting rights — the full privatization of fishery. They show that cost-reducing subsidies can decrease resource stocks even under full privatization, and resource stocks can be driven down to extinction levels. Further, Clark et al. (2010) argue that the possibility of single owners finding it optimal to drive the resource to extinction should not be dismissed out of hand. While I find little effect of subsidies on resource stocks under individual quota-based management, these papers suggest that my result is unlikely to hold in all situations.

I also find that, in countries with traditional input/output management, Direct Payments and Cost Reducing Transfers are harmful to resource stocks while General Services are generally beneficial. Since Direct Payments and Cost Reducing Transfers both reduce the cost

44.737*2.09=93.5 US$ thousand. Therefore, an additional 1 dollar for GSs increases the output value by 93.5/229.347=0.40 dollar. Similarly, an additional 1 dollar for CRTs decreases the output value by (770*0.83*(0.1/100)*0.01*2.09*1000)/(0.04*0.01*27.20*1000)=1.23 dollar.

of fishing operations, it seems reasonable to find negative effects for these subsidies. It is less clear however why General Services appear to create beneficial effects. The answer probably lies in the fact that General Services subsidies reflect both investments in management, research, and enforcement (hereafter collectively described as management investments), and investments in infrastructure (hereafter infrastructure investments). These two investments are similar in magnitude, but potentially different in effect.[23] While management investments are generally perceived as beneficial, infrastructure investments may not be. This is because infrastructure investments may be useful for monitoring but they also reduce the cost of landing for fishers (UNEP 2004). Therefore, the beneficial effect of General Services could be driven by the beneficial effect of management investments dominating the negative effect of infrastructure investments. Alternatively, it could be the case that both management and infrastructure investments are beneficial for resource stocks, thus leading to the overall beneficial effect of General Services. To distinguish between these two possibilities, however, we need to wait until more data is accumulated. Until this issue is resolved, a cautious approach may be to maintain the total amount of General Services at the current level.

1.5 Conclusion

For over ten years, policy makers have been debating the efficacy of fishery subsidies. At present, no firm consensus has emerged. One of the reasons for the lack of consensus is most likely the striking lack of empirical evidence linking fishery subsidies to resource stocks. The aim of this paper was to provide such evidence.

The paper has two main findings based on panel data drawn from 23 OECD countries

[23]For 1996, 1997, and 2003, the mean and standard deviation of management investments are US$ 95 and US$ 188, respectively. The mean and standard deviation of infrastructure investments, on the other hand, are US$ 129 and US$ 484, respectively. Excluding Japan, the means and standard deviations for the former are US$ 76 and US$ 167, and those for the latter are US$ 20 and US$ 60. The magnitude of the latter becomes much smaller, but is still not negligible.

for the period 1996-2011. First, fishery subsidies have little effect on stocks, on average, in countries with individual quota-based management. Second, subsidies do affect resource stocks in countries without such management. In these countries, Cost Reducing Transfers are harmful while General Services are beneficial for resource stocks. Direct Payments also seem harmful, but this result is not statistically robust. These results are largely consistent with the predictions of theory; that is, subsidies that decrease the costs of fishing are harmful while those that help shift the fishery away from open access are beneficial. Some caution is however warranted. It is possible that the 16-year panel data is not long enough to detect the full effect of subsidies. Moreover, since a number of conditions are required in order for individual quota-based management to work properly, the results do not mean that the existence of such management is sufficient in preventing any harmful effects of subsidies.

With these limitations in mind, the policy implications of this paper are threefold. First, improving overall management practices should be of the highest priority in each country. In particular, the results indicate that individual quota-based management seems to be more effective in preventing any harmful effects of subsidies compared to traditional input/output management. Second, countries should keep up their effort to reduce cost-reducing subsidies. Although these subsidies are generally perceived as harmful, there has been little empirical evidence supporting such a view. My results consistently indicate that such subsidies reduce resource stocks in countries without individual quota-based management. Finally, management and infrastructure subsidies should not be categorically prohibited. At the Doha Round of the WTO, a group of countries insisted on universal or near-universal prohibitions of fishery subsidies. The results of this paper, however, oppose such an idea. A more cautious approach would be to maintain the amount of General Services at the current level until further empirical analyses clarify which subcategories should or should not be prohibited.

Appendix A: Instrumental Variable Estimation

1.5.1 Econometric model

Estimations in the main text presume that reverse causality is less of a concern since lagged subsidies are used. To examine the validity of this assumption, this section aggregates subsidies over three categories to create one value and uses this as the only subsidy variable in the model. With the only one endogenous variable in the model, it is possible to discuss the direction of the potential bias. In fact, reverse causality is likely to lead to an underestimate of the causal effect in this model, because fishers are expected to ask for subsidies when they face or anticipate resource decline. The sample is limited to Non-Quota countries. The equation of interest and the identification assumption are given by:

$$MFSOC_{it} = \alpha_i + \mu_t + \rho \; AGG_{it-5} + \gamma X_{it-5} + u_{it} \tag{1.5}$$

$$E[u_{it}|\alpha_i, \mu_t, AGG_{it-5}, X_{it-5}] = 0 \tag{1.6}$$

where AGG is ln aggregate fishery subsidies per output value.

To obtain further insight, an instrumental variable estimation is implemented. The instrument used is the share of seats in parliament for green parties.[24] Green parties emerged in the 1970s and 1980s and their main concerns were and continued to be the environment and social justice. As fishery subsidies are generally believed to be harmful, with a larger share of green parties less fishery subsidies can be expected.[25]

To be a valid instrument, the share of green parties must not be affected by resource stocks. As fishing industries in OECD countries are extremely small, they are less likely to be the main reason for people to vote for green parties. Hence, this condition seems

[24] Data on the share of green parties in Korea, Turkey, Poland, and Mexico is not included in Armingeon et al. (2012), and hence collected from various sources.

[25] For example, policies of England and Wales green party includes "MC327; The Green Party would press at EU level for an end to all subsidies that can result in increased fishing pressure, including concessionary tax rates for fuel, vessel modification and improving port and fish processing facilities." Note that this policy aims to reduce all of the three types of subsidies.

satisfied.[26] In addition, the share of green parties must not affect resource stocks other than through fishery subsidies. This is also likely to be satisfied with the same reason: given the small size of these fishing industries, fishery policies are unlikely to be of central importance in parliament. Note, however, that if green parties affect other fishery policies to enhance resource conservation, the resulting IV estimate is an underestimate of the causal effect.

1.5.2 Results

The results are shown in Table 6. Column 1 shows the result using a simple OLS. The parameter estimate is positive but not significant. Considering the small sample, this is probably reasonable. Column 2 shows the result including a 5-year lagged dependent variable. The point estimate becomes 6 times larger, but it remains insignificant. Column 3 shows the result of the IV estimation and Column 4 shows the corresponding first stage estimation. As expected, the share of green parties is negatively correlated with the aggregate subsidies. The parameter estimate for the aggregate subsidies is now statistically significant and much larger than the OLS estimates in Column 1 and 2. Column 5 and 6 show the IV estimation including the 5-year lagged dependent variable. These results are similar to those in Column 3 and 4, though the point estimate for the aggregate subsidies becomes somewhat larger.

As discussed above, if green parties try to preserve resource stocks through other fishery policies, the IV estimates should be underestimates of the causal effect. In this regard, the results suggest that fishery subsidies are, on average across the three types, beneficial for resource stocks. Recall that, among the three categories, General Services is by far the largest both in terms of magnitude and standard deviation. Therefore, the results in this section imply that the causal effect of General Services is positive.

[26] The mean ratio of output value to GDP is less than 0.01 in the sample countries.

Table 1.6: Aggregate subsidy in Non-Quota countries

	Dependent variable					
	MFSOC	MFSOC	MFSOC	Subsidy	MFSOC	Subsidy
Agg Subsidy	0.013	0.074	2.368^{a}		2.647^{a}	
	(0.151)	(0.206)	(0.682)		(0.779)	
Green				-0.436^{a}		-0.409^{b}
				(0.112)		(0.122)
Estimation	OLS	OLS	IV	IV	IV	IV
LagDep	NO	YES	NO	NO	YES	YES
N	67	67	67	67	67	67
Countries	8	8	8	8	8	8
R2	0.353	0.374	.	0.225	.	0.252
RMSE	1.297	1.288	2.169	0.770	2.261	0.764
Fstat				15.097		11.237

Notes: Standard errors are clustered at the country level. a, b, and c mean statistical significant at the 1 %, 5%, and 10% levels, respectively. All the specifications include country and year fixed effects, and input/output prices as control variables. LagDep: Lagged dependent variable. Fstat: First stage F statistics.

Appendix B: Separate Estimation

Estimations in the main text use all the observations while allowing Quota and Non-Quota countries to have different parameters for subsidy variables. This raises a concern that the results may be driven by this particular specification.[27] To show this is not the case, Table 7 and 8 present separate estimates for Quota and Non-Quota countries, respectively. Although standard errors are larger than those in the main text due to the smaller sample size, point estimates are overall similar in magnitude and sign. This assures that it is not the particular specification that generates these point estimates. The specification simply increases the degrees of freedom in the estimation.

[27] I thank an anonymous referee for pointing this out.

Table 1.7: Three subsidies in non-quota countries

	Dependent variable: MFSOC index					
	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
Non-Quota:						
- DP	-0.368^b	-0.369^c	-0.470^b	-0.577^a	-0.442	0.231
	(0.135)	(0.162)	(0.162)	(0.146)	(0.275)	(0.156)
- CRT	-0.010	-0.040	-0.119^a	-0.106	-0.058	0.026
	(0.067)	(0.052)	(0.031)	(0.060)	(0.057)	(0.061)
- GS	-0.048	-0.030	0.581	0.545	0.536	0.553
	(0.037)	(0.059)	(0.318)	(0.400)	(0.435)	(0.299)
- GS*Japan	0.058	0.071	-0.543	-0.534	-0.536	-2.323
	(0.047)	(0.085)	(0.314)	(0.404)	(0.448)	(2.412)
N	88	82	76	70	65	59
Countries	8	8	8	8	8	8
R2	0.529	0.459	0.491	0.432	0.435	0.427
RMSE	1.089	1.183	1.171	1.204	1.217	1.254

Notes: Standard errors are clustered at the country level. a, b, and c mean statistical significance at the 1 %, 5%, and 10% levels, respectively. All the specifications include country and year fixed effects, and input/output prices as control variables. DP: Direct Payments, CRT: Cost Reducing Transfers, GS: General Services.

Table 1.8: Three subsidies in quota countries

	Dependent variable: MFSOC index					
	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
Quota:						
- DP	0.012	0.023	-0.079	-0.148	-0.119	-0.077
	(0.070)	(0.061)	(0.094)	(0.094)	(0.171)	(0.119)
- CRT	0.001	0.004	0.014	0.130^b	0.039	-0.065
	(0.033)	(0.040)	(0.047)	(0.047)	(0.089)	(0.194)
- GS	0.118	0.075	-0.023	-0.142	-0.042	-0.129
	(0.150)	(0.149)	(0.150)	(0.123)	(0.197)	(0.159)
N	156	144	133	122	112	101
Countries	15	15	15	15	15	15
R2	0.547	0.598	0.578	0.509	0.412	0.394
RMSE	0.798	0.692	0.678	0.643	0.648	0.616

Notes: Standard errors are clustered at the country level. a, b, and c mean statistical significance at the 1 %, 5%, and 10% levels, respectively. All the specifications include country and year fixed effects, and input/output prices as control variables. DP: Direct Payments, CRT: Cost Reducing Transfers, GS: General Services.

Bibliography

Acemoglu Daron, Johnson Simon, Robinson James, and Yared Pierre. 2008. "Income and Democracy." *American Economic Review*, 98(3):808–842.

Armingeon Klaus, Knopfel Laura, Weisstanner David and Engler Sarah. 2014. "Comparative Political Data Set III 1990-2012." Bern: Institute of Political Science, University of Berne.

Bayramoglu Basak, Copeland Brian R, and Jacques Jean-Francois. 2014. "Trade and Fisheries Subsidies." Working paper.

Brander James A and Taylor M. Scott. 1997. "International Trade and Open-Access Renewable Resources: The Small Open Economy Case." *Canadian Journal Of Economics-revue Canadienne D Economique*, 30(3):526–552.

Bromley Daniel W. 2009. "Abdicating responsibility: the deceits of fisheries policy." *Fisheries*, 34(6):280–290.

Cancino Jose P., Uchida Hirotsugu, and Wilen James E. 2007. "TURFs and ITQs: Collective vs. Individual Decision Making." *Marine Resource Economics*, 22(4):391–406.

Clark Colin W., Munro Gordon R., and Sumaila U. Rashid. "Subsidies, Buybacks, and Sustainable Fisheries." 2005. *Journal of Environmental Economics and Management*, 50 (1):47–58.

Clark Colin W., Munro Gordon R., and Sumaila U. Rashid. "Limits to the Privatization of Fishery Resources" 2010. *Land Economics*, 86(2):209–218.

Copeland Brian R. and Taylor M. Scott. 2009. "Trade, Tragedy, and the Commons." *American Economic Review*, 99(3):725–749.

Costello Christopher, Gaines Steven D., and Lynham John. 2008. "Can Catch Shares Prevent Fisheries Collapse?" *Science*, 321(5896):1678–1681.

FAO. 2009. “The State of World Fisheries and Aquaculture 2008.” FAO, Rome.

Froese Rainer, Zeller Dirk, Kleisner Kristin, and Pauly Daniel. 2012. “What Catch Data Can Tell Us About the Status of Global Fisheries.” *Marine biology*, 159(6):1283–1292.

Grafton R. Quentin. 1996. “Individual transferable quotas: theory and practice.” *Reviews in Fish Biology and Fisheries*, 6(2): 5–20.

Hsu, A., J. Emerson, M. Levy, A. de Sherbinin, L. Johnson, O. Malik, J. Schwartz, and M. Jaiteh. 2014. “The 2014 Environmental Performance Index.” New Haven, CT: Yale Center for Environmental Law & Policy. Available: www.epi.yale.edu.

Jinji Naoto. “Fisheries Subsidies and Management in Open Economies.” 2012. *Marine Resource Economics*, 27(1):25–41.

Mesnil Benoit. “Public-Aided Crises in the French Fishing Sector.” 2008. *Ocean & coastal management*, 51(10):689–700.

Milazzo Matteo. “Subsidies in World Fisheries: A Re-Examination.” 1998. World Bank Technical Paper No.406. Fisheries Series.

Munro Gordon and Sumaila Ussif R. 2002. “The Impact of Subsidies Upon Fisheries Management and Sustainability: the case of the north atlantic.” *Fish and fisheries*, 3(4): 233–250.

Munro, Gordon R., B. Turris, Colin Clark, Ussif Rashid Sumaila, and Megan Bailey. 2009. “Impacts of Harvesting Rights in Canadian Pacific Fisheries.” Statistical and Economic Analysis Series. Publication. No.1-3 iv + 61p.

OECD. 2000. “Transition to Responsible Fisheries: Economic and Policy Implications.” OECD Publishing, Paris.

OECD. 2006a. "Financial Support to Fisheries: Implications for Sustainable Development." OECD Publishing, Paris.

OECD. 2006b. "Using Market Mechanisms to Manage Fisheries: Smoothing the Path." OECD Publishing, Paris.

Pauly Daniel and Zeller Dirk. (Editors). 2015. "Sea Around Us Concepts, Design and Data (seaaroundus.org)."

Schrank William E. 2003. "Introducing Fisheries Subsidies." FAO, Rome.

Sharp Renée and Sumaila U. Rashid. 2009. "Quantification of US Marine Fisheries Subsidies." *North American Journal of Fisheries Management*, 29(1):18–32.

Schrank E. William and Keithly R. Walter, JR. 1999. "The Concept of Subsidies." *Marine Resource Economics*, 14(2):151–164.

Sumaila U. Rashid, Khan Ahmed S., Dyck Andrew J., Watson Reg, Munro Gordon, Tydemers Peter, and Pauly Daniel. 2010. "A Bottom-Up Re-Estimation of Global Fisheries Subsidies." *Journal of Bioeconomics*, 12(3):201–225.

Sumaila U. Rashid, Dyck Andrew, and Cheung William WL. 2013. "Fisheries Subsidies and Potential Catch Loss in SIDs Exclusive Economic Zones: Food Security Implications." *Environment and Development Economics*, 18(04):427–439.

Sumaila U. Rashid and Pauly Daniel. 2006. "Catching More Bait: A Bottom-Up Re-Estimation of Global Fisheries Subsidies (2nd version)." Fisheries Centre Research Reports v.14(6).

Sumaila U. Rashid, Teh Louise, Watson Reg, Tyedmers Peter, and Pauly Daniel. .2008 "Fuel Price Increase, Subsidies, Overcapacity, and Resource Sustainability." *ICES Journal of Marine Science: Journal du Conseil*, 65(6):832–840.

UNEP. 2004. "Analyzing the Resource Impact of Fisheries Subsidies: A Matrix Approach." UNEP, Geneva.

Yagi Nobuyuki. 2008. "Negotiation on Fisheries Subsidies at WTO Doha Round." *Nippon Suisan Gakkaish*, 5(74):776–783. (in Japanese)

Yagi Nobuyuki, Senda Yoshihito, and Ariji Masahiko. 2008. "Panel Data Analyses to Examine Effects of Subsidies to Fishery Productions in OECD Countries." *Fisheries Science*, 74(6):1229–1234.

Yagi Nobuyuki, Ariji Masahiko, and Senda Yoshihito. 2009. "A Time-Series Data Analysis to Examine Effects of Subsidies to Fishery Productions in Japan." *Fisheries Science*, 75 (1):3–11.

This chapter is a modified version of the following article. Sakai, Yutaro. "Subsidies, Fisheries Management, and Stock Depletion." *Land Economics* 93.1 (2017): 165-178.

Chapter 2

The Vaccination Kuznets Curve: Do Vaccination Rates Rise and Fall with Income?

2.1 Introduction

Vaccination is one of the greatest inventions in human history. This medical intervention is so powerful that during the 1940s-1950s, people believed that the war against infectious diseases was almost over.[1] Since then, however, we have failed to eradicate any disease—except for smallpox—and the outbreak of various diseases continues to occur in even the most developed countries. Effective vaccines are indeed available for many diseases, but vaccination rates are not high enough to prevent outbreaks. Moreover, there is a growing concern that vaccination rates are actually falling in some segments of the population, particularly in high-income groups.

This paper examines the relationship between childhood vaccination rates and per capita income using three datasets that differ in their level of aggregation and country coverage. At the country and county level, I examine the relationship between childhood vaccination rates and per capita income of the region. At the individual level, I examine the relationship between the probability of a child being up-to-date with a vaccine schedule and per capita income of the family. While the raw data shows that vaccination rates and the probability of being up-to-date typically increase as per capita income increases, I find that they initially rise but then begin to fall with income conditional on region and year fixed effects.[2]

[1]In 1948, U.S. Secretary of State George Marshall expressed his view that the conquest of all infectious diseases was imminent. This great optimism was due not only to vaccination but also to the growing number of antibiotics and the discovery of other chemicals that could effectively kill mosquitoes and other insect pests (Garrett 1994).

[2]In the country-, county-, and individual-level analyses, the term "region" corresponds to a country, county, and state, respectively.

The inclusion of region- and year-fixed effects in the estimation is therefore key to these results. For example, good local institutions may help increase both income and vaccination rates, creating a spurious positive correlation between these variables in the raw data. Region-fixed effects will help eliminate this correlation. Similarly, as regions became richer over time, vaccine safety improved simultaneously, which raised the demand for vaccines. This secular change can again create a spurious positive correlation. Year-fixed effects will help eliminate this correlation. Therefore, a method that allows for both region- and year-fixed effects may uncover quite different relationships between per capita income and vaccination rates from what the raw data suggests.

To investigate this possibility, I employ three different datasets. The country-level data is obtained from the World Health Organization (WHO) that consists of 70 countries with six vaccines for the 1980-2014 period. The county- and individual-level datasets are obtained from the United States (U.S.). The county-level dataset includes the period 1995-2008, consisting of 229 counties with seven vaccines. The individual-level dataset is provided by the National Immunization Survey (NIS), which includes the vaccination status of eight childhood vaccines for >160,000 individuals during the 2005-2014 period. While the results naturally differ across these quite different samples, vaccination rates/probability of being up-to-date and per capita income often exhibit a hump-shaped relationship.[3] In particular, the country-level data suggests that vaccination rates peak around the per capita income of \$25,000-\$40,000, and fall below the herd immunity threshold levels around \$50,000, which poses a significant risk of disease outbreaks to the population.[4]

[3]Even though I include fixed effects and other control variables in the estimation, a region-specific time-varying omitted variable (e.g., education) may exist in the error term, correlated with both income and vaccination rates. If so, it may not be income itself that causes vaccination rates to rise and fall. Although possible, it is somewhat difficult to imagine a variable (other than income) that systematically affects vaccination rates first positively and then negatively as it increases. Moreover, even if such a variable exists, vaccination rates continue to rise and fall along the same pattern outlined in this paper, as that variable increases. Therefore, the importance of my findings does not crucially hinge on whether the estimations identify the causal effect of income or not.

[4]The incidence of an infection will decline if a certain fraction of the population is immune to the disease, assuming a population is randomly mixed. This fraction is called the herd immunity threshold. Thus, keeping the vaccination rate above this level is crucial in preventing disease outbreaks (Fine & K Eames

These results indicate that both low- and high-income parents are less likely to follow the standard vaccination schedule, and that such behaviour is reflected in the vaccination rate at the population level. Moreover, this is not just a U.S. specific phenomenon but a global one. But why do parents in both tails of the income distribution not vaccinate their children? Low-income parents do not vaccinate presumably because their limited financial resources make it difficult for them to follow the standard vaccination schedule. It is, however, somewhat puzzling why high-income parents do not vaccinate. One possibility is simply that higher-income parents have a different information set. I argue, however, that there are other plausible explanations in which we can assume the same information set across parents. These explanations include avoidance measures,[5] medical care, and social segregation.

The literature on vaccination is extensive. Aside from the mounting evidence that low-income parents are less likely to vaccinate (e.g., Wu et al. 2008; Klevens & Luman 2001), there is some evidence in the U.S. that high income parents are also less likely to vaccinate (Smith et al. 2004, 2011; Wei et al. 2009). At the population level, two studies use data in California to find that vaccination rates are lower in higher income areas (Atwell et al. 2013; Yang et al. 2016). These studies are suggestive but incomplete in several ways. First, they do not distinguish between different vaccines and diseases. This is problematic in understanding these parents' behaviours because different diseases and vaccines pose different risks and consequences. Moreover, as the herd immunity threshold varies by diseases, vaccine-by-vaccine analyses are necessary to examine whether these parents' behaviours are actually eroding herd immunity for any specific disease. Second, many studies do not distinguish between the effect of income and the effect of regional differences. For instance, it is possible that high-income parents do not vaccinate because they live in an area where high quality medical service is readily available rather than because they have high income. Finally, and related to the first two points, the literature does not provide detailed discussion about the

2011).

[5] Yang et al. (2016) touch this possibility but do not provide detailed discussion.

potential mechanisms behind these behaviours. In this paper, I aim to fill in these gaps in the literature.[6]

This paper also has an obvious connection to the Environmental Kuznets Curve (EKC) literature. Ever since Grossman & Krueger (1991, 1994) found evidence that environmental degradation initially rises and then falls as income increases, a number of empirical studies have tried to confirm its existence (e.g., Shafik & Bandyopadhyay 1992; Cole et al. 1997; List & Gallet 1999; Harbaugh et al. 2000). At the same time, four branches of theoretical explanations have been proposed: income effects with non-homothetic tastes (Lopez 1994); threshold effects (John & Pecchenino 1994; Stokey 1998); increasing returns (Andreoni & Levinson 2001); and technological progress coupled with neoclassical convergence (Brock & Taylor 2010).[7] In this paper, I provide the first evidence that vaccination rates also initially rise and then fall as income rises, which could be labelled the "Vaccination Kuznets Curve (VKC)."[8] In contrast to the EKC, the VKC raises an alarm that economic development may bring falling vaccination rates and rising disease outbreaks. As such this paper is meant to be provocative rather than conclusive. I provide preliminary evidence and suggestive explanations but certainly more work is warranted to identify the underlying mechanism at work.

The rest of the paper proceeds as follows. In Section 2, I show that raw data overall exhibit a positive correlation between vaccination rates and per capita income at the country, county, and individual level. In Section 3, I briefly argue how these positive correlations can be spurious and discuss how I use my econometric model to examine such possibilities.

[6] The finding of this paper is also related to the large literature on the effect of material standard of living on infectious diseases, which was initiated by a serious of works by Thomas McKeown. He argued that the decline of mortality since the 18th century is mostly due to the improved standard of living rather than targeted medical interventions such as vaccination. My paper adds a new angle to this argument because it suggests that the improved standard of living in turn lowers the vaccination rate and may increase mortality in the worst case.

[7] See the chapter 2 of Copeland & Taylor (2003) for a discussion of various effects.

[8] Troesken (2014) uses cross-country data to show that smallpox mortality and GDP per capita had a clear U-shape relationship at the beginning of the 20th century. This is indirect evidence that the Vaccination Kuznets Curve may have already existed a century ago.

Section 4 shows the summary statistics of my datasets. In Section 5, I demonstrate that after removing the effect of confounding factors, vaccination rates and income exhibit a hump-shaped relationship. I discuss potential mechanisms behind my findings in Section 6 and conclude in Section 7.

2.2 Data

I use an individual-level dataset and two population-level datasets to examine the relationship between income and vaccination rates. The individual-level dataset allows me to examine how income affects parents' vaccination decisions for their children. This dataset, however, does not tell us whether any individual-level behaviour constitutes a genuine danger to the population by eroding herd immunity. If the vaccination rate falls below the herd immunity threshold due to some parents' vaccination decisions, it is a significant threat to the population. To examine this possibility, I also use two population-level datasets.

The three datasets consist of a country-level panel dataset from the WHO, a county-level panel dataset from the U.S., and an individual-level repeated cross-section dataset from the U.S.—each of which serves for a different purpose. The country-level dataset includes a large number of countries over an extended period of time, which allows me to examine the potential global issue of non-vaccination at the high-income end. A concern with this dataset, however, is its highly aggregated nature and data reliability. Thus, the county-level dataset in the U.S. is used to validate the previous results. This dataset is preferable in that the data reliability is high and there should be less unobservable heterogeneity across counties within the U.S. Finally, the individual-level data in the U.S. is employed to examine the relationship between parents' income and their vaccination decisions.

2.2.1 Country-level data

The country-level vaccination data is obtained from the WHO's Department of Immunization, Vaccines and Biologicals. The data is an estimate of the "infant" vaccination coverage rates, and is presented as the percentage of a target population that has been vaccinated. For those vaccines given at birth like Bacille Calmette Guerin (BCG), the target population is the number of live births. For other infant vaccines such as diphtheria toxoid, tetanus toxoid and pertussis (DTP), the target population is children who survived their first birthday.

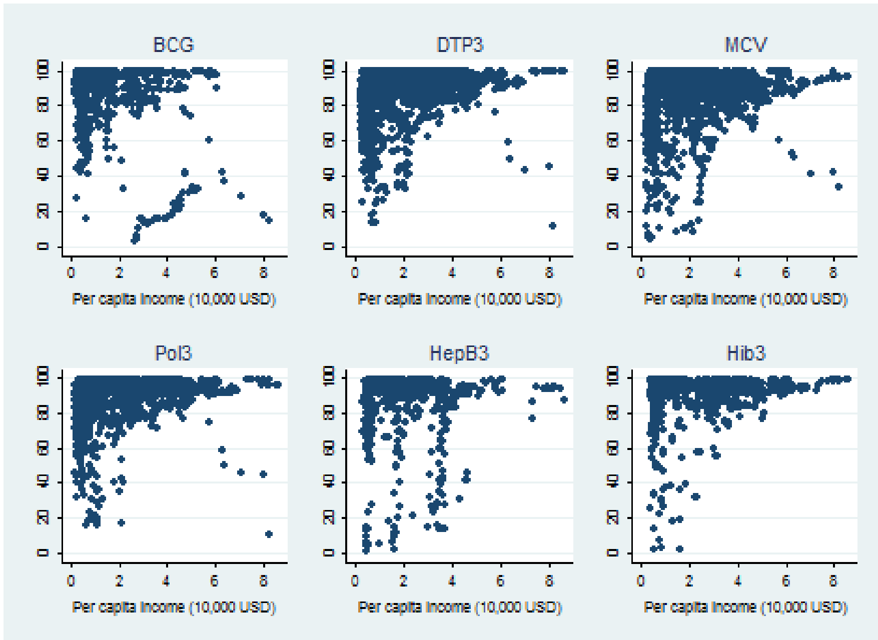
The dataset covers nearly all the countries in the world, but the analysis uses only a subset of them. I exclude countries that are categorized as "low" and "lower middle" income countries by the World Bank. As the World Bank updates its country classification every year, I use the one in the year 2000, which is in the middle of the sample period (1980-2014). This procedure is to make sure that the sample does not include countries where the supply of vaccines is severely limited. In these countries, vaccination rates are presumably determined by limited supply and do not reflect choice behaviour. Data reliability is also a concern for these low-income countries. The final sample includes 70 countries during the period 1980-2014. Alternatively, dropping countries with the mean GDP per capita less than \$6,000, \$7,000, \$8,000 \$9,000 or \$10,000 gives a similar result.

Figure 2.1 depicts the relationship between vaccination rates and GDP per capita (hereafter per capita income) in the raw data for the following six vaccines: the first dose of BCG (BCG), the third dose of DTP (DTP3), the first dose of measles-containing vaccine (MCV), the third dose of Polio vaccine (Pol3), the third dose of Hepatitis B vaccine (HepB3), and the third dose of Haemophilus influenzae type B vaccine (Hib3).[9] It shows a general pattern that vaccination rates are higher when per capita income is higher.[10]

[9] In addition to these "conventional vaccines," the dataset also includes seven other types of vaccines. Their data coverage is, however, quite limited both in terms of countries and years.

[10] The outliers in these graphs all originate from the United Arab Emirates, Sweden, and Ireland. Excluding these countries from the sample does not qualitatively change the results.

Figure 2.1: Vaccination rates and per capita income:
Cross country data



Source: World Health Organization
Note: BCG: The 1st dose of Bacille Calmette Guerin vaccine for tuberculosis, DTP3: The 3rd dose of diphtheria toxoid, tetanus toxoid and pertussis vaccine, MCV: The 1st dose of measles-containing vaccine, Pol3: The 3rd dose of Polio vaccine, HepB3: The 3rd dose of Hepatitis B vaccine, Hib3: The 3rd dose of Haemophilus influenzae type B vaccine

2.2.2 County-level data

The county-level vaccination data is originally from the National Immunization Survey (NIS), which is a random telephone survey to parents, followed by a survey sent to children's immunization providers. The survey began in 1994 and targets children between the ages of 19 and 35 months living in the U.S. Due to confidentiality reasons, the NIS public-use datasets do not include the information on the county of residence. Fortunately, using the NIS data, Smith & Singleton (2011) estimate vaccination rates in counties where the combined sample size from the NIS from at least one of the seven biennial periods during 1995 - 2008 is ≥ 35. This gives us a sample of 229 counties.

The dataset includes seven types of vaccines: the fourth dose of DTP (DTP4), the first dose of measles-mumps-rubella vaccine (MMR), the third dose of Pol (Pol3), the third dose of Hib (Hib3), the third dose of HepB (HepB3), the first dose of varicella vaccine (VRC), and the fourth dose of pneumococcal conjugate vaccine (PCV4). When compared to the country-level dataset, several things are worth noting. First, this dataset does not include BCG because the U.S. does not require BCG in its standard vaccination schedule. Second, because the U.S. requires four doses of DTP vaccines instead of three, this dataset includes DTP4 as opposed to DTP3. Finally, while the country-level dataset includes MCV, the county-level dataset includes MMR, a specific type of MCV. Figure 2.2 shows the relationship between vaccination rates and per capita personal income (hereafter per capita income) at the county level, for the seven vaccines.[11] It shows a general pattern that vaccination rates are higher when per capita income is higher.[12]

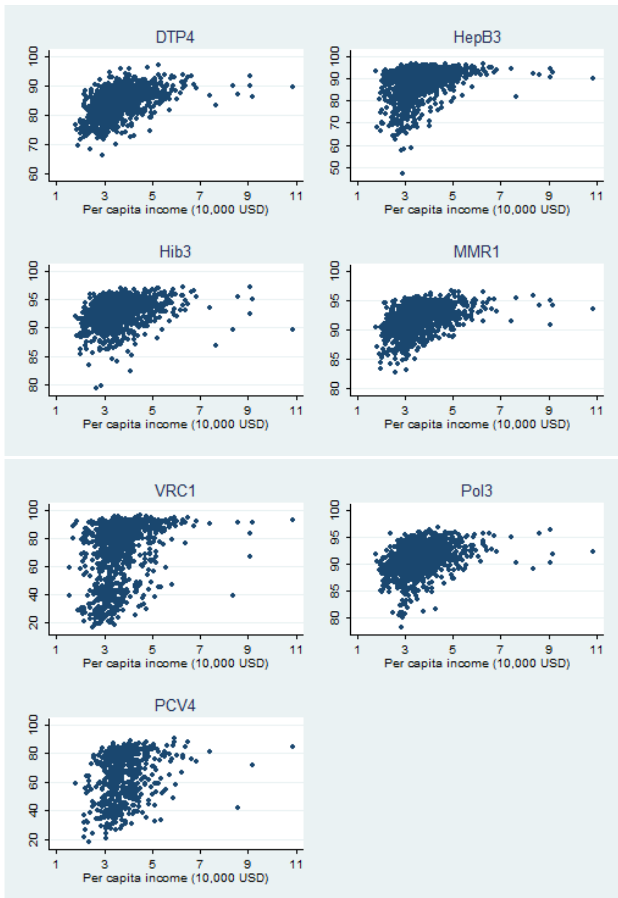
One potential caveat of this dataset is sample selection, because the 229 counties are not randomly selected from 3,141 counties in the U.S. This sample selection is an issue if these counties have some unobservable characteristics that are systematically correlated with vaccination rates. Fortunately, the 229 counties are selected purely based on the number of observations in the NIS, which is determined by the number of counties in each statistical area.[13] Then, even if the 229 counties have some unobservable characteristics that are correlated with vaccination rates, these characteristics must be time-invariant. Therefore, county-fixed effects in my estimation will take care of any potential issue regarding the sample selection.

[11]The personal per capita income is obtained from the Bereau of Economic Analysis. It is constructed from the "personal income" rather than the national income. Note, however, that personal income and national income take similar values at the country level. According to http://thismatter.com/economics/national-accounts.htm, the main difference between personal income and national income is that personal income includes transfer payments, such as private pension payments, retirement benefits, unemployment insurance benefits, veteran benefits, disability payments, welfare, and farmer subsidies.

[12]Most of the observations above $60,000 are sampled from New York county in the state of New York. Dropping this county does not change the result qualitatively.

[13]The NIS ensures that a similar number of samples are obtained in each of the 78 Immunization Action Plan areas (50 states, Washington DC, and 27 other large urban areas). Each area, however, has a different number of counties, ranging from only three counties in Delaware to 254 counties in Texas. This suggests that the counties in Delaware are included in the NIS sample every year while the majority of the counties in Texas are not included in the NIS sample for a given year. As a result, the 229 counties (out of 3,141 counties) in our dataset do not represent the entire number of counties in the U.S. Rather, they over-represent the Immunization Action Plan by favoring areas with a smaller number of counties.

Figure 2.2: Vaccination rates and per capita income:
US county data



Source: Smith & Singleton (2011)
Note: The dataset includes 229 counties during the period 1995-2008. DTP4: The 4th dose of diphtheria toxoid, tetanus toxoid and pertussis vaccine, MMR1: The 1st dose of measles-mumps-rubella vaccine, Pol3: The 3rd dose of Polio vaccine, HepB3: The 3rd dose of Hepatitis B vaccine, Hib3: The 3rd dose of Haemophilus influenzae type B vaccine, VRC1: The 1st dose of Varicella vaccine, PCV4: The 4th dose of Pneumococcal Conjugate vaccine.

2.2.3 Individual-level data

The individual-level vaccination data again comes from the NIS. The data is available from the year 1994 but the analysis in this section uses data from the year 2005 when a key detailed income variable became available. The NIS includes the vaccination status of children for nine different vaccines: DTP, Pol, MCV, Hib, HepB, VRC, PCV, ROT, and FLU.[14] FLU is, however, excluded from the analysis because the recommended number of doses for young children changes from season to season and the up-to-date variables for flu vaccines in the dataset do not accurately reflect the latest recommendation.[15] As a result, the dataset in this section includes the same seven vaccines as the county-level dataset in the previous section. Note however that the individual-level dataset analyses MCV while the county-level dataset in the previous section analyses MMR. In addition to the seven vaccines, the first does of ROT is also analysed in this section, which is not included in the county-level dataset due to confidentiality reasons.

To conduct a comparable analysis to those in other datasets, I need the information about parents' vaccination decisions and per capita income. As the NIS provides individual-level data, the outcome variable here is a binary variable that assigns the value of 1 if a given child is up-to-date with the standard schedule for a vaccine at the age of 19-35 months and 0 if not. Turning to the explanatory variable, the income variable provided in the NIS is not per capita income, but family income. Moreover, it is provided as a range rather than an exact level, with the top income category censored. Therefore, I use the following three steps to construct per capita income. First, I assign each family the lower boundary of the income bin as their family income.[16] Then, I divide this family income by the number of family members to obtain per capita income. Finally, this nominal per capita income is converted

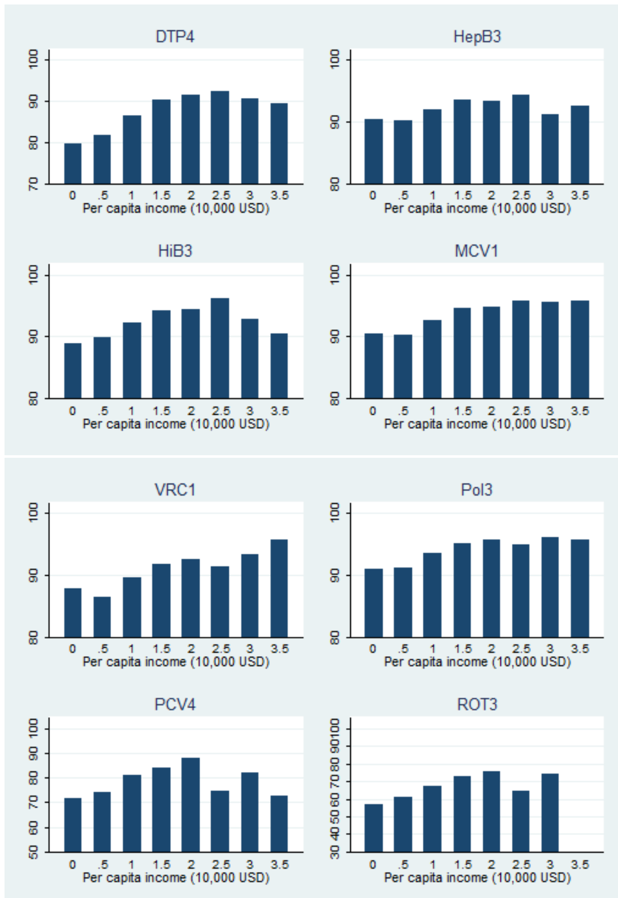
[14] ROT: rotavirus vaccine, FLU: seasonal influenza vaccine.

[15] See "A Codebook for the 2014 Public-Use Data File" in the National Immunization Survey.

[16] Family income is given as 12 income categories: 0-7,500; 7,500-10,000; 10,000-17,500; 17,500-20,000; 20,000-25,000; 25,000-30,000; 30,000-35,000; 35,000-40,000; 40,000-50,000; 50,000-60,000; 60,000-75,000 and 75,000+ (in USD). I chose the lower boundary because the highest income group (75,000+) does not have an upper boundary or midpoint.

into real per capita income in 2005 US dollar using the consumer price index.

Figure 2.3: Probability of being up-to-date with a vaccine schedule and per capita income: US individual data



Source: CDC, NCRID and NCHS (2006-2015), 2005-2014 National Immunization Survey.
Note: DTP4: The 4th dose of diphtheria toxoid, tetanus toxoid and pertussis vaccine, MCV1: The 1st dose of measles-containing vaccine, Pol3: The 3rd dose of Polio vaccine, Hep3: The 3rd dose of Hepatitis B vaccine, HiB4: The 4th dose of Haemophilus influenzae type B vaccine, VRC1: The 1st dose of Varicella vaccine, PCV4: The 4th dose of Pneumococcal Conjugate vaccine, ROT3: The third dose of Rotavirus vaccine. Per capita income is calculated as family income divided by the number of family members.

Figure 2.3 shows the relationship between the fraction of children who are up-to-date with a vaccine schedule ("vaccination rate") and per capita income. The graph suggests that the fraction of children being up-to-date increases with per capita income in the low income range ($0 - $20,000) for all the vaccines. In the high income range ($20,000-$35,000), however, this tendency is less clear. In fact, for DTP4, HiB3 and PCV4, the fraction decreases as per capita income increases. Alternatively, for VRC1, the fraction keeps increasing with per capita income.

2.3 Econometric model

Overall, these three datasets show a positive relationship between vaccination rates and per capita income. As briefly discussed in the introduction, however, these positive relationships do not necessarily mean that these variables are directly related. A positive correlation can be generated by many factors including vaccine delivery costs, vaccine safety, population density, culture, and institution. To examine such possibilities, I conduct regression analyses in this section. For the country- and county-level data, the econometric model is given by:

$$y_{it} = \alpha_i + \mu_t + \beta_1 G_{it} + \beta_2 G_{it}^2 + \beta_3 G_{it}^3 + \boldsymbol{X_{it}\gamma} + u_{it} \tag{2.1}$$

where y_{it} is the vaccination rate in country (county) i at year t, G_{it} is per capita income, α_i and μ_t are respectively country- (county-) and year-fixed effects, $\boldsymbol{X_{it}}$ is a vector of controls, and u_{it} is the unobserved error term. The quadratic and cubic terms of income are included to capture any non-linear relationship between per capita income and vaccination rates. In addition to this cubic function regression, I also estimate a model with dummy variables corresponding to each 10,000 USD income range for per capita income. This dummy variable regression is more flexible than the cubic function regression, so the comparison between the two results will allow me to examine how well the cubic function approximates the underlying relationships.

As discussed in the introduction, the key in this equation is the inclusion of country- (county-) and year-fixed effects. These fixed effects, however, do not control for factors that vary over time in a country-specific (county-specific) manner. If such factors are correlated with vaccination rates and per capita income, parameter estimates may still suffer from omitted variable bias. To mitigate this concern, I also control for demographic variables in my estimation. For the country-level analysis, I include the total population, the shares of population aged 15-64 and over 65, the share of female population, the share of rural population, and population density collected from the World Development Indicator. For the county-level analysis, I include the total population, the shares of people between 14-65 and above 65, the share of male population, the shares of white, black and native Indian population, and population density collected from the Census.[17] [18]

For the individual-level analysis, I use the linear probability model given by:[19]

$$y_{ijt} = \alpha_{jt} + \beta_1 G_{ijt} + \beta_2 G_{ijt}^2 + \beta_3 G_{ijt}^3 + \boldsymbol{X_{ijt}\gamma} + u_{ijt} \tag{2.2}$$

where y_{ijt} is a binary variable indicating whether a child i in state j is up-to-date with a vaccine schedule at year t, G_{ijt} is per capita family income, α_{jt} is the state-year-fixed effect, $\boldsymbol{X_{ijt}}$ is a vector of controls, and u_{ijt} is the unobserved error term. As the data is repeated cross-section data, no individual-level fixed effects are included.

The inclusion of state-year-fixed effects is key in this estimation because they will control for any state-level public health policy and demographic condition in each year that can affect vaccination rates. Also, the state-level prevalence of each disease is captured by these fixed effects.[20] In addition, a number of individual-level characteristics are controlled in the estimation. These characteristics may affect vaccination decisions and per capita income in various ways. For example, consider the age of the mother. It is natural that the age is positively related to income. At the same time, a higher age may mean more experience as a mother and more knowledge about vaccination, which will affect her vaccination decisions for her children. A similar logic can be applied to other characteristics. Therefore, I control for household characteristics (number of household members, number of children less than 18

[17] Disease prevalences are not included as an control variable mainly because they are likely to be an outcome of income. Controlling for outcome variables will induce selection bias in the estimation.

[18] Although the degree of income inequality is likely to affect vaccination rates, I do not include the Gini coefficient as a control variable due to its large numbers of missing observation. When the Gini coefficient is added to the regression, they are only marginally significant, with economically negligible effects on vaccination rates.

[19] I prefer the linear probability model because Probit and Logit models may suffer from the incidental parameter problem. Probit and Logit models that include only state- and year-fixed effects (but not state-year-fixed effects) give very similar results.

[20] Several papers show that the state-level disease prevalence, the mortality or the length of the previous flu season, as a proxy for the subjective risk of infection, affect people's vaccination behaviours (Li et al. 2004; Ahituv et al. 1996; Philipson 1996; Mullahy 1999).

years old, language with which interview was conducted, state of residence of child at birth versus current state, relationship of respondent to child), mother's characteristics (education, age, marital status) and child's characteristics (age, gender, first born status, race/ethnicity, Hispanic origin) in the estimation.[21]

2.4 Summary statistics

Table 2.1 shows summary statistics of the three datasets. For the country-level data, the mean vaccination rate is highest for Hib3, followed by Pol3 and DTP3. HepB3 and Hib3 have a relatively small number of observations because the dataset dose not include these vaccines in the 1980s. BCG also has a smaller number of observations because many developed countries do not use this vaccine any more.

For the county-level data, the average vaccination rates are higher for most of the vaccines when compared to the country-level dataset. The two vaccines that are not included in the country-level dataset, VRC and PCV4, have a relatively low vaccination rate and a high variance. While per capita income in the country-level dataset ranges between $1,800 - $86,000, per capita income in the county-level dataset ranges from $15,000 to $110,000. Therefore, as compared to the country-level dataset, the county-level dataset include less observations in the low income range while it includes more observations in the high income range.

For the individual data, the mean rates vary across vaccines, ranging from >90 percent for MCV and Pol to 66 percent for ROT. This seems to partially reflect the fact that the

[21] A child's insurance status is not included in the estimation, because the insurance is likely to be an outcome of the family income and hence controlling for it will induce a selection bias. To see this, suppose that conditional on fixed effects and other control variables, income is as good as randomly assigned across families. Then, the OLS estimation can identify the causal effect of income on vaccination. Once we control for the insurance status, however, this is no longer the case because comparison is made across families with the same insurance status, within which income is not necessarily as good as random. This is because the insurance choice reflects not only income difference but also many factors such as ability. Thus, the comparison within the same insurance group gives us the mixture of the effect of income and the effect of ability, even though the income is randomly assigned across all the families.

Table 2.1: Summary statistics

Variable	N	Mean	SD	Min	Max
Country-level data:					
3rd dose of Pol	2034	89.46	12.53	11.00	99.00
3rd dose of DTP	2030	88.34	13.56	11.00	99.00
1st dose of BCG	1154	88.13	18.09	3.00	99.00
1st dose of MCV	1990	85.70	16.15	4.00	99.00
3rd dose of Hib	964	90.45	13.13	2.00	99.00
3rd dose of HepB	938	86.87	19.06	1.00	99.00
Per capita income	2178	2.028	1.555	0.18	8.61
County-level data:					
3rd dose of Pol	1287	90.94	2.64	78.10	96.80
4th dose of DTP	1287	84.18	4.40	66.20	97.00
1st dose of MMR	1287	91.80	2.13	82.80	96.60
3rd dose of Hib	1287	92.81	2.20	79.20	97.30
3rd dose of HepB	1287	88.19	6.62	47.10	96.60
1st dose of VRC	1099	72.00	20.75	16.10	96.50
4th dose of PCV	556	61.31	17.11	17.70	91.00
Per capita income	2946	3.562	0.874	1.472	10.84
Individual-level data:					
3rd dose of Pol	161002	93.30	24.99	0	100
4th dose of DTP	161002	85.48	35.22	0	100
1st dose of MCV	161002	92.58	26.20	0	100
3rd dose of Hib	161002	91.93	27.22	0	100
3rd dose of HepB	161002	92.01	27.11	0	100
1st dose of VRC	161002	89.61	30.50	0	100
4th dose of PCV	161002	78.68	40.95	0	100
3rd dose of ROT	92501	65.67	47.47	0	100
Per capita income	161002	1.037	0.66	0	3.75

Note: The couontry-level dataset includes 70 countries during the period 1980-2014. The county-level dataset includes 229 counties during the period 1995-2008. The individual-level dataset includes the period 2005-2014. Per capita income is presented in $10,000 in 2005. Pol: Polio vaccine, DTP: Diphtheria toxoid, tetanus toxoid and pertussis vaccine, BCG: Bacille Calmette Guerin vaccine, MCV: Measles-containing vaccine, Hib3: Haemophilus influenzae type B vaccine, HepB: Hepatitis B vaccine, VRC: varicella (chickenpox) vaccine, PCV: pneumococcal conjugate vaccine, ROT: rotavirus vaccine rota virus vaccine was introduced in 2006 and the up-to-date variable for the vaccine became available in 2009 in the public-use data file. ROT vaccine has a very high variation while MCV and Polio vaccine have a relatively small variation. The lowest value of per capita income is \$0, which reflects the fact that I assign 0 income to families in the lowest income bin. The highest value of per capita income is \$37,500, which reflects the fact that the family income is top-coded at \$75,000 and each family has at least one parent and one child.

In both country- and county-level data, the variations in the vaccination rates between and within regions are similar in magnitude. Therefore, the identification is driven by both the variations for a given region over time and the variations across regions for a given year. The variations in the country level dataset is, however, larger by an order of magnitude relative to those in the county level dataset. While the mean vaccination rates are similar across these datasets, the standard deviations in the country-level data are around 10 for all the vaccines, while those in the county-level data are less than five for four vaccines. This leads to a coefficient of variations of approximately 18% for the country-level dataset, as opposed to approximately 5% for the county-level dataset. This small variation in the county-level dataset is due, in part, to the small number of counties in this dataset.

In the case of the individual-level dataset, since I control for state-year-fixed effects, the identification is driven by within-state-year variations in the vaccination rates. In each state-year cell, the mean probabilities of being up-to-date with a vaccination schedule range around 0.8-0.9 while the standard deviations range around 0.2-0.4, which leads to a coefficient of variation of around 45-50%. Therefore, sufficient variations exist to estimate the parameters in this dataset.

2.5 Result

2.5.1 Country-level result

The OLS estimates for each of the six vaccines are reported in Table 2.2. Per capita income variables are separately not significant for most of the vaccines, because they are highly correlated with each other. This means that conditional on other income variables, each income variable does not have much information to explain the vaccination rate. They are, however, jointly significant at the conventional level, which means they jointly have enough information. One exception is HepB3 with the p-value being 0.809. For each vaccine, the point estimates for the income variables exhibit both positive and negative signs, indicating a potential non-monotonic relationship between vaccination rates and per capita income. To see this, suppose that per capita income increases by $\$1,000$. For Pol3, other things being equal, this will increase the vaccination rate by 1.18 points if per capita income is $\$5,000$, but will decrease it by 0.07 points if per capita income is $\$30,000$. Similarly, for BCG, this will increase the vaccination rate by 0.81 points if per capita income is $\$5,000$, but will decrease it by 0.27 points if per capita income is $\$30,000$. As for the control variables, there is no clear pattern across vaccines as to which variables affect vaccination rates.

Table 2.2: Estimation results, Cross country

	Pol3	DTP3	BCG	MCV	Hib3	HepB3
Income	14.240	7.861	10.108	14.231	31.654	13.966
	(8.560)	(8.530)	(12.883)	(9.745)	(14.843)	(19.913)
Income squared	-3.165	-0.787	-1.979	-3.202	-8.209	-3.794
	(1.966)	(2.363)	(3.235)	(2.392)	(3.392)	(4.525)
Income cubed	0.149	-0.047	-0.037	0.186	0.531	0.283
	(0.153)	(0.200)	(0.236)	(0.182)	(0.229)	(0.309)
N	2034	2030	1154	1990	964	938
Countries	65	65	42	65	63	56
P(G=0)	0.003	0.053	0.000	0.031	0.042	0.809
R2	0.400	0.488	0.506	0.586	0.309	0.377
RMSE	8.232	8.027	7.705	9.074	9.169	12.004

Notes: Income is in \$10,000. Standard errors are clustered at the country level. All the specifications include country- and year-fixed effects, and demographic control variables. P(G=0) shows p-values for the joint test of income variables.

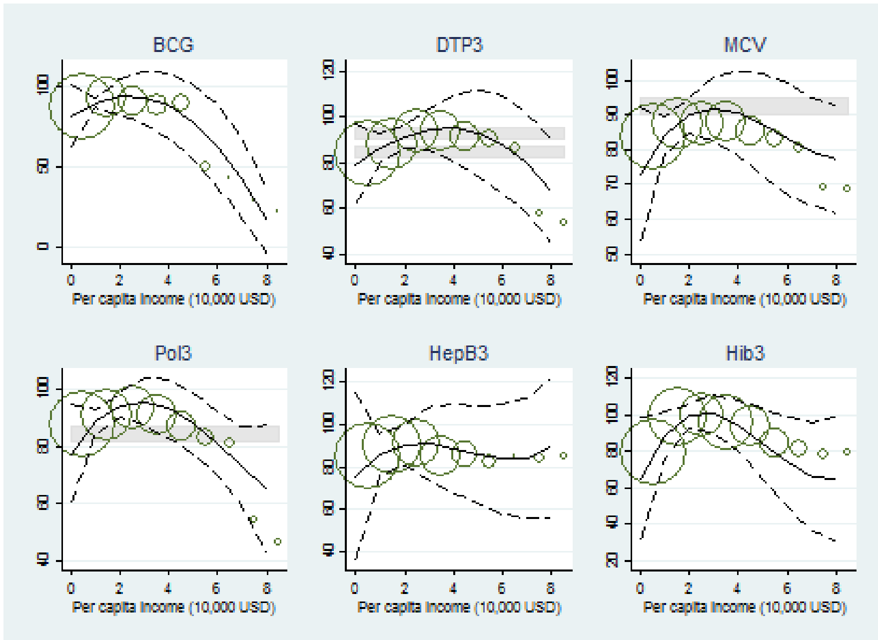
To understand the relationship between vaccination rates and per capita income, I calculate the predicted vaccination rates for an "average country" that takes the average value for the fixed effects and control variables. The predicted vaccination rate is given by (Grossman & Krueger 1991):

$$\hat{y_{it}} = \bar{\alpha_i} + \bar{\mu_t} + \bar{\boldsymbol{X}}\hat{\boldsymbol{\gamma}} + \hat{\beta}_1 G_{it} + \hat{\beta}_2 G_{it}^2 + \hat{\beta}_3 G_{jt}^3 \tag{2.3}$$

where $\bar{\alpha_i}$ and $\bar{\mu_t}$ are respectively the average value of country- and year-fixed effects, $\bar{\boldsymbol{X}}$ is a vector of the average value of control variables, and $\hat{\beta}_i$ $(i = 1, 2, 3)$ is the estimated parameter value. The relationships between the predicted vaccination rate and per capita income are presented in Figure 2.4. The solid lines show the predicted rates from the cubic function regression while circles show the predicted rates from the dummy variable regression. The size of the circles are proportional to the relative number of observations in each income range. The shaded areas correspond to the estimates for the herd immunity threshold for measles (90-95%), polio (82-87%), pertussis (90-95%), and diphtheria (82-87%) provided in Anderson & May (1991).

The graphs show that the predicted vaccination rates follow a hump-shaped curve as per capita income increases for all the vaccines. The predicted rates from cubic and dummy regressions coincide very precisely, suggesting that the cubic function is a good approximation for the underlying relationship between vaccination rates and per capita income. Moreover, the size of these circles indicate that the hump shape is not simply driven by a small number of observations in the high-income range. Vaccination rates for BCG, MCV, Pol3, HepB3 and Hib3 peak around $30,000 while that for DTP3 starts declining at around $40,000. In percentage terms, the turning points are around 35-45 percent of the maximum income in the sample. More importantly, the predicted vaccination rates fall below the herd immunity thresholds at around $50,000 for pertussis and polio, which is a modest income level as many countries are expected to reach this level within a decade or two. As for measles, the

Figure 2.4: Vaccination rates and GDP per capita conditional on fixed effects and controls: Cross country data



Notes: Simulated vaccination rates are obtained by first regressing actual vaccination rates on income, fixed effects and controls, and then calculating predicted values fixing the value of these fixed effects and controls at their means. The solid line is the mean predicted rate while the dashed lines show 95 percent confidence interval from the regression with the cubic function of income. Each circle shows the predicted vaccination rate from the regression with dummy variables corresponding to each $10,000 income range. The size of each circle is proportional to the relative number of observations in each income range. The shaded areas correspond to the estimates for the herd immunity threshold provided in Anderson & May (1991): diphtheria (82-87%), pertussis (90-95%), polio (82-87%), and measles (90-95%).

vaccination rate barely reaches the threshold level and starts decreasing.

2.5.2 County-level result

The estimation results are found in Table 2.3. Per capita income variables are jointly significant for all the vaccines at the conventional level. Two exceptions are Pol3 and Hib3. While Hib3 is significant at the 0.15 level (p-value: 0.114), Pol3 is not significant at all (p-value: 0.916). Again for all the vaccines, the point estimates for income variables exhibit both positive and negative signs, indicating a potential non-monotonic relationship between vaccination rates and per capita income. To see this, suppose per capita income increases by $1,000. For MMR1, other things being equal, this will lead to an increase in the vaccination rate by 0.17 points when per capita income is $20,000, but will lead to a decrease by 0.1 points when per capita income is $50,000. Similarly, for HepB3, this will lead to an increase in the vaccination rate by 0.39 points when per capita income is $20,000, but will lead to a decrease by 0.24 points when per capita income is $50,000.

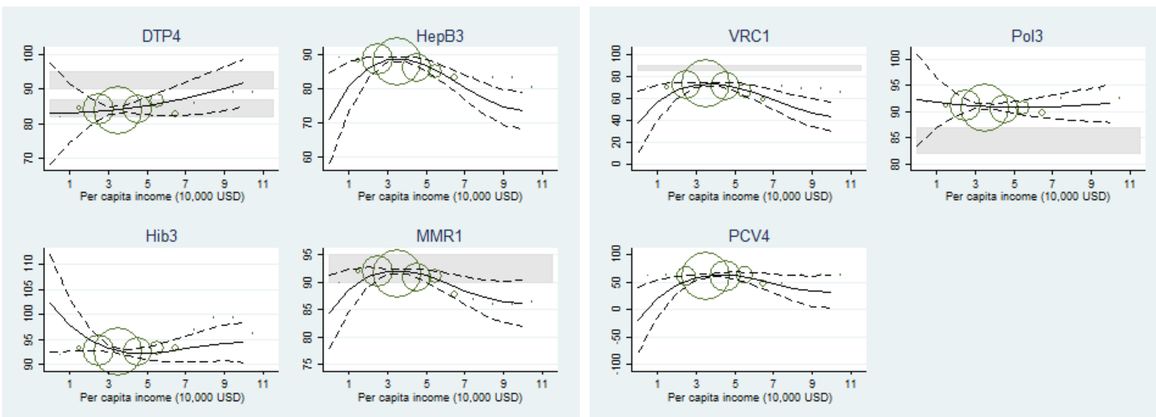
Table 2.3: Estimation results, US county

	Pol3	DTP4	MMR1	Hib3	HepB3	VRC1	PCV4
Income	-0.538	-0.018	5.000	-5.056	11.432	21.726	46.622
	(2.386)	(3.610)	(1.851)	(2.742)	(3.688)	(7.706)	(16.645)
Income squared	0.056	0.090	-0.981	0.790	-2.203	-3.987	-7.962
	(0.399)	(0.530)	(0.310)	(0.470)	(0.614)	(1.252)	(2.747)
Income cubed	-0.001	-0.000	0.050	-0.036	0.108	0.187	0.382
	(0.021)	(0.025)	(0.016)	(0.025)	(0.031)	(0.061)	(0.132)
N	1287	1287	1287	1287	1287	1099	556
Counties	229	229	229	229	229	229	229
P(G=0)	0.916	0.046	0.004	0.114	0.000	0.000	0.040
R2	0.470	0.353	0.236	0.328	0.847	0.958	0.942
RMSE	1.536	2.251	1.367	1.380	2.436	3.966	3.633

Notes: Income is in $10,000. Standard errors are clustered at the county level. All the specifications include county- and year-fixed effects, and demographic control variables. P(G=0) shows p-values for the joint test of income variables.

Figure 2.5 shows the predicted vaccination rates for an average county and the estimates for the herd immunity thresholds for diphtheria (82-87%), pertussis (90-95%), chickenpox (85-90%), polio (82-87%), and measles (90-95%), provided in Anderson & May (1991). Because the majority of the counties in the sample is concentrated in the middle income range, the predictions from the cubic and dummy regressions do not coincide very well in the lower and upper income ranges. Nonetheless, a careful examination reveals that both regressions suggest that vaccination rate peak in the middle income range for HepB3, MMR1, VRC1 and PCV4. The turning points for these vaccines are around $40,000. In percentage terms, the turning points are around 35 percent of the maximum income in the sample, which is similar to those found in the country-level analysis. Alternatively, DTP4 monotonically increases with income and Hib3 show a U-shape curve while Pol3 shows a flat curve. Therefore, the results are not as consistent across vaccines when compared to those in the country-level analysis in the previous section. Even so, it is assuring that four out of seven vaccines show a hump-shaped relationship with per capita income, the same pattern that was found at the country level. In terms of herd immunity, the predicted vaccination rate starts decreasing without reaching the herd immunity threshold level for chickenpox, and it falls below the herd immunity threshold at around $50,000 for measles. In contrast, it is stable and above the threshold level for polio. The rate is above the threshold for diphtheria at all the income range, while it reaches the threshold level at above the per capita income of $10,000 for pertussis.

Figure 2.5: Vaccination rates and per capita income conditional on fixed effects and controls: US county data



Notes: Simulated vaccination rates are obtained by first regressing actual vaccination rates on income, fixed effects and controls, and then calculating predicted values fixing the value of these fixed effects and controls at their means. The solid line is the mean predicted rate while the dashed lines show 95 percent confidence interval. Each circle shows the predicted vaccination rate from the regression with dummy variables corresponding to each $10,000 income range. The size of each circle is proportional to the relative number of observations in each income range. The shaded areas correspond to the estimates for the herd immunity threshold provided in Anderson & May (1991): diphtheria (82-87%), pertussis (90-95%), chickenpox (85-90%), polio (82-87%), and measles (90-95%).

2.5.3 Individual-level result

The estimation results are shown in Table 2.4. The income variables are jointly significant at the conventional level for all the vaccines. Again, the point estimates for the income variables exhibit both positive and negative signs, indicating a potential non-monotonic relationship between the probability of beingup-to-date and per capita income. In terms of the control variables, they indicate that the probability of a child being up-to-date is higher if the child is older, if the number of children in the family is smaller, if the interview was conducted in Spanish,[22] if the mother has a higher education, and if the family lives in the same place as the child was born. It is particularly notable that the mother's education has a monotonic relationship with the probability for all the vaccines; the higher the mother's education, the higher the probability of the child being up-to-date with every single vaccine.

Table 2.4: Estimation results, US individual

	Pol3	DTP4	MCV1	HiB3	HepB3	VRC1	PCV4	ROT3
Income	0.141	2.553	0.333	2.997	0.271	-1.044	6.271	13.833
	(1.363)	(1.877)	(1.356)	(1.506)	(1.393)	(1.462)	(2.103)	(3.169)
Income squared	0.316	0.819	0.476	-0.477	0.922	1.673	-0.422	-5.849
	(1.089)	(1.478)	(1.084)	(1.229)	(1.141)	(1.168)	(1.696)	(2.717)
Income cubed	-0.037	-0.382	-0.114	-0.108	-0.280	-0.340	-0.248	1.029
	(0.256)	(0.341)	(0.255)	(0.297)	(0.278)	(0.275)	(0.404)	(0.671)
N	161002	161002	161002	161002	161002	161002	161002	92501
P(G=0)	0.044	0.000	0.014	0.000	0.005	0.000	0.000	0.000
R2	0.024	0.055	0.024	0.045	0.020	0.025	0.096	0.107

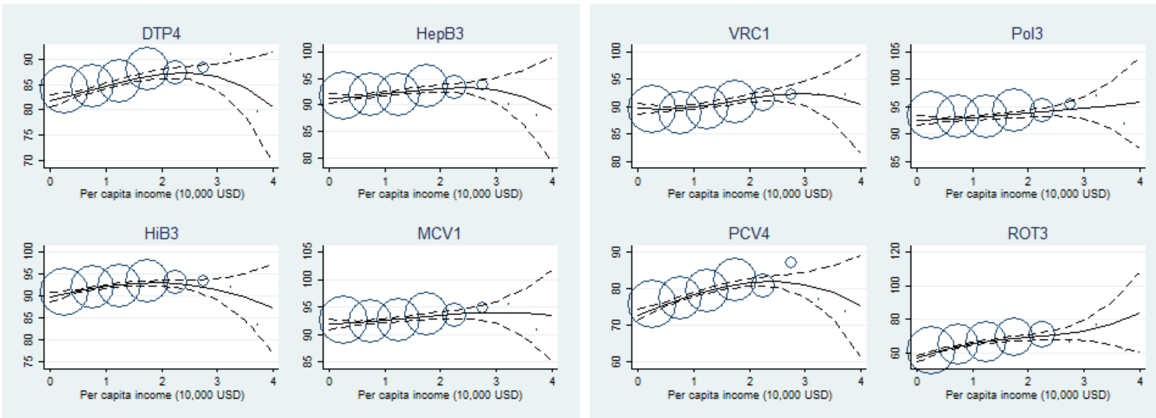
Notes: Income is in $10,000. All the specifications include state-year-fixed effects and other control variables. P(G=0) shows p-values for the joint test of income variables.

The relationships between the predicted probability of being up-to-date and per capita income are presented in Figure 2.6. The graph shows that the mean predicted probability of being up-to-date monotonically increases with income for Pol3 and ROT3 for the entire income range. Alternatively, for other six vaccines, it shows that the probability of being up-to-date initially rises but then falls as per capita income increases. The turning points are around $20,000-$30,000. As the income data is top-coded in this dataset, the turning points are not directly comparable to those in the country- and county-level analysis. The upper bound of the 95 percent confidence interval, however, actually rises as income increases, making it hard to draw a decisive conclusion about the behaviour of the probability in the high income range. This comes partly from the fact that the income is top-coded in this dataset so that I do not have many observations in the high income range, as can be seen the size of the circles in the high income range. Yet, the fact that a hump shape is observed in six out of eight vaccines is suggestive that the probability indeed decreases in the high

[22] Fry (2011) finds the same result but does not provide any interpretation.

income range for some vaccines.

Figure 2.6: Probability of being up-to-date with a vaccine and per capita income conditional of fixed effects and controls: US individual data



Notes: Simulated vaccination rates are obtained by first regressing actual vaccination rates on income, fixed effects and controls, and then calculating predicted values fixing the value of these fixed effects and controls at their means. The solid line is the mean predicted rate while the dashed lines show 95 percent confidence interval. Each circle shows the predicted vaccination rate from the regression with dummy variables corresponding to each $10,000 income range. The size of each circle is proportional to the relative number of observations in each income range.

2.5.4 Discussion

In this section, I used three datasets to examine the relationship between per capita income and childhood vaccination rates. First, the country-level dataset showed that vaccination rates initially rise but then fall as income increases. The analysis demonstrated that vaccination rates peak around the per capita income of $30,000 - $40,000, and fall below the herd immunity at modest income levels for many diseases. Recognizing that the highly aggregated nature of the country-level data is a potential concern, I then moved on to the U.S. county-level data to examined if similar results can be obtained. Among the seven vaccines examined, I found that four of them again show a rise and fall in vaccination rates as income increases. This county-level result adds more credibility to my country-level result. Finally, I investigated the U.S. individual-level data and found that the probability of a child being up-to-date is lower in both low and high income ends for many vaccines. Taken together, several findings are in order: First, vaccination rates first rise but then fall with income. Second, vaccination rates fall below the herd immunity threshold levels for many diseases at a modest income range. Third, this is a global phenomenon. Four, both low- and high-income parents are less likely to vaccinate their children. Finally, the specific income/vaccination profile varies by vaccines/diseases.

There may, however, appear to be some inconsistency across the results from the three analyses. First, while the country-level results suggest that the vaccination rates and income have a hump-shaped relationship for all the vaccines, the county-level results suggest that DTP, Pol, and Hib do not exhibit such a relationship. Recall, however, that the country-level dataset consists of 70 countries while the county-level dataset consists only of US counties. As the relationship between income and vaccination rates is likely to vary by regions, the different results in country- and county-level analyses merely suggest that the relationship is different across 70 countries than it is within the US counties. For example, if a region is densely populated, the vaccination rate may not decline as the region becomes richer, due to the high probability of disease outbreaks in the region. As well, if public health policies are successful in raising the publics interest in vaccination, the vaccination rate may not decline, either. Therefore, the different results across these two analyses are likely to reflect these differences across countries.

Second, although the individual and county level analyses overall show similar results, there are some differences, too. For Pol, both analyses find a flat relationship between the vaccination rate and income. For HepB, VRC, MMR, and PCV, both analyses find a similar hump-shaped relationship between vaccination rates and income. In contrast, for DTP and Hib, the individual level analysis finds a hump-shaped relationship for both vaccines, while the county-level analysis shows a monotonic increase for DTP and a somewhat U-shaped relationship for Hib. Because these two datasets are both from the US, it is somewhat puzzling to find these differences.

To understand these results, notice first that the individual- and population-level analyses for the same population may not necessarily find the same relationship between income and the vaccination rate. The reason is that when aggregating up the individual-level results to the population level, the form of the income distribution and how it changes as the population becomes richer matter. For example, suppose that the income distribution becomes more skewed to the right as the population becomes richer. In this case, even if the individual-level analysis finds that the probability of being up to date with a vaccination schedule rises and falls with income, the population level analysis may find a monotonic increase in the vaccination rate with income, because the fraction of high income agents who do not vaccinate does not increase as the populations income increases.

Keeping this in mind, the real puzzle here is that although the income distribution and how it changes with income are common across vaccines, some vaccines exhibits a hump shape at both individual and county levels while DTP and Hib exhibit a different pattern across these two levels. One possibility is that the decrease in the probability of being up to date with a vaccination schedule for DTP and Hib may not decline at the high-income end as much as other vaccines. Due to the top coding of the income in the individual-level dataset, it is difficult to assess how much the probability actually falls. If the fall in the probability is small, the vaccination rate at the county level may not fall at the high-income end. Another possibility is that the peak probability of being up to date for DTP and Hib may exist at higher income levels than other vaccines. Again, due to the top coding, such income levels are difficult to assess from the data in hand. If these peaks exist at higher income levels, it is possible that the small county-level dataset I use does not capture the decreasing part of the vaccination rates for these vaccines.

It is also important to note that the size of the non-vaccinators in the low and high income ends change with these disease and vaccination characteristics. For example, when medical care becomes less effective, there are less non-vaccinators in the high income range because the NV curve becomes flatter and the vaccination bracket expands to the right. The intuition is that since the benefit of medical care increases with income while the cost of medical care is constant, a higher income is required for medical care to be useful if the cost is higher. In an extreme case, the non-vaccinators in the high income range disappear, because the intersection between theV and NV curves occur at y¿ymax. Following the same logic, we may not observe the high-income non-vaccinators for highly infectious diseases. In Sakai (2016), I use data in the US to show that the fraction of children who are up-to-date with a vaccination schedule typically declines at the high income end. Two exceptions to this pattern are the rota virus vaccine and the polio vaccine. As the rota virus is extremely infectious while there is no effective treatment for polio, the data pattern for these vaccines seems consistent with the model prediction.

2.6 Potential mechanisms

The results indicate that both low- and high-income parents are less likely to follow the standard vaccination schedule for their children, and that these parents' behaviours are indeed a threat to the population. Low-income parents do not vaccinate their children presumably because of their limited financial resources, which makes it difficult to follow the schedule. It is, however, somewhat puzzling that high-income parents do not vaccinate. A potential explanation is, simply, that high income parents have a different information set. For example, high-income parents may perceive the risk of vaccination side effects to be larger, when compared to middle-income parents. Alternatively, high-income parents may better understand the concept of herd immunity and are more likely to take advantage of it. Either way, different information sets may be a reason why high-income parents are less likely to vaccinate. For this to be true, however, we need more than just different information sets. Rather, we need parents at some income levels to be systematically misinformed; otherwise we should not observe different behaviours across income groups on average. Such a systematic misinformation across income groups is possible but somewhat doubtful. Therefore, more plausible explanations should assume no differential information sets. There are at least three such possibilities: avoidance measures, medical care, and social segregation.

First, it is possible that high-income parents use avoidance measures to reduce the risk of infection; the limited literature suggests this as a potential mechanism. For example, Yang et al. (2016) mention protective parenting techniques as a potential substitute for vaccination. Reich (2014) finds that mothers who chose not to vaccinate their children think that they can minimize the risk of infection through breast feeding, organic food, and careful monitoring of their children's social interactions. Also, a popular book for vaccine-hesitant parents recommends natural foods, immune-boosting supplements, breastfeeding, and avoiding daycares and nurseries (Sears 2011). There is no clear evidence as to the effectiveness of these avoidance measures; however, as long as parents believe these measures are sufficiently effective, they may choose these avoidance measures over vaccination.[23] [24]

Second, high-income parents may have better access to medical technologies that treat or mitigate disease symptoms. While the infectious diseases analyzed in this paper are potentially fatal, medical treatment and/or supportive measures can help avoid fatality. For example, haemophilus influenzae type B, pneumococcus, diphtheria, tetanus, pertussis, hepatitis B, and chickenpox are treated using antibiotics or anti-viral drugs. Although there is no cure for polio, measles, mumps, rubella, and the rota virus, supportive measures can still be used to mitigate disease symptoms. In addition, early diagnosis and treatment are more desirable. Thus, having better access to these medical services allows parents to minimize the consequence of these diseases. In the working paper version (Sakai 2016), I provide a simple model of parents' vaccination decision where they have access to medical care in the event of an infection. The model shows that if the medical care is expensive but sufficiently

[23] I do not exclude the possibility of misinformation or misbeliefs that is common across parents.

[24] In a related context, the literature shows that people do not always use avoidance measures to reduce the risk of infection. Under certain circumstances, the marginal benefit of avoidance measures decreases with the disease prevalence, and people use less avoidance measures in response to higher risk of infection. This possibility is known as fatalism and examined in detail by Kremer (1996) and Auld (2003, 2006).

effective—or so parents believe—we should find that middle-income parents vaccinate while high-income parents do not.[25][26]

The third explanation is related to the first two. That is, high-income parents may live in an area where the (subjective) risk of infection is lower or the access to medical facilities is better. It is well documented that people are geographically segregated according to their socioeconomic status, including income (e.g. Massey et al. 2009). As the transmission of infectious diseases is affected by demographic and environmental factors such as population density, temperature, airflow and humidity, the risk of infection must vary by region. At the same time, the quality of medical services are likely to be better in high-income areas. Therefore, these geographical differences may explain the different vaccination decisions across income groups. Being aware of this possibility, I include state-year-fixed effects in my estimation to control for state-level geographical segregation. This should control for the subjective risk of infection as long as it is perceived as common within each state in a given year. It is, however, possible that geographical segregation within each state in a given year exists and affects parents' vaccination decisions. To examine this possibility, we need to compare families within a smaller geographical unit such as counties or cities. The smaller the geographical unit, it is more likely that the risk of infection is common across families in the same unit.[27]

Given these potential mechanisms, we may be able to explain some of the empirical

[25] Although I am discussing the parents' vaccination decision as an independent decision in this section, it is interdependent across families because others' vaccination decisions affect a family's decision through the change in the risk of infection. Thus, a formal model should take such an interaction into account as in Sakai (2016).

[26] To examine this possibility, one way is to conduct the same analysis in regions with high and low medical standards and compare these results. If medical care is the reason for not to vaccinate, high income families who live in regions with low medical standards are more likely to vaccinate than high income families who live in high medical standards.

[27] By extending the same logic, it is clear that (non-geographical) social segregation can also lead to non-vaccination at the high income end. For example, high-income families may socialize mainly with high-income families in places where population density is low and hence the risk of infection is low. This cannot be controlled by region-fixed effects even if the geographical unit is small. This segregation mechanism, however, will not bring the probability of a child being up-to-date with vaccine schedules all the way to zero, because eventually the decreasing risk from segregation is offset by the increasing risk from being surrounded by unvaccinated children.

results. Recall that the individual-level analysis showed that, among the eight vaccines, polio and rota virus vaccines do not exhibit a decrease in the probability of a child being up-to-date at the high income end. This may be reasonable for two reasons. First, the rota virus is highly infectious, and thus avoidance measures are unlikely to be effective. Second, there is no cure for both polio and rota virus. Therefore, if avoidance measures and medical care are the reason for high-income parents to choose not to vaccinate their children, it makes sense that they decide to vaccinate against rota virus and polio. In order to interpret the population-level results, we need to consider not only the individual-level behaviours but also the income distribution within a population and how economic development affects it. This may be the reason why there are some difference in the US county-level and US individual-level results.

2.7 Conclusion

The occasional outbreak of various diseases remains a serious public health concern in even the most developed countries. The main cause of these outbreaks is that vaccination rates are not high enough to achieve herd immunity. Commonly, low vaccination rates were thought to be a result of low income people having limited access to medical facilities. While this is surely true, more recently, there is a growing recognition that certain high income groups choose not to vaccinate their children. The aim of this paper was to examine whether, and if so, why, there is systematic tendency for high-income parents to choose not to vaccinate their children.

Using two population-level datasets and one individual-level dataset, I provided evidence that both low and high income parents are less likely to vaccinate at the individual level, and that such behaviour is reflected in the population level data. In both U.S. and cross-country data, I showed that vaccination rates initially rise but then fall as income increases. More importantly, the data showed that vaccination rates for polio and pertussis fall below their herd threshold levels at modest income levels, while the vaccination rate for measles barely reaches the threshold level and starts decreasing as income increases. Given the significance and universal nature of this phenomenon, I named it the "Vaccination Kuznets Curve (VKC)."

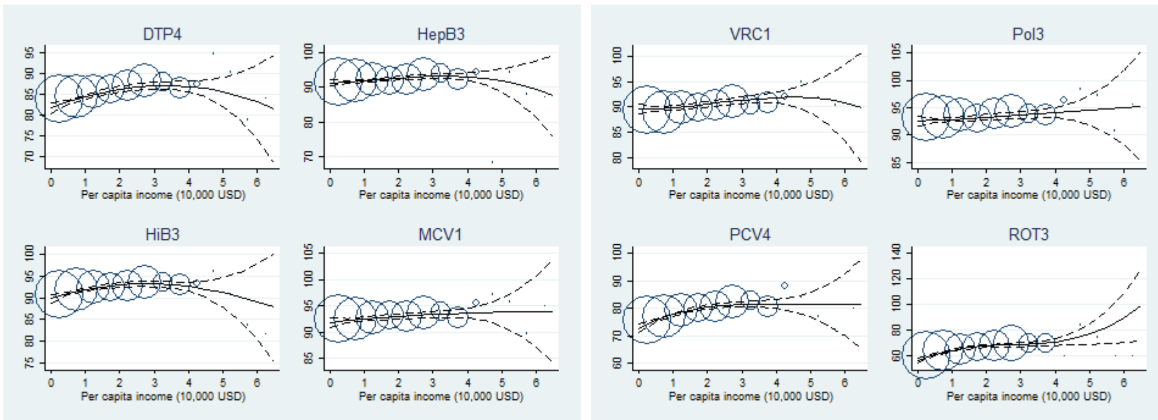
I provided several plausible explanations for the VKC, including avoidance measures, medical care, and social segregation. My explanations are all tied to income; however, it is even possible that the VKC is driven by other region-specific time-varying factors that are correlated with income. Whatever the mechanism, the VKC indicates the possibility that vaccination rates will fall and disease outbreaks will eventually rise in the near future. The raw data has not shown a clear decline in vaccination rates partly because public health authorities have been successful in raising the public's interest in vaccination, but this trend is not guaranteed to continue. In fact, recent outbreaks of childhood diseases, such as measles and pertussis in North America and Europe, may be just the beginning of the wave of further outbreaks, as suggested by this paper.

2.8 Appendix

In the main text, I assigned each family the lower boundary of the income bin as their family income in the individual-level analysis. In this section, I use the mean of each income bin as their family income. Also, I assume a log-normal distribution to obtain the estimate of the mean income of the highest income group, whose income is top-coded.

The result changes only marginally as in Figure 2.7. In the previous result, six out of eight vaccines exhibit a hump-shaped relationship between the probability of being up-to-date and income. The new result shows that five out of eight vaccines show a hump-shaped relationship. The difference is that in the new result, the measles vaccine no longer shows a decline at the high-income end. Thus, the evidence of a hump-shaped relationship at the individual level still exists when assuming a log-normal distribution, although it may seem somewhat weaker than the original result.

Figure 2.7: Probability of being up-to-date with a vaccine and per capita income conditional of fixed effects and controls: US individual data, log-normal distribution



Notes: Simulated vaccination rates are obtained by first regressing actual vaccination rates on income, fixed effects and controls, and then calculating predicted values fixing the value of these fixed effects and controls at their means. The solid line is the mean predicted rate while the dashed lines show 95 percent confidence interval. Each circle shows the predicted vaccination rate from the regression with dummy variables corresponding to each $10,000 income range. The size of each circle is proportional to the relative number of observations in each income range.

Bibliography

Ahituv, A., Hotz, J. V., & Philipson, T. (1996). The responsiveness of the demand for condoms to the local prevalence of aids. *Journal of Human Resources*, 869–897.

Anderson, M. R. & May, M. R. (1991). *Infectious diseases of humans: dynamics and control*. Oxford University Press.

Andreoni, J. & Levinson, A. (2001). The simple analytics of the environmental kuznets curve. *Journal of Public Economics*, *80*, 269–286.

Atwell, E. J., Otterloo, V. J., Zipprich, J., Winter, K., Harriman, K., Salmon, A. D., Halsey, A. N., & Omer, B. S. (2013). Nonmedical vaccine exemptions and pertussis in california, 2010. *Pediatrics*, *132*, 624–630.

Auld, C. M. (2003). Choices, beliefs, and infectious disease dynamics. *Journal of health economics*, *22*, 361–377.

Auld, C. M. (2006). Estimating behavioral response to the aids epidemic. *Contributions in Economic Analysis & Policy*, *5*, 1–29.

Brock, A. W. & Taylor, S. M. (2010). The green solow model. *Journal of Economic Growth*, *15*, 127–153.

Cole, A. M., Rayner, J. A., & Bates, M. J. (1997). The environmental kuznets curve: an empirical analysis. *Environment and Development Economics*, *2*, 401–416.

Copeland, R. B. & Taylor, S. M. (2003). *Trade and the environment: Theory and evidence*. Princeton University Press.

Fine, P. & K Eames, H. D. L. (2011). “herd immunity”: a rough guide. *Clinical Infectious Diseases*, *52*, 911–916.

Fry, J. S. (2011). Barriers to up-to-date pertussis immunization in oregon children. *Scholar Archive*, *594*.

Garrett, L. (1994). *The coming plague: newly emerging diseases in a world out of balance.* Farrar, Straus and Giroux.

Grossman, G. M. & Krueger, A. B. (1994). Economic growth and the environment. *The Quarterly Journal of Economics*, *110*, 353–377.

Grossman, M. G. & Krueger, B. A. (1991). Environmental impacts of a north american free trade agreement. *NBER Working Paper No. 3914*.

Harbaugh, T. W., Levinson, A., & Wilson, M. D. (2000). Reexamining the empirical evidence for an environmental kuznets curve. *Review of Economics and Statistics*, *84*, 541–551.

John, A. & Pecchenino, R. (1994). An overlapping generations model of growth and the environment. *The Economic Journal*, *104*, 1393–1410.

Klevens, M. R. & Luman, T. E. (2001). Us children living in and near poverty: risk of vaccine-preventable diseases. *American Journal of Preventive Medicine*, *20*, 41–46.

Kremer, M. (1996). Integrating behavioral choice into epidemiological models of aids. *The Quarterly Journal of Economics*, *111*, 549–573.

Li, Y.-C., Norton, C. E., & Dow, H. W. (2004). Influenza and pneumococcal vaccination demand responses to changes in infectious disease mortality. *Health services research*, *39*, 905–926.

List, A. J. & Gallet, A. C. (1999). The environmental kuznets curve: does one size fit all? *Ecological Economics*, *31*, 409–423.

Lopez, R. (1994). The environment as a factor of production: the effects of economic growth and trade liberalization. *Journal of Environmental Economics and Management*, *27*, 163–184.

Massey, S. D., Rothwell, J., & Domina, T. (2009). The changing bases of segregation in the united states. *The Annals of the American Academy of Political and Social Science*, *626*, 74–90.

Mullahy, J. (1999). It'll only hurt a second?: Microeconomic determinants of who gets flu shots. *Health Economics*, *8*, 9–24.

Philipson, T. (1996). Private vaccination and public health: An empirical examination for us measles. *Journal of Human Resources*, 611–630.

Reich, A. J. (2014). Neoliberal mothering and vaccine refusal imagined gated communities and the privilege of choice. *Gender & Society*, 0891243214532711–0891243214532711.

Sakai, Y. (2016). The vaccination kuznets curve: Rise and fall of vaccination rates with income. *University of Calgary, Graduate Student Working Paper Series*, *01-2016*.

Sears, W. R. (2011). *The vaccine book: making the right decision for your child*. Little, Brown.

Shafik, N. & Bandyopadhyay, S. (1992). Economic growth and environmental quality: time-series and cross-country evidence. *Policy, research working papers*.

Smith, J. P., Chu, Y. S., & Barker, E. L. (2004). Children who have received no vaccines: who are they and where do they live? *Pediatrics*, *114*, 187–195.

Smith, J. P., Humiston, G. S., Marcuse, K. E., Zhao, Z., Dorell, G. C., Howes, C., & Hibbs, B. (2011). Parental delay or refusal of vaccine doses, childhood vaccination coverage at 24 months of age, and the health belief model. *Public Health Reports (Washington, D.C.: 1974)*, *126 Suppl 2*, 135–146.

Smith, J. P. & Singleton, A. J. (2011). County-level trends in vaccination coverage among children aged 19-35 months: United states, 1995-2008. *Morbidity and mortality weekly report. Surveillance summaries: MMWR / Centers for Disease Control*, *60*, 1–86.

Stokey, L. N. (1998). Are there limits to growth? *International Economic Review*, *39*, 1–31.

Troesken, W. (2014). *The Pox of Liberty: How the Constitution Left Americans Rich, Free, and Prone to Infection*. University of Chicago Press.

Wei, F., Mullooly, P. J., Goodman, M., McCarty, C. M., Hanson, M. A., Crane, B., & Nordin, D. J. (2009). Identification and characteristics of vaccine refusers. *BMC Pediatrics*, *9*, 18–18.

Wu, C. A., Wisler-Sher, J. D., Griswold, K., Colson, E., Shapiro, D. E., Holmboe, S. E., & Benin, L. A. (2008). Postpartum mothers' attitudes, knowledge, and trust regarding vaccination. *Maternal and Child Health Journal*, *12*, 766–773.

Yang, T. Y., Delamater, L. P., Leslie, F. T., & Mello, M. M. (2016). Sociodemographic predictors of vaccination exemptions on the basis of personal belief in california. *American Journal of Public Health*, *106*, 172–177.

Chapter 3

Income, Vaccination Decisions and the Vaccination Rate

3.1 Introduction

Vaccination is considered one of the greatest inventions in human history. It has eradicated smallpox and drastically reduced the incidence of many infectious diseases. A recent report by the World Health Organization (WHO), however, raises growing concern about parents who delay or refuse vaccination for their children, both in developed and developing countries.[1] While conventional knowledge suggests that the ones who do not vaccinate typically belong to a low socioeconomic bracket, anecdotal and empirical evidence indicates that high income parents are also less likely to follow the standard vaccination schedule.[2] Given this reality, how can we understand these parents' vaccination choices and subsequent public health implications?

This paper develops a simple model of vaccination decisions in a population where agents differ only in their exogenous income. While each agent perceives the risk of infection as independent of their decisions, it is endogenously determined by every agent's vaccination choice and the resulting vaccination rate in the population. Using this model, I first derive three conditions under which both low and high income agents do not vaccinate. I then use the model to examine how disease and vaccination characteristics affect the income/vaccination profile within a population. Finally, I introduce additional assumptions about the income distribution to show that the equilibrium vaccination rate may first rise and then fall as the population's income increases.

[1] The report of the SAGE working group on vaccine hesitancy.

[2] See, for example, Wei et al. (2009) Smith et al. (2004, 2011), Yang et al. (2016), and Sakai (2016).

A central challenge in this paper is to understand the vaccination choice of high income parents. One may reasonably argue that higher-income parents behave differently because they have different information or beliefs. In this paper, however, I show that a simple model can explain the vaccination choices of both low and high income parents, even if everyone shares the same information and beliefs.[3] My explanation is tied to substitutes for vaccination: as the income of parents increases, alternative options through which parents can protect their children become available.[4] These options can be either avoidance measures that reduce the risk of infection, or medical care that mitigates disease symptoms. If these alternative options are sufficiently effective–or so parents believe–, high-income parents may decide not to vaccinate their children.

Stated in this way, the point may seem obvious. However, the availability of a substitute for vaccination does not more than offset the cost or the risk of infection. While such a substitute will certainly reduce the benefit of vaccination, it is not clear why the substitute makes non-vaccination the preferable option for high income parents. Another complication is that the risk of infection–which determines the benefit of vaccination–depends on how many parents in the population vaccinate their children. Thus, to understand who does or does not vaccinate, we need to solve everyone's vaccination decision problems at the same time. To do so, I develop a simple model where agents differ in their income and the vaccination rate is endogenously determined. To make my point as clearly as possible, I focus the analysis on medical care as the substitute and assume that the choice of medical care is binary. Agents will face similar trade-offs if an avoidance measure is available instead of medical care. In such a case, however, their decision problems may involve an additional complication known as fatalism in some cases (Kremer 1996; Auld 2003, 2006). I discuss the implication of avoidance in detail in a subsequent section.

[3] I do not exclude the possibility of misinformation and misbelief; people may share the same incorrect information and belief.

[4] Yang et al. (2016) mention such a possibility but do not provide a formal model to support their argument.

The model has three key features. First, it assumes a population that consists of a continuum of agents ("parental units") who have different levels of exogenous income. Heterogeneity in income is required to examine how income affects vaccination decisions, while the continuum assumption keeps the model tractable. Second, it focuses on the trade-off agents face in weighing the risks of side effects and disease. The side effects of vaccination may be mild such as pain and fever, or they may be more serious such as Guillain-Barre Syndrome and other autoimmune reactions. I assume the risk and the duration/symptoms of the side effects are common across all the agents. In contrast, medical care can shorten the duration of the disease or mitigate symptoms. Finally, the model incorporates the opportunity cost of infection and vaccination side effects by assuming that in both of these events, parents have to sacrifice their work time to take care of their sick child. Given that the model represents a game among an infinity of heterogeneous agents, this novel way of introducing the opportunity cost is a useful simplification in determining the equilibrium while capturing the main trade-offs that agents face.

Within this framework, I am able to show why non-vaccination at both tails of the income distribution is a very natural outcome. The model clarifies the roles of two different types of costs involved in vaccination: costs that are common to all the agents and opportunity costs that vary by agents. Common costs such as the price of vaccination, filling in forms, finding medical records, and the transportation costs to a clinic prevent low-income agents from vaccinating. By contrast, opportunity costs are key to understanding why high-income agents may choose not to vaccinate. While both side effects and infection involve opportunity costs, high income agents may mitigate the opportunity cost of infection by using a substitute for vaccination. The model shows the conditions under which non-vaccination at both tails of the income distribution occurs, and how the equilibrium is determined in such a situation. Further, with additional assumptions about the income distribution, I show that the equilibrium vaccination rate may first rise and then fall with economic development.

This alarming prediction is consistent with the empirical regularity found in Sakai (2016), where I label it the Vaccination Kuznets Curve.

Although the formal theoretical analysis of vaccination decisions under income heterogeneity I provide is novel, this paper draws on two branches of the economic epidemiology literature. One branch studies vaccination decisions in a population where agents differ in their cost of vaccination (e.g., Brito et al. 1991; Xu 1999; Kureishi 2009; Chen & Toxvaerd 2014). These papers recognize that the cost of vaccination involves time loss in the event of side effects. It is, then, a natural extension to consider that the cost of infection also involves a similar time loss. By introducing income heterogeneity, this paper analyzes agents' vaccination decisions when both the costs of vaccination and the costs of infection vary by agents through the difference in their value of time.[5]

The other branch studies the dynamics of infectious diseases in a population consisting of forward-looking agents (e.g., Francis 1997; Goldman & Lightwood 2002; Gersovitz & Hammer 2003, 2004; Barrett & Hoel 2007; Toxvaerd 2010a,b). One theme of this literature is to examine how prevention and treatment interact in disease management (e.g., Wiemer 1987; Gersovitz & Hammer 2004; Rowthorn & Toxvaerd 2012). In my model, the substitution between vaccination and medical care interacts with the heterogeneity in income to generate a hump-shaped relationship between income and vaccination decisions.

The empirical literature on vaccination choice is also extensive. While many studies find that low-income people are less likely to vaccinate (e.g., Wu et al. 2008; Klevens & Luman 2001), some studies find that high income is also an obstacle for vaccination (e.g., Wei et al. 2009; Smith et al. 2004, 2011). In addition to these studies based on individual level evidence, there is also population level evidence that vaccination rates are lower in higher income regions (Yang et al. 2016; Atwell et al. 2013). In an accompanying paper (Sakai 2016), I show that after controlling for fixed effects and other control variables, both

[5]In a somewhat different context, Oster (2016) proposes a model of limited information and salience to explain parents' vaccination behaviours.

low and high income parents are less likely to vaccinate within the US. The paper also shows that vaccination rates first rise and then fall with income at the population level both across counties in the US and across countries. The present paper provides the first theoretical model that is both consistent with individual level evidence and also demonstrates a natural link to the population level evidence.

The rest of the paper is organized as follows. In Section 2, I lay out the payoffs of agents with and without vaccination. In Section 3, I then discuss individual vaccination choice and derive three conditions under which both low and high income agents do not vaccinate. While each agent perceives the risk of infection as given, it is determined by every agent's vaccination decisions and the resulting vaccination rate in the population. Thus, in Section 4, I demonstrate how to link agents' vaccination choices to the vaccination rate and find the equilibrium vaccination rate. Section 5 investigates how disease and vaccination characteristics affect the equilibrium vaccination rate and the income/vaccination profile within a population. Section 6 discusses how these individual-level behaviours may generate a rise and fall in the vaccination rate at the population level. Section 7 examines an alternative model that focuses on avoidance measures. Section 8 concludes. All the proofs are in the Appendix.

3.2 Payoffs

Consider the problem of an agent who faces the risk of being infected with a non-fatal virus. The agent has an exogenous income $y \in [0, y_{max}]$, which is the product of the agent's labour productivity y and the fixed work time of 1. The agent decides whether to vaccinate or not, and spends the rest of the income for consumption. Vaccination costs c_v and gives the agent perfect immunity, but it may involve side effects with a probability p_s. In the event of side effects, the agent loses a fraction S of work time, which reduces the agent's income to

$(1-S)y$.[6] Thus, with vaccination, the agent's expected utility $u_v(y)$ is given by:

$$u_v(y) = p_s * u((1-S)y - c_v) + (1-p_s) * u(y - c_v) \tag{3.1}$$

Without vaccination, the agent will contract the disease with a probability p_d. This probability is perceived as given by each agent, even though it is endogenously determined by the vaccination rate in the population. In the event of an infection, the agent loses a fraction D of work time, which reduces the agent's income to $(1-D)y$. If the agent uses medical care with the cost of c_m, however, the loss in work time is reduced to d. Therefore, without vaccination, the agent's expected utility $u_{nv}(y)$ is given by:

$$u_{nv}(y) = p_d * u(y_t(y)) + (1-p_d) * u(y) \tag{3.2}$$

$$y_t(y) = \max\{(1-D)y, (1-d)y - c_m\} \tag{3.3}$$

$$1 \geq D > d \geq 0 \tag{3.4}$$

where $y_t(y)$ is the net income when infected after making the medical care decision.

3.3 Individual choice

An agent's problem is to decide whether to vaccinate or not:

$$u = \max_{v,nv}\{u_v(y), u_{nv}(y)\} \tag{3.5}$$

To make the vaccination decision, the agent first decides whether to use medical care or not in the event of an infection. Because the benefit of medical care is the income it saves $(D-d)y$ while the cost of medical care is c_m, there is a threshold income $\tilde{y} = \frac{c_m}{D-d}$ above which the agent uses medical care. As a result, the net income in the event of an infection is given by:

[6] This S may in principle include the time parents have to sacrifice to take their child to a vaccination clinic. In Eq.(3.1), however, S is modelled as the time loss that only occurs in the event of side effects.

$$y_t(y) = \begin{cases} (1-D)y & \text{if } y < \tilde{y} = \frac{c_m}{D-d} \\ (1-d)y - c_m & \text{if } y \geq \tilde{y} \end{cases} \tag{3.6}$$

Given the medical care decision, the agent decides whether to vaccinate or not by comparing the two expected utilities $u_v(y)$ and $u_{nv}(y)$. Notice that this is essentially a choice between two gambles: one with the risk of side effects and the other with the risk of infection. Thus, the degree of risk aversion is a key parameter. In what follows, I start with the risk neutral case and leave the risk averse case to a subsequent section. The risk neutral case below greatly helps us understand the intuition behind the agent's choices.

3.3.1 Risk-neutral case

When the agent is risk neutral, expected utility becomes expected income given by:

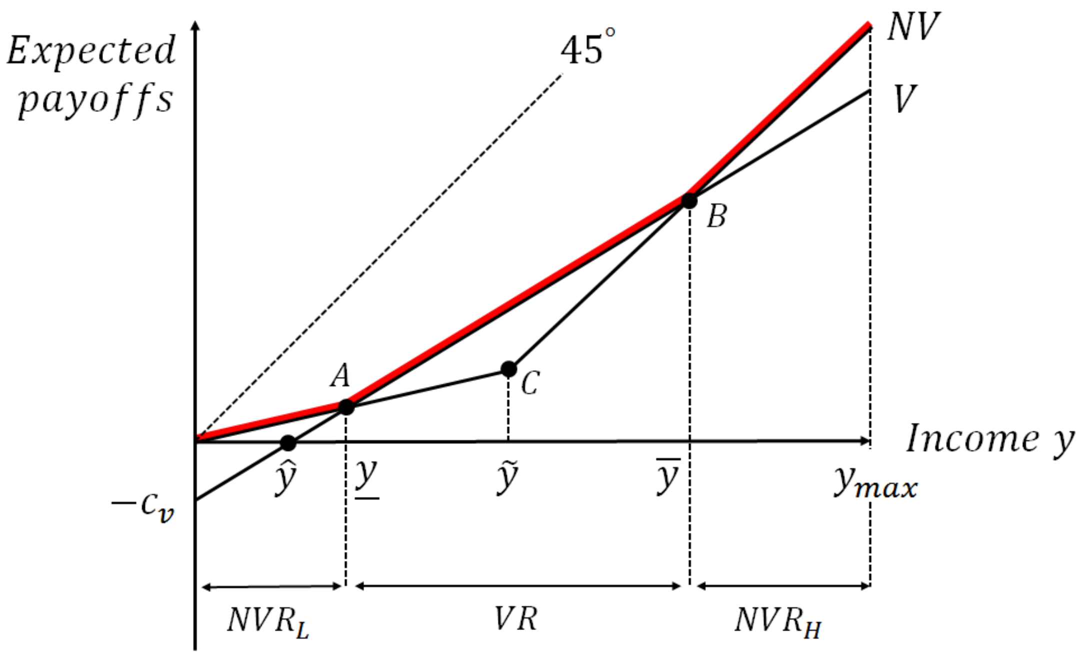
$$u_v(y) = y - p_s S y - c_v \tag{3.7}$$

$$u_{nv}(y) = \begin{cases} y - p_d D y & \text{if } y < \tilde{y} \\ y - p_d d y - p_d c_m & \text{if } y \geq \tilde{y} \end{cases} \tag{3.8}$$

Each payoff is given by the original income minus the expected income loss minus the expected medical expenses. Notice that in the $y-u$ space, $u_v(y)$ is a straight line starting from $(0, -c_v)$ with the slope of $(1 - p_s S)$, while $u_{nv}(y)$ is a broken line starting from the origin with the initial slope of $(1 - p_d D)$ and broken at $y = \tilde{y}$ with the subsequent slope of $(1 - p_d d)$. Figure 3.1 shows a potential relationship between the two payoffs in the $y-u$ space. In the figure, the payoff with vaccination is labelled as the V curve and the payoff without vaccination as the NV curve. The upper contour of the two curves (i.e., red curve) show the individual vaccination choice and the corresponding payoff at each income level. Figure 3.1 depicts the situation where the agent does not vaccinate if the income is lower than $\underline{y}$ or higher than $\bar{y}$. The low income range where the agent does not vaccinate $[0, \underline{y})$ is labelled as NVR_L, the middle income range where the agent vaccinate $[\underline{y}, \bar{y})$ is labelled VR, and the high income range where the agent does not vaccinate $[\bar{y}, y_{max}]$ is labelled NVR_H.

Notice that both V and NV curves are flatter than the 45 degree line, because of the expected income loss from side effects and infection. If there is no opportunity cost for infection and side effects (i.e., $S = D = d = 0$) and the cost of illness is only monetary, both curves would have a slope of 45 degree, which means they would either coincide with each other or never interact in the $y - u$ space.[7] Thus, without these opportunity costs, if vaccination is a preferable choice at a middle income level, it is also preferable at any higher income levels. Therefore, Figure 3.1 indicates that the opportunity cost is key in understanding why high income parents may choose not to vaccinate their children.

Figure 3.1: Non-linear relationship between income and the vaccination choice



[7]In this case, medical care is not well defined. In a two-good framework where the utility is defined over the consumption and health $u = u(y, H)$, we can define medical care as the tool to gain better health status by sacrificing consumption. In any case, without considering the opportunity cost of illness, we will not find non-vaccination at the high income end.

Usefulness of vaccination

Figure 3.1 shows one of many possibilities about the relationship between income and the vaccination choice. To examine why this relationship is non-linear as in Figure 3.1, it proves useful to proceed in four steps. To start, the V curve must be steeper than the NV curve in the low income range. This condition is given by:

$$p_s S < p_d D \tag{3.9}$$

As p_s is the probability of vaccination side effects and S is the fraction of work time loss in the event of side effects, $p_s S$ corresponds to the expected time loss from side effects. Similarly, $p_d D$ corresponds to the expected time loss from infection (without medical care). Therefore, Condition (3.9) states that the expected time loss from side effects is smaller than that from infection. This is a basic condition that any useful vaccination should satisfy, because otherwise no one uses such vaccination even if it was free. Therefore, for the rest of the paper, I assume this condition holds.

Monetary cost of vaccination

Next, consider the agent's choice if income is low. It is clear from Figure 3.1 that as long as there is a positive monetary cost of vaccination, the agent does not vaccinate if income is sufficiently low.

$$c_v > 0 \tag{3.10}$$

This positive cost can be either the price of vaccination or the transportation cost to a clinic. In some cases, the vaccination clinic also charge for some administrative costs.[8] When Condition (3.10) holds, there are two income ranges as shown in Figure 3.1. One

[8]Molinari et al. (2007) estimate that for Georgia' 2003 cohort, the out-of-pocket cost of childhood immunization averages \$53 per visit, which is the sum of *the coinsurance or copayments to the fees charged for the well-child visit, the vaccine, and the vaccine-administration fee.* Their estimates do not include the transportation cost to the clinic.

range is $y \in [0, \hat{y})$ where the agent simply cannot afford vaccination. In this range, the agent is credit constrained because the income is less than the sum of the monetary cost of vaccination c_v and the expected cost of side effects $p_s S y$. The other range is $y \in [\hat{y}, \underline{y})$ where the agent affords vaccination but chooses not to do it. Because the benefit of vaccination is the income it saves $(p_d D - p_s S)y$ while the cost of vaccination is c_v, the benefit does not exceed the cost when income y is sufficiently small. Therefore, the agent does not find it worthwhile to vaccinate if the income falls into this income range.

If Condition (3.10) does not hold (i.e., vaccination is free), the agent vaccinates at all income levels. Since the vaccination is useful and costless, it is always better to vaccinate than to not vaccinate. This situation is depicted in the panel (a) of Figure 3.2. Both V and NV curves start from the origin but the V curve is steeper than the NV curve because vaccination is useful. Therefore, the intersection A disappears and so does the low income non-vaccination range NVR_L. Many countries use subsidies to lower the monetary cost of vaccination, which is understood as an effort to shrink NVR_L. It is, however, clear from the figure that such a policy does not eliminate the high income non-vaccination range NVR_H. Whether NVR_H exists or not depends on the availability of a viable substitute, which I discuss in the next section.

A viable substitute

Now, consider the agent's choice if income is high. For the agent to choose not to vaccinate at the high income end, the NV curve must be steeper than the V curve at the high income end in as Figure 3.1. This condition is given by:

$$p_s S > p_d d \tag{3.11}$$

The left hand side is the expected time loss from side effects, while the right hand side is the expected time loss from infection when medical care is utilized. Therefore, Condition (3.11) states that the expected time loss from infection is smaller than that from side effects when medical care is utilized. I label such a substitute as a viable substitute.[9]

The existence of a viable substitute, however, does not guarantee non-vaccination at the high income end, because the income in the population is bounded from above. To see this, notice that the benefit of medical care relative to vaccination is the income it saves $(p_s S - p_d d)y$ while the cost of medical care relative to vaccination is $(p_d c_m - c_v)$. Thus, the net benefit of medical care is increasing in income. In particular, if the net benefit is positive with the highest income in the population y_{max}, there must exist a high income range at which the agent chooses not to vaccinate and relies on medical care in the event of an infection. Thus, the condition we need is

$$(p_s S - p_d d) * y_{max} > (p_d c_m - c_v) \tag{3.12}$$

Note that this condition is identical to $u_v(y_{max}) < u_v(y_{max})$. I label a substitute that satisfies both Conditions (3.11) and (3.12) as a feasible substitute. When a substitute is viable but not feasible, the agent keeps using vaccination as the income rises, because medical care is too expensive and/or not sufficiently effective. The panel (b) of Figure 3.2 depicts this situation. In this case, the intersection B locates above the maximum income of the population, and as a result, the high income non-vaccination range NVR_H disappears. This case is important because it suggests that as the population's income rises, agents at the high income end who previously vaccinated their children will stop doing so.

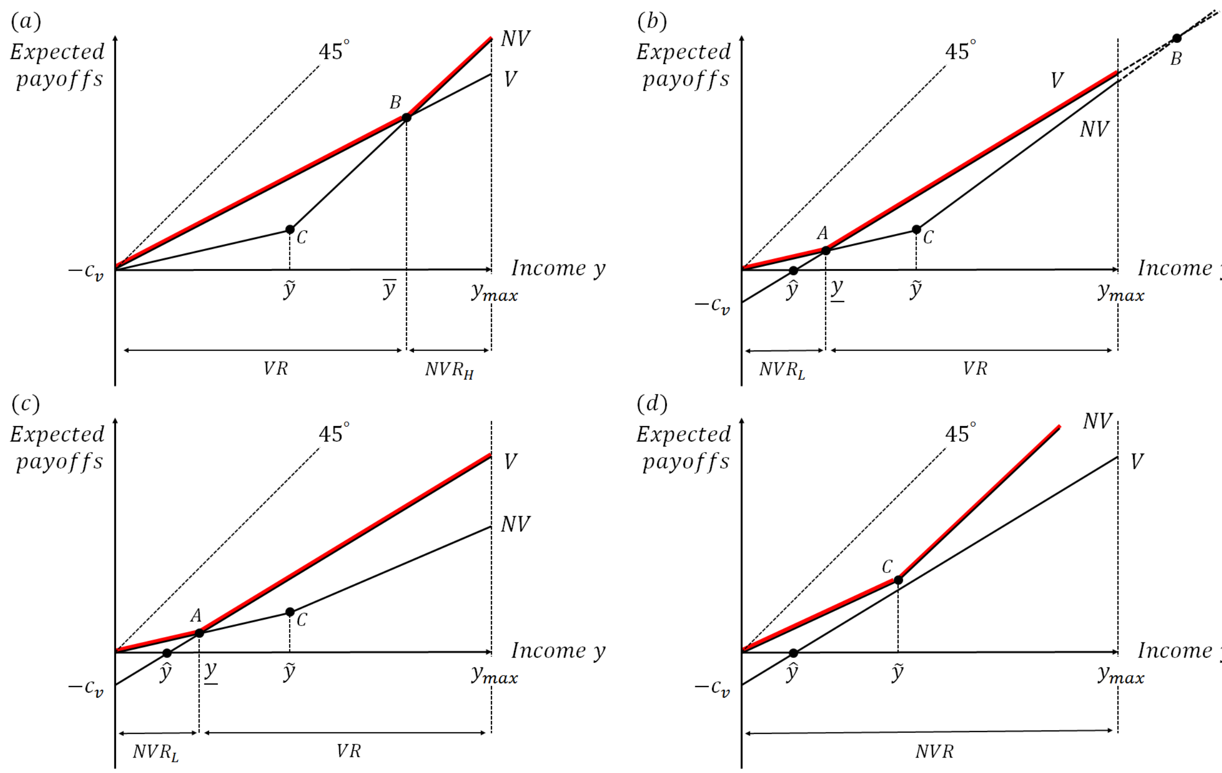
If Condition (3.11) does not hold (i.e., substitute is not viable), Condition (3.12) does not hold either because the right hand side of Condition (3.12) becomes negative.[10] In such a case, the agent does not use medical care at any income level because it saves less work time and costs more than vaccination. This situation is depicted in the panel (c) of Figure 3.2. Because the V curve is steeper than the NV curve, the intersection B disappears and

[9] Note that while p_s is given and exogenous for parents, they may view that they could decrease p_d by shielding their children. This possibility is discussed in Section 3.7.

[10] Here I am assuming that the expected cost of medical care relative to vaccination $(p_d c_m - c_v)$ is positive, because otherwise medical care becomes a dominant option as it is more effective and cheaper than vaccination.

so does the high income non-vaccination range NVR_H. Notice that if medical technology advances and the time cost of infection after using medical care becomes smaller ($d \downarrow$), we will move from the panel (c) to (b) in Figure 3.2, and possibly to Figure 3.1.

Figure 3.2: Linear relationship between income and vaccination choice
(a) Free vaccination, (b) Viable but expensive substitute
(b) Non-viable substitute, (d) Feasible and cost-effective substitute



Cost-effectiveness

Finally, consider the agent's choice if income is in the middle range. To have an income range where the agent chooses to vaccinate, the V and the NV curves must intersect twice as in Figure 3.1. For this to be true, there must exist an income level y^v such that

$$(p_d D - p_s S)y^v > c_v \quad \& \quad (D - d)y^v < c_m$$

In both inequalities, the left hand side corresponds to the income saved by a medical instrument. Therefore, the first inequality states that the benefit of vaccination exceeds the cost of vaccination, while the second inequality states that the benefit of medical care is smaller than the cost of medical care. The second inequality does not include any probability because the choice of medical care is made after the uncertainty about infection is resolved. Thus, these conditions ensure that the agent chooses to vaccinate when income equals to y^v. Notice that if vaccination is not viable (i.e., $p_d D < p_s S$), such a y^v does not exist. By reorganizing these conditions, we can find a simpler condition:

$$\frac{p_d D - p_s S}{c_v} > \frac{D - d}{c_m} \tag{3.13}$$

In both sides of the inequality, the numerators are the time saved while the denominators are the cost of the corresponding medical instruments. Thus, Condition (3.13) states that vaccination saves more work time "per dollar" relative to medical care. In other words, vaccination is more cost effective than medical care. Note that this condition is identical to saying that vaccination is a preferable option to non-vaccination with $y = \tilde{y}$, at which medical care becomes available (i.e., $u_v(\tilde{y}) > u_{nv}(\tilde{y})$).

If a viable substitute exists and it is more cost effective than vaccination, the agent never vaccinates. This is depicted in the panel (d) of Figure 3.2. The NV curve locates above the V curve at any income level, and the two intersections A and B disappear.

Summary

In the previous four sections, I show that opportunity costs are key behind the existence of non-vaccination at the high income end, and find five conditions that lead to non-vaccination both at the low and high income ends. Two of the conditions are, however, implied by the others. First, Condition (3.13) is a sufficient condition for Condition (3.9). That is, if vaccination is more cost effective than medical care, vaccination must be useful at the same time. Second, Condition (3.12) and (3.13) are sufficient for Condition (3.11) to hold.[11] The

[11] Proof is as follows. Condition (3.13) implies that $p_d c_m - c_v > -(\frac{p_s S - p_d d}{p_d D - p_s S})c_v$. Combined with Condition (3.12), it must be that $(p_s S - p_d d) * y_{max} > -(\frac{p_s S - p_d d}{p_d D - p_s S})c_v$. This inequality cannot hold if $p_s S - p_d d < 0$.

intuition is that if the agent prefers vaccination at a middle income range while prefers medical care at a higher income range, it must be that medical care is viable ($p_s S > p_d d$). Therefore, a set of conditions that generates non-vaccination at both low and high income ends is: vaccination is costly ((3.10)); the net benefit of medical care is positive at the highest income ((3.12)); and vaccination is more cost effective than medical care ((3.13)). Each condition corresponds to $u_v(0) < u_{nv}(0)$, $u_v(y_{max}) < u_{nv}(y_{max})$, and $u_v(\tilde{y}) > u_{nv}(\tilde{y})$, respectively. The discussion thus far is summarized as Proposition 1.

Proposition 1. *Suppose an agent is risk neutral. For a given risk of infection p_d, if Conditions* (3.10)*,* (3.12)*, and* (3.13) *hold, there exists two threshold income levels $\underline{y}$ and $\bar{y}$ such that the agent does not vaccinate if $0 \leq y < \underline{y}$, vaccinates if $\underline{y} \leq y < \bar{y}$ and does not vaccinate if $\underline{y} \leq y \leq y_{max}$.*

Proof. See Appendix 3.9.1. □

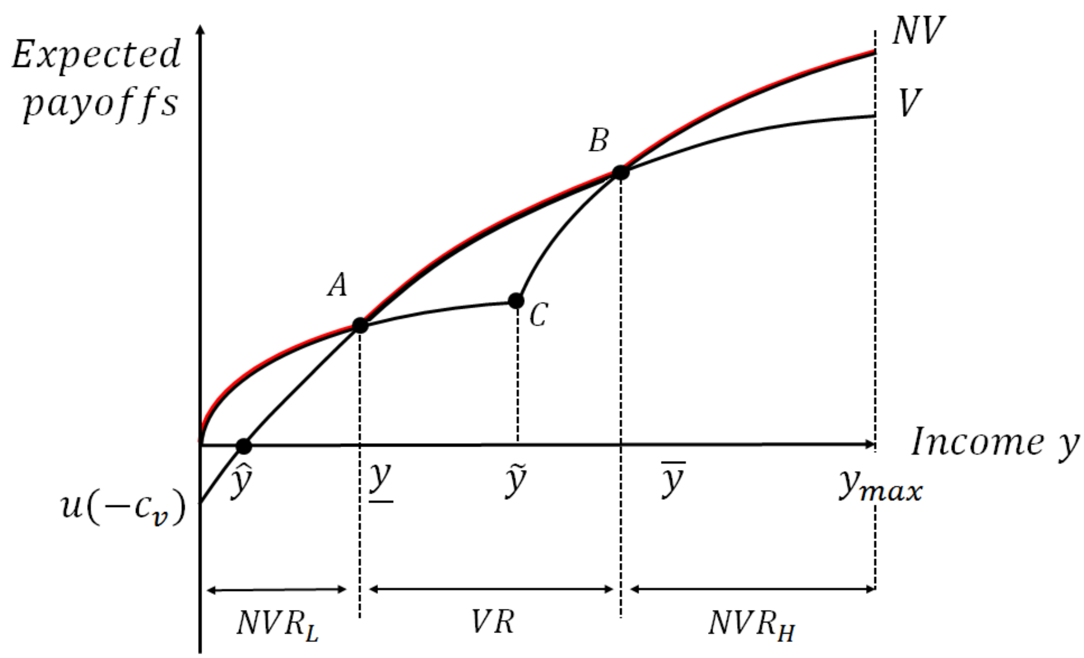
Condition (3.10) is a standard condition stating that vaccination is costly. Conditions (3.12) and (3.13) are more unique stating that a viable substitute for vaccination exists but it is less cost effective than vaccination. If any of these conditions is not satisfied, at least one of the income range NVR_L, VR, or NVR_H disappears and the relationship between income and the vaccination choice becomes linear as in Figure 3.2. In particular, it appears that the panels (b) and (c) match the common view that people with low income are the ones who are less likely to vaccinate. Therefore, the figure suggests that technological progress in medical care and economic development together may be responsible for the increasing evidence that high income parents do not vaccinate their children.

Note that the risk of infection p_d is endogenously determined in the model, so we need these conditions to be satisfied in equilibrium. In Appendix, I discuss a set of sufficient conditions that ensure the non-linear relationship between income and the vaccination decision in equilibrium.

3.3.2 Risk-averse case

The risk neutral case helps identify the three conditions that lead to non-vaccination both at the low and high income ends. A similar set of conditions can be found for the risk averse case. Figure 3.3 depicts a situation where a risk averse agent chooses not to vaccinate if income is below $\underline{y}$ or above $\bar{y}$.

Figure 3.3: Non-linear relationship between income and the vaccination choice



First, consider the agent's choice when income is low. Just as in the risk neutral case, as long as vaccination is costly, there will be two low income ranges at which the agent does not vaccinate. When the income falls into the range $[0, \hat{y})$, the agent cannot afford vaccination, while when the income falls into the range $[\hat{y}, \underline{y})$, the agent chooses not to vaccinate. Next, consider the agent's choice when income is high. For the agent to not vaccinate at high levels of income, we require that the net benefit of medical care is positive at the highest income. This condition is given by $u_{nv}(y_{max}) > u_v(y_{max})$. Finally, consider the agent's choice if income is in the middle range. For the agent to vaccinate at some level of income, vaccination must be a preferable option for the agent at $y = \tilde{y}$, at which medical care becomes available. This condition is stated as $u_{nv}(\tilde{y}) < u_v(\tilde{y})$ where $\tilde{y} = \frac{c_m}{D-d}$. These conditions are somewhat abstract in the risk averse case, so I provide a set of sufficient conditions in Proposition 2.

Proposition 2. *Suppose an agent is risk averse. For a given risk of infection p_d, if the following conditions* (3.14)-(3.17) *hold, there exists threshold income levels $\underline{y}$ and $\bar{y}$ such that the agent does not vaccinate if* $0 \leq y < \underline{y}$, *vaccinates if* $y = \tilde{y} = \frac{c_m}{D-d}$, *and does not vaccinate if* $\underline{y} \leq y \leq y_{max}$.

$$c_v > 0 \tag{3.14}$$

$$p_s S > d \tag{3.15}$$

$$(p_s S - d) * y_{max} > c_m - c_v \tag{3.16}$$

$$\frac{p_d D - S}{c_v} > \frac{D - d}{c_m} \tag{3.17}$$

Proof. See Appendix 3.9.2. □

Condition (3.15) is a stricter version of (3.11) because it states that the expected time loss from side effects is larger than the actual time loss from infection when medical care is utilized. Also, Condition (3.17) is a stricter version of (3.13), because it requires a higher cost-effectiveness for vaccination than medical care. Note that contrary to the risk neutral case, we need Condition (3.15) as an independent condition because Conditions (3.16) and (3.17) do not imply Condition (3.15). Here again, we see that advances in medical technologies and economic development may create an environment where these conditions are satisfied.

Proposition 2 guarantees non-vaccination at both low and high income ends and a specific level of income $\tilde{y}$ at which the agent vaccinates. Notice, however, that it does not say anything about what happens at other income levels in the range $[\underline{y}, \bar{y}]$. Since the V and the NV curves are not straight lines in Figure 3.3, there is no guarantee that these curves intersect only twice. Thus, it is possible that the agent switches between vaccinating and not vaccinating multiple times in the middle income range. We need more structure in the model to ensure that the agent always vaccinates within the income range $[\underline{y}, \bar{y}]$.[12]

[12]Note again that the risk of infection p_d is endogenous, so we need these conditions to hold in equilibrium. A discussion about how to obtain a set of sufficient conditions is found in Appendix.

3.4 Equilibrium

The agent makes the vaccination decision based on the perception that the risk of infection p_d is given. However, the risk of infection is endogenously determined by the vaccination rate in the population. To determine the equilibrium vaccination rate, we need to aggregate the decisions across agents. As each agent's vaccination decision depends on the vaccination rate and this in turn depends on these vaccination decisions, this is a fixed-point problem. To solve this problem, notice that Figure 3.1 relates individual agents' vaccination decisions to the vaccination rate in the population; the fraction of the population that falls into the middle income range $\underline{y} < y < \bar{y}$ corresponds to the vaccination rate in the population. For convenience, I name this income range the "vaccination bracket."[13]

To solve for the equilibrium vaccination rate, let $F(y)$ and $f(y)$ denote the cumulative and probability density functions of the income distribution for y, respectively. Further, let v^I denote the vaccination rate from the individual choice problem and v^G denote the vaccination rate in the general population. Since v^I is given by the fraction of agents in the vaccination bracket, we find that:

$$v^I = F(\bar{y}) - F(\underline{y}) \tag{3.18}$$

Now, suppose the risk of infection p_d rises. Then, the V curve stays the same because vaccination is perfectly effective in preventing infection and consequently the payoff with vaccination does not change. Alternatively, the NV curve shifts downward because the agent is more likely to get infected at any income level. As a result, the vaccination bracket expands and the vaccination rate rises:

[13]For simplicity purposes, I assume in this section that Conditions (3.14)-(3.17) hold and that the agent always vaccinates in the range $\underline{y} \leq y < \bar{y}$. This assumption is, however, not crucial in the equilibrium derivation. If the agent switches between vaccinating and not vaccinating in the middle income range, Eq.(3.18) becomes $v^I = \sum_{i=1}^{n} F(\bar{y}_i) - F(\underline{y_i})$ where i stands for the ith vaccination bracket. Alternatively, if there is no high-income non-vaccination range, it becomes $v^I = 1 - F(\underline{y})$. In any case, we can find an equilibrium following the same logic provided in this section.

$$\frac{\partial v^I}{\partial p_d} = f(\bar{y})\frac{\partial \bar{y}}{\partial p_d} + f(\underline{y})\frac{\partial \underline{y}}{\partial p_d} \geq 0 \tag{3.19}$$

Therefore, the risk of infection p_d and the vaccination rate from the individual choice problem v^I move in the same direction. Since a higher vaccination rate in the general population should lead to a lower risk of infection (i.e., $\frac{dp_d}{dv^G} \leq 0$), we find that:

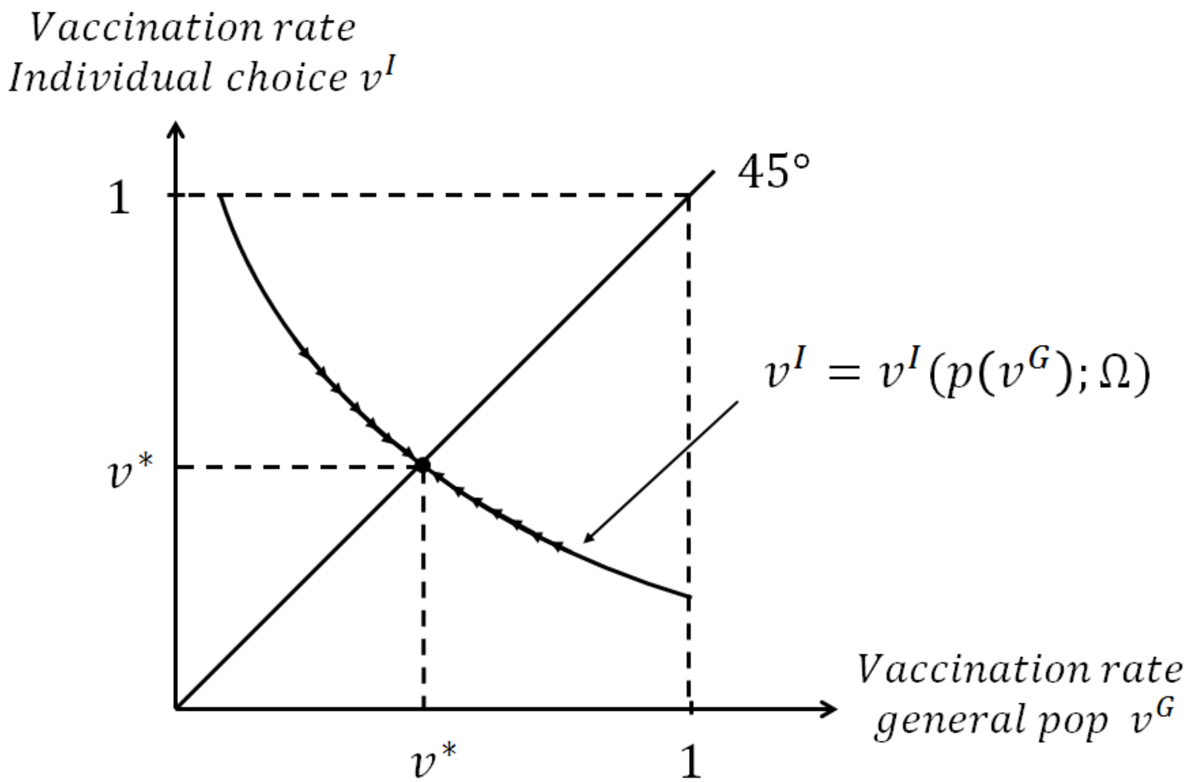
$$\frac{dv^I}{dv^G} = \frac{\partial v^I}{\partial p_d} * \frac{dp_d}{dv^G} \leq 0 \tag{3.20}$$

Therefore, v^I and v^G have a simple negative (or flat) relationship as shown in Figure 3.4. Since the vaccination rate is bounded by 0 and 1, the figure is defined within the unit square. The downward sloping curve is $v^I = v^I(p(v^G); \Omega)$ where Ω is the set of parameters in the model. Depending on the parameter values, the v^I curve may hit the vertical axis below $(0, 1)$ and the horizontal axis to the left of $(1, 0)$. It has, however, always a unique intersection with the 45 degree line at $v^G = v^I = v^*$. When $v^G < v^*$, the individual choice problem leads to $v^I > v^*$ because the risk of infection is too high. Alternatively, when $v^G > v^*$, the individual choice problem leads to $v^I < v^*$ because the risk of infection is too low. Thus, the unique solution for the fixed point problem is given by $v = v^*$.

At the equilibrium, agents with income $y = \underline{y}$ and $y = \bar{y}$ are indifferent between vaccinating and not vaccinating. Thus, agents with income $\underline{y} \leq y \leq \bar{y}$ vaccinate, and the fraction of these agents coincide with v^*. As a result, the equilibrium conditions are given by:[14]

[14]This decentralized equilibrium is not efficient. To see this, notice first that the social welfare in the equilibrium is given by $SW = \int_0^{\underline{y}} u_{nv}(y; pd)f(y)dy + \int_{\underline{y}}^{\bar{y}} u_v(y)f(y)dy + \int_{\bar{y}}^{y_{max}} u_{nv}(y; pd)f(y)dy$. If we marginally increase $\bar{y}$, the marginal agents at $y = \bar{y}$ do not incur any cost because they are indifferent between vaccinating and not vaccinating. However, all the non-vaccinators in the population are better off because the vaccination rate rises by $dp_d = p_d'(v)f(\bar{y})d\bar{y}$. Thus, we can increase the social welfare by marginally increasing $\bar{y}$. Similarly, we can increase the social welfare by marginally decreasing $\underline{y}$.

Figure 3.4: The fixed-point problem



$$u_v(\underline{y};p_d,\Omega) = u_{nv}(\underline{y};p_d,\Omega) \tag{3.21}$$

$$u_v(\bar{y};p_d,\Omega) = u_{nv}(\bar{y};p_d,\Omega) \tag{3.22}$$

$$p_d = p_d(v) \tag{3.23}$$

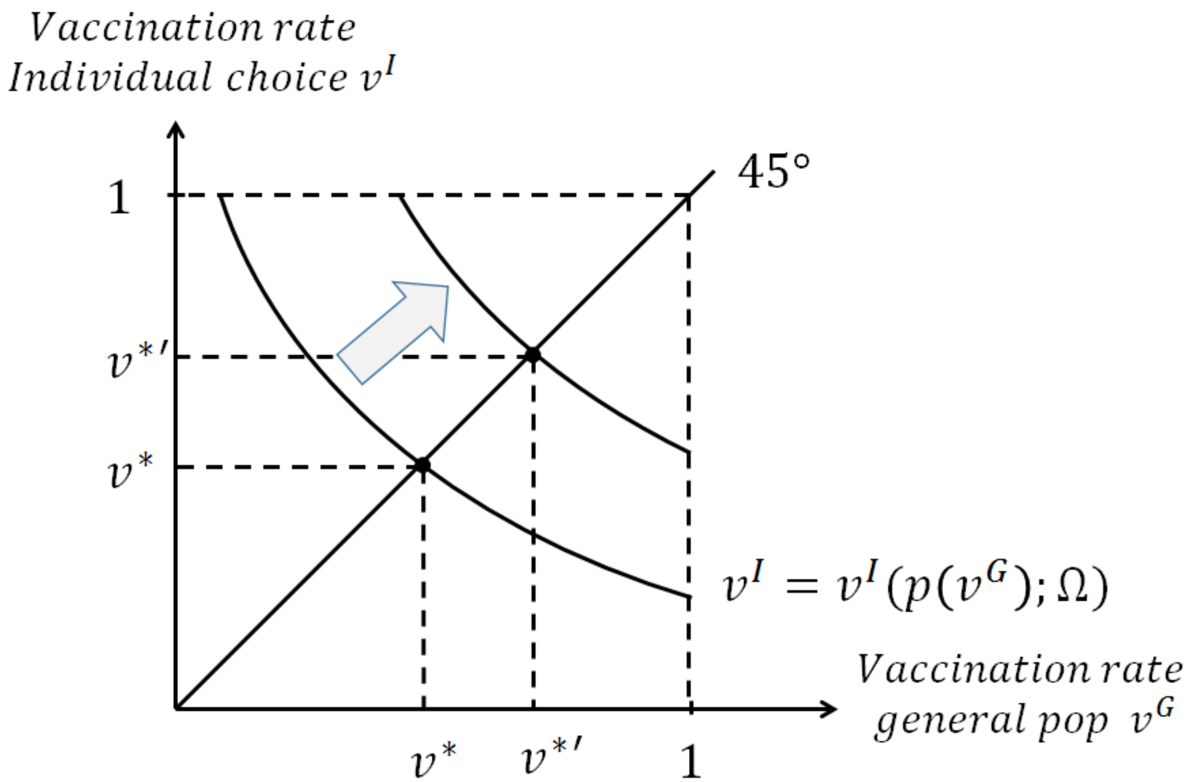
$$v = F(\bar{y}) - F(\underline{y}) \tag{3.24}$$

3.5 Disease and vaccine characteristics

Using the model developed in the previous section, we can examine how disease and vaccination characteristics affect the equilibrium vaccination rate.

Proposition 3. *Suppose agents in a population are risk neutral. Assuming Conditions* (3.10)*,* (3.11)*, and* (3.13) *hold, the equilibrium vaccination rate rises if a disease is more*

Figure 3.5: Comparative statics



severe ($D\uparrow$), when medical care is less effective ($d\uparrow$), when vaccination is less expensive ($c_v\downarrow$), when medical care is more expensive ($c_m\uparrow$), when vaccination is safer ($p_s\downarrow$), and when vaccination side effects are milder ($S\downarrow$).

Proof. By totally differentiating the system of equations (3.21)-(3.24) and reorganizing them, it is easy to show that $\frac{dv}{dD} > 0$, $\frac{dv}{dd} > 0$, $\frac{dv}{dc_v} < 0$, $\frac{dv}{dp_s} < 0$, and $\frac{dv}{dS} < 0$. $\square$

These results can be easily understood by using diagrams. For example, suppose that the disease becomes more severe (i.e., $D\uparrow$). In Figure 3.1, this shifts the NV curve downward because the agent's expected payoff when infected is lower at any income level. The V curve stays the same because vaccination is perfectly effective in preventing infection. As a result, the vaccination bracket expands. This in turn shifts v^I curve upward as in Figure 3.5 and consequently the equilibrium vaccination rate rises from v^* to v'^*. Therefore, the equilibrium vaccination rate is higher for more severe diseases.

It is also important to note that the size of the non-vaccinators in the low and high income ends change with these disease and vaccination characteristics. For example, when medical care becomes less effective ($d \uparrow$), there are less non-vaccinators in the high income range because the NV curve becomes flatter and the vaccination bracket expands to the right. The intuition is that since the benefit of medical care increases with income while the cost of medical care is constant, a higher income is required for medical care to be useful if the cost is higher. In an extreme case, the non-vaccinators in the high income range disappear, because the intersection between the V and NV curves occur at $y > y_{max}$. Following the same logic, we may not observe the high-income non-vaccinators for highly infectious diseases. In Sakai (2016), I use data in the US to show that the fraction of children who are up-to-date with a vaccination schedule typically declines at the high income end. Two exceptions to this pattern are the rota virus vaccine and the polio vaccine. As the rota virus is extremely infectious while there is no effective treatment for polio, the data pattern for these vaccines seems consistent with the model prediction.

3.6 Vaccination Kuznets Curve

3.6.1 Theory

Up to here, the discussion is limited to the vaccination rate within a population. In this section, I examine the implication of the model at the population level. Suppose that there are three countries: low income, middle income, and high income countries. For simplicity, I assume that the income distribution of each country is uniform and given by:

$$f(y; y^i_{max}) = \begin{cases} \left(\frac{1}{y^i_{max}}\right) y & \text{if } y \in [0, y^i_{max}] \\ 0 & \text{otherwise} \end{cases} \tag{3.25}$$

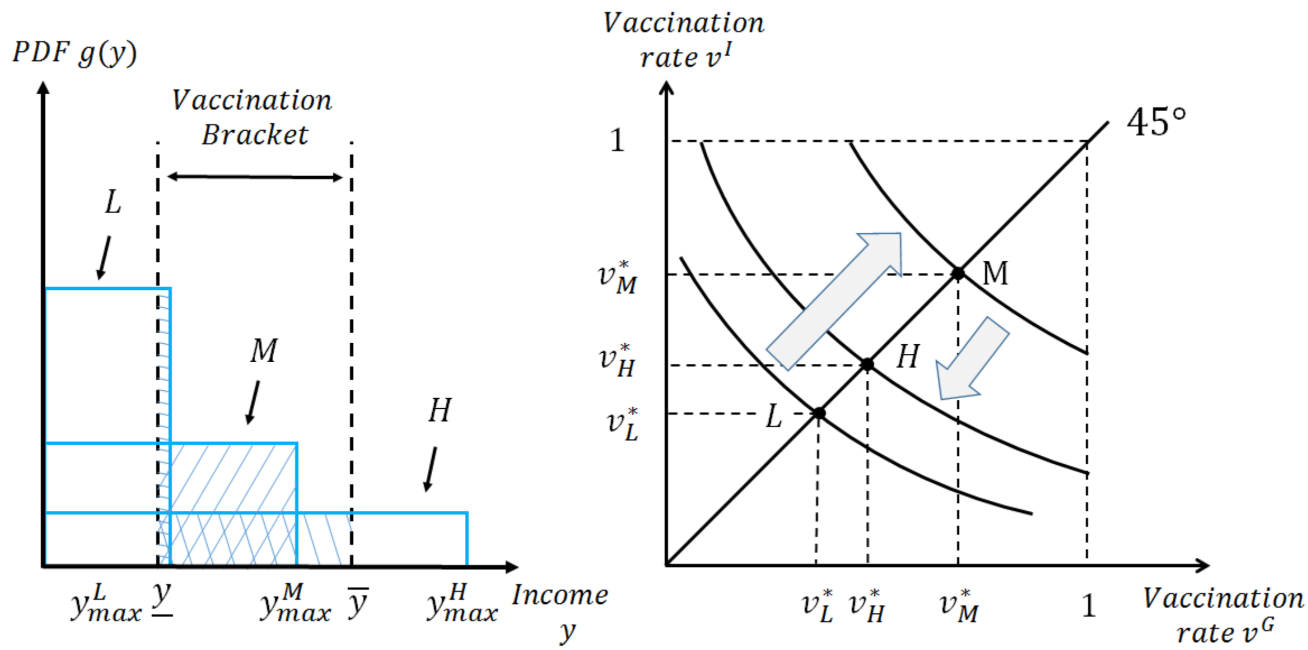
where $y^i_{max} \in \{y^L_{max}, y^M_{max}, y^H_{max}\}$ is the maximum income in each country. This income distribution means that as the mean income of the population rises, the income in the population is spread out with the same probability density at any level in the range $[0, y_{max}]$. The income distributions of the three countries are depicted in the left panel of Figure 3.6.

For a given vaccination rate in the population v^G, the individual vaccination decisions generate a vaccination bracket. Notice that the location of the bracket is determined independent of the income distribution of the population. Because the vaccination rate from the individual problem v^I is given by the fraction of the agents who fall into the bracket (i.e., shaded area), Figure 3.6 shows that v^I is small in the low-income country for this specific v^G. Alternatively, v^I is large in the middle-income country while it is somewhat lower than that in the high-income country. If this relationship holds for any $v^G \in [0, 1]$, the v^I curve first rises and then falls as we move from the low income country to the high income country as in the right panel of Figure 3.6.[15] Then, the equilibrium vaccination rate also first rises from v_L^* to v_M^* and then falls to v_H^*. Notice that this prediction does not depend on the assumption of the uniform income distribution. For any income distribution, as long as economic development continues to shift a fraction of people to the right of the bracket, the vaccination rate starts falling at some point.

The prediction of lower vaccination rates at high income countries may be surprising. However, in Sakai (2016), I use both county-level data in the US and country-level data from the WHO to show that the vaccination rates typically exhibit a hump-shaped relationship with income, which I label the Vaccination Kuznets Curve. Therefore, the model's prediction is in fact consistent with the actual data.

[15] Depending on the parameter values, the three v^I curves in Figure 3.6 may intersect with each other and the equilibrium vaccination rate may not simply rise and fall as we move across these three specific populations. However, the figure illustrates that the equilibrium vaccination rate is generally lower in both low and high income countries relative to in middle income countries.

Figure 3.6: Vaccination Kuznets Curve



3.6.2 Simulation

In this section, I use numerical simulations to examine how the following four factors affect the relationship between the simulated vaccination rate and income: the efficacy of medical technologies, the degree of risk aversion, the degree of income inequality, and the shape of the risk function. I consider the MMR vaccine in this section and assume the parameter values and functional forms as follows.

For the income distribution, I will not invoke the uniform income distribution until the last subsection. Aside from computational convenience, this distribution is preferable because the Gini coefficient of this distribution is fixed at 1/3. Thus, the change in y_{max} captures the consequence of economic development while keeping the degree of income inequality constant. Concerning the range of y, it is convenient to adjust the unit of y as a dollar. As the average lifetime income in the US is approximately \$2 x 10^6, I change the maximum income of the population in the range $y_{max} \in [0, 4 \text{ x } 10^6]$. In this way, the US corresponds to this population when $y_{max} = 4 \text{ x } 10^6$.

Next, I need to assign a value for each parameter. The cost of vaccination c_v is assumed to be \$0.24.[16] Turning to the cost of medical care, the cost per hospitalization if a child contracts measles is \$4,032-46,060.[17] As I consider medical care that can effectively mitigate disease symptoms or shorten the duration of the disease, I assume parents pay for the most expensive medical care: $c_m = \$46,060$. As for the probability of side effects, it depends on the type of side effects. For example, after the MMR vaccine, a fever occurs in up to 1 out of 6 doses, a seizure caused by fever occurs in about 1 out of 3,000 doses, and a serious allergic reaction occurs in less than 1 out of 1 million doses.[18] I consider moderate to serious side effects and choose $p_s = 10^{-4}$ as the baseline value. The time costs of side effects and infection are somewhat difficult to assess, but I use $S = 0.3, D = 0.5, d = 0.1$ as baseline values.

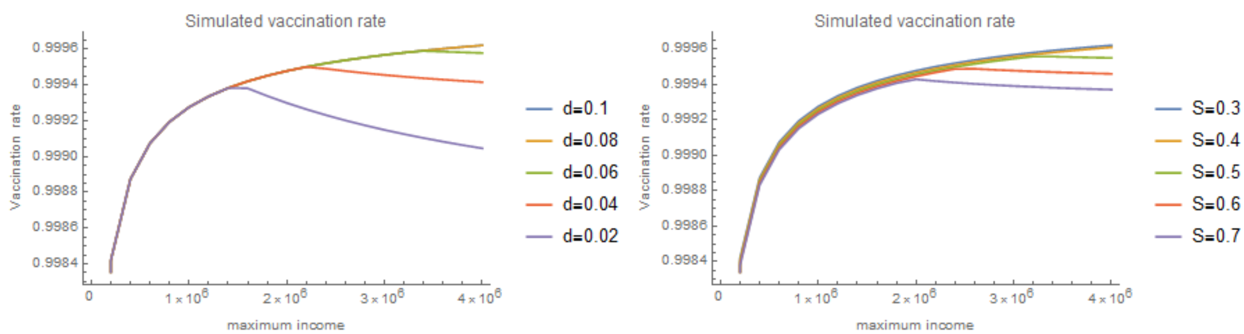
Finally, the risk function is assumed to be $p_d(v) = 1 - v$. This function implies that if no one else is vaccinated, a child will certainly become infected (i.e., $p_d(0) = 1$). This seems reasonable as more than 90% of children contracted measles by age 15 in the pre-vaccination era.[19] Alternatively, if everyone else is vaccinated, there is no risk of infection (i.e., $p_d(1) = 0$). The assumption of a liner risk function has a theoretical foundation because in a simple endemic Susceptible-Infected-Recovered (SIR) model with perfect vaccination, the equilibrium risk of infection is indeed a linear function of the vaccination rate.[20] I examine how the shape of the risk function affects the equilibrium vaccination rate in a subsequent section.

[16] See https://www.msfaccess.org/content/rightshot
[17] See https://www.cdc.gov/vaccines/programs/vfc/pubs/methods/
[18] See https://www.cdc.gov/vaccines/vac-gen/side-effects.htm
[19] See https://www.cdc.gov/vaccines/pubs/pinkbook/meas.html
[20] More precisely, the equilibrium risk of infection in the SIR model takes the form of $p_d(v) = -av + b$, where $a > b > 0$. This function indicates that the risk reaches zero at $v = \frac{b}{a} < 1$, which is called the herd immunity threshold.

Vaccination side effects and medical care

The left panel of Figure 3.7 shows the relationship between the simulated vaccination rate and the maximum income of the population with five levels of medical care. Since d is the time cost of infection after using medical care, a smaller d corresponds to more effective medical care. The first thing to notice is that the simulated vaccination rate indeed initially rises but then falls with income when medical care is sufficiently effective (i.e., $d \leq 0.06$). Thus, we find the VKC. As medical care becomes more effective ($d \downarrow$), the peak of the VKC moves to the left and the peak vaccination rate declines. The increasing parts of the curve coincide across five scenarios because this is the income range where no one uses medical care. This left panel suggests that technological advancement in medical care has the potential to generate the VKC.

Figure 3.7: Simulated vaccination rate and income:
medical care d (left), side effects S (right)



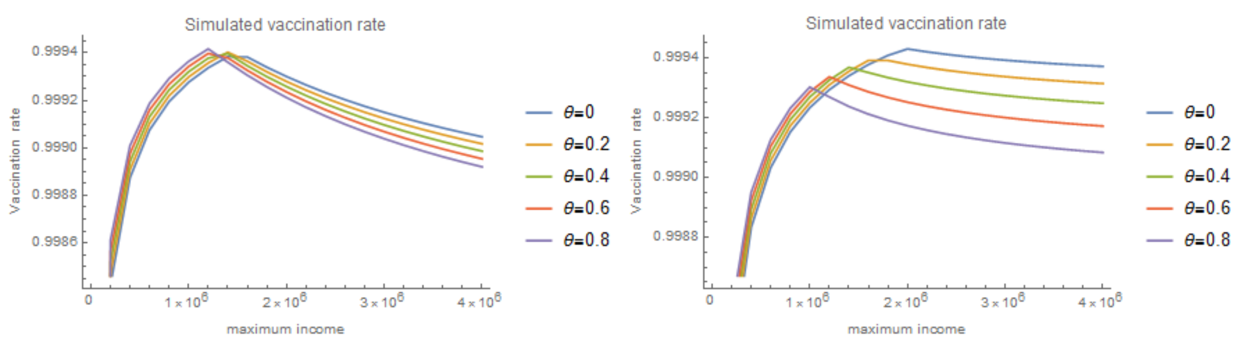
The right panel of Figure 3.7 shows the simulated vaccination rate with five levels of vaccination side effects. Again, the VKC emerges when side effects are sufficiently large. As the side effect becomes larger ($S \uparrow$), the peak of the VKC moves to the left while the entire curve shifts downward. As opposed to the left panel, the increasing parts of the VKC do not coincide with each other because the magnitude of side effects is relevant, even at the low income range. This panel suggests that if parents overestimate the consequence of vaccination side effects, the vaccination rate is likely to decline with economic development.

Alternatively, the development of safer vaccines may prevent the vaccination rate from falling.

Degree of risk aversion

Next, I turn to the analysis for the degree of risk aversion. I employ the CRRA utility function $u(y) = \frac{y^{1-\theta}}{1-\theta}$ and change the value of θ. In the left panel of Figure 3.8 shows the relationship between the simulated vaccination rate and the maximum income of the population with five degrees of risk aversion, where I assume that $d = 0.02$. $\theta = 0$ corresponds to the risk neutral case and a larger θ corresponds to a more risk averse case. With the assumed parameter values, the VKC emerges for any degree of risk aversion. As the degree of risk aversion rises, the peak vaccination rate rises. However, the vaccination rate starts falling at a lower level of income and it falls at a faster rate. This suggests that the possibility of the VKC becomes a more serious threat to public health as the degree of risk aversion rises.

Figure 3.8: Simulated vaccination rate and income:
S=0.7 (left), d=0.02 (right)



In the right panel of Figure 3.8, I instead assume that $S = 0.7$ and examines how the degree of risk aversion affect the simulated vaccination rate. The panel shows that the VKC emerges for any degree of risk aversion. In contrast to the left panel, as the degree of risk aversion rises, the peak vaccination rate declines and the vaccination rate falls at a faster rate. As a result, the possibility of the VKC is even more threatening to public health.

Income inequality

How income inequality affects vaccination rates is another interesting question. To answer this question, I modify the uniform income distribution as follows:

$$f(y; y_{mean}, k) = \begin{cases} \frac{1}{2k} & \text{if} \;\; y \in [y_{mean} - k, \;\; y_{mean} + k] \\ 0 & \text{otherwise} \end{cases} \tag{3.26}$$

In this income distribution, agents are distributed in the range $y \in [y_{mean} - k, y_{mean} + k]$ with the same density at any income level. As the Gini coefficient of this distribution is given by $\frac{k}{3y_{mean}}$, an increase in k captures an increase in income inequality while keeping the mean of the distribution constant.

I also examine the case of log-normal income distribution given by:

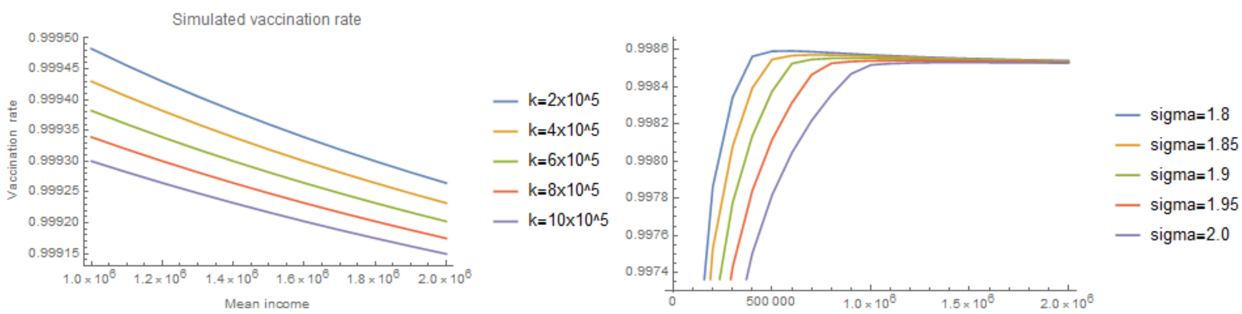
$$f(y; \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma y} exp\left(-\frac{(lnx - \mu)^2}{2\sigma^2}\right) \tag{3.27}$$

In this distribution, agents are distributed in the range $y \in (0, \infty)$. The mean income of this population is $y_{mean} = exp(\mu + \frac{\sigma^2}{2})$, and the Gini coefficient is given by erf$(\sigma/2)$ where $erf()$ is the Gauss error function. I increase the value of σ while keeping the value of y_{mean} constant to examine how a larger income inequality affects the vaccination rate.

The left panel of Figure 3.9 shows the simulated vaccination rates that correspond to five k values. In all cases, the vaccination rate simply decreases with income. The increasing part of the VKC vanished because y_{mean} is bounded from below at k. It is notable that the vaccination rate is lower as income inequality rises ($k \uparrow$).

The right panel shows the simulated vaccination rates that corresponds to five σ values. A larger σ corresponds to larger income inequality. In all cases, the vaccination rate rises but then falls as the mean income of the population increases. Similar to the left panel, the vaccination rate is always lower when income inequality is larger.

Figure 3.9: Simulated vaccination rate and income:
uniform distribution (left), log-normal distribution (right)



Risk function

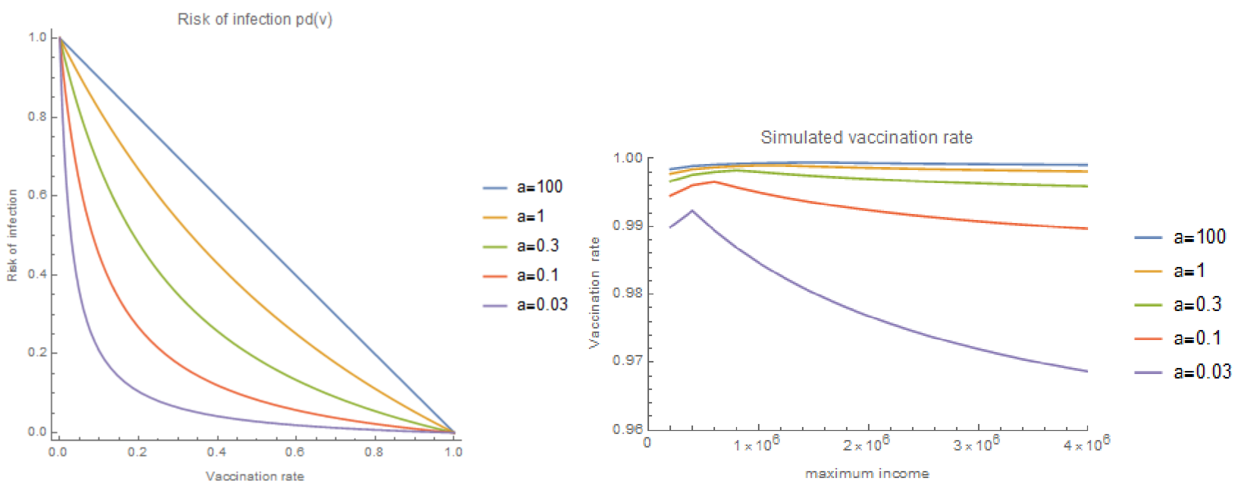
Finally, I examine how the risk function affects the vaccination rate. The linear risk function $pd_d(v) = 1 - v$ implies that if the vaccination rate is 91%, as in the US in 2014, the risk of infection is 9%. Given that the number of measles cases in 2014 was only 667, the 9% risk of infection is very high. Also, the simulated vaccination rates in the previous two subsections are all above 0.99. To show that these high numbers come from the assumption about the risk function, I modify the risk function as follows:

$$p_d(v; a) = \frac{a(1+a)}{v+a} - a \tag{3.28}$$

This risk function is symmetric with respect to the 45 degree line and goes through $(0, 1)$ and $(1, 0)$ in the $v - p_d$ space. The function approaches $p_d(v) = 1 - v$ as a approaches infinity. The left panel of Figure 3.10 shows the risk function shapes that correspond to five values of a. When $a = 100$, the function is indistinguishable from the original linear risk function. As a becomes smaller, the slope of the curve become flatter in the range of high vaccination rates.

The right panel of Figure 3.10 shows the simulated vaccination rates that correspond to five values of a, where I assume $d = 0.02$. We see that as a decreases, the vaccination rate decreases at any income level. More importantly, the rise and fall of the vaccination rate becomes much larger as a decreases. Thus, the very small fluctuations of the simulated

Figure 3.10: Simulated vaccination rate and income:
risk function (left), simulated rate (right)



vaccination rates in the previous subsections are simply due to the linear risk function. Although the true shape of the risk function is unknown, it seems reasonable that the function is approximated more precisely by Eq.(3.26) with a small a, at least in the range of high vaccination rates. Thus, the possibility of the VKC should not be discarded on the ground that the fall in the vaccination rate seems trivial with the linear risk function.

3.7 Avoidance model

In the previous sections, I showed how effective medical care could be responsible for the hump-shaped relationship between income and the vaccination decision and between income and the vaccination rate. This section considers avoidance measures as an alternative mechanism. Avoidance measures are those that reduce the risk of infection such as the following: wearing a mask, avoiding daycare and nurseries, undertaking home-schooling, and alternating children's diets to boost their immune systems.

Suppose that an agent faces the risk of infection p_d. The agent has a binary choice of an avoidance measure with the cost of c_a, which reduces the risk of infection from p_d to p_a. Assuming risk neutrality, the agent's problem is given by:

$$u = \max_{v,nv}\{u_v(y), u_{nv}(y)\}$$

$$u_v(y) = y - p_s S y - c_v \tag{3.29}$$

$$u_{nv}(y) = \begin{cases} y - p_d D y & \text{if } y \leq \hat{y} = \frac{c_a}{(p_d - p_a)D} \\ y - p_a D y - c_a & \text{if } y > \hat{y} \end{cases} \tag{3.30}$$

Notice that Equations (3.29) and (3.30) are almost identical to Equations (3.7) and (3.8). The only difference is that the probability of infection is reduced from p_d to p_a with the cost of c_a in Equation (3.30), as opposed to the consequence of infection being reduced from D to d with the cost of c_m in Equation (3.8). Thus, a similar set of conditions is required to find non-vaccination at both tails of the income distribution: vaccination is costly; the avoidance measure is a preferable option at the highest income; and the avoidance measure is less cost effective than vaccination. Similar to the case of medical care, we need to take into account the endogeneity of p_d to obtain a set of sufficient conditions. However, two further considerations are required.

First, the risk of infection p_d is not only a function of the vaccination rate, but also a function of the fraction of agents who use the avoidance measure, which I denote as r_a. This is because the risk of infection should decrease if more agents use the avoidance measure even when the vaccination rate stays constant. To solve for the equilibrium, it proves useful to treat the problem as a fixed point problem in terms of the risk of infection. Suppose the risk of infection in the general population is p_d^G. Then, the individual vaccination decisions determine the fraction of agents in the vaccination bracket $v^I = F(\bar{y}) - F(\underline{y})$ and the fraction of agents who use the avoidance measure $r_a^I = 1 - F(\bar{y})$. This leads to the risk of infection $p_d^I(v^I, r_a^I)$, where $\frac{\partial p_d^I}{\partial v^I} < 0$ and $\frac{\partial p_d^I}{\partial r_a^I} < 0$. As the avoidance measure is less effective in preventing infection relative to vaccination (i.e., $|\frac{\partial p_d^I}{\partial v^I}| > |\frac{\partial p_d^I}{\partial r_a^I}|$), we find that:

$$
\begin{aligned}
\frac{dp_d^I}{dp_d^G} &= \frac{\partial p_d^I}{\partial v^I}\left[f(\bar{y})\frac{\partial \bar{y}}{\partial p_d^G} - f(\underline{y})\frac{\partial \underline{y}}{\partial p_d^G}\right] + \frac{\partial p_d^I}{\partial r_a^I}\left[-f(\bar{y})\frac{\partial \bar{y}}{\partial p_d^G}\right] \\
&= \underbrace{\frac{\partial \bar{y}}{\partial p_d^G}}_{?}\underbrace{f(\bar{y})\left(\frac{\partial p_d^I}{\partial v^I} - \frac{\partial p_d^I}{\partial r_a^I}\right)}_{\ominus} - \underbrace{f(\underline{y})\frac{\partial p_d^I}{\partial v^I}\frac{\partial \underline{y}}{\partial p_d^G}}_{\oplus} \gtreqless 0
\end{aligned}
\tag{3.31}
$$

Therefore, if the upper threshold income $\bar{y}$ increases with the population's risk of infection p_d^G, p_d^G and p_d^I have a negative relationship, which gives us a unique equilibrium. If not, however, p_d^G and p_d^I may have a negative relationship over some ranges, which leads to the possibility of multiple equilibria. To examine which case occurs under what circumstance, we need to consider the other complication, that is, the possibility of fatalism.

In the set up above, I have assumed that the benefit of the avoidance measure is given by the difference in the probabilities of infection $(p_d - p_a)$. A key observation here is that this benefit depends on the base risk of infection p_d, as opposed to the benefit of medical care $(D - d)$ being independent of it. Thus, not only p_d but also $(p_d - p_a)$ is endogenous in the avoidance model.

In some cases, it may be reasonable to think that the gap between these two probabilities rises as the base risk of infection rises. This would imply that the avoidance measure is most beneficial in an environment where more people are potentially sick and carriers of the disease. This set up might be reasonable for some types of avoidance behaviour such as wearing a mask to avoid germs, but it will not be appropriate for others.

In other cases, the marginal benefit of avoidance measures may decline as the risk of infection rises. This implies the avoidance measure is less beneficial in an environment where most people are potentially sick and carriers of the disease. For example, if not taking public transit is my avoidance strategy but the population of workers at my office is highly contagious, then the benefit of this type of avoidance measures falls with greater prevalence. Therefore, this type of individual behaviour can lead to quite different outcomes than the previous type of avoidance measures. Agents can decide not to invest in avoidance if the population is expected to be quite contagious; this in turn can produce the equilibrium result of more sickness. Alternatively, they may decide to practice avoidance if the population is expected not to be contagious; this in turn can produce the equilibrium result of less sickness because of less contact. This sort of expectations-driven behaviour is thought to have been important in the AIDS epidemic, where avoidance is modelled by limiting the number of sexual partners. In that case, an increase in the prevalence of AIDS can produce less avoidance by agents because its marginal benefit has fallen so dramatically. This possibility is known as fatalism in the literature and examined in detail by Kremer (1996) and Auld (2003, 2006).

To see how the possibility of fatalism plays a role in the present context, let us define the net benefit of vaccination and the avoidance measure as the difference between the utility with and without these instruments.

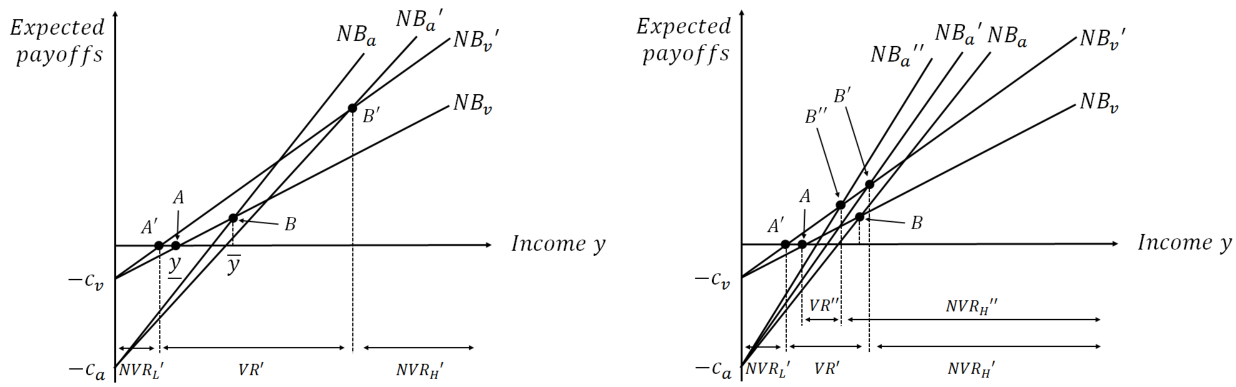
$$NB_v = [y - p_s S y - c_v] - [y - p_d D] = (p_d D - p_s S)y - c_v$$

$$NB_a = [y - p_a D - c_m] - [y - p_d D] = (p_d - p_a)Dy - c_m$$

In the y-u space, NB_v is a straight line beginning from $(0, -c_v)$ with the slope of $(p_d D - p_s S)$ while NB_a is a straight line beginning from $(0, -c_a)$ with the slope of $(p_a - p_d)D$. The panel (a) of Figure 3.11 depicts these two curves. This is essentially the same graph as Figure 3.1. Ignore the NB_v' and NB_a' curves for now. When the agent's income is below $\underline{y}$, the net benefit of vaccination and avoidance are both negative and the agent does not do anything. When the agent's income is in between $\underline{y}$ and $\bar{y}$, the net benefit of vaccination is positive and larger than that of avoidance, so the agent uses vaccination. When the agent's income is above $\bar{y}$, the net benefit of avoidance is larger than that of vaccination, so the agent uses avoidance rather than vaccination.

Now, suppose the risk of infection p_d rises. This will rotate the NB_v curve counter-clockwise around $(0, -c_v)$, because the benefit of vaccination rises. This moves A to A'. The NB_a curve may rotate clockwise or counter-clockwise around $(0, -c_a)$, depending on

Figure 3.11: Risk of infection and the benefit of avoidance measure
(a) Benefit declines with the risk, (b) Benefit rises with the risk



whether the benefit of avoidance $(p_d - p_a)$ rises or falls. If it becomes smaller, then the NB_a curve rotates clockwise, which moves B to B'. As a result, the vaccination bracket expands and the vaccination rate rises. In Equation (3.31), the fact that B' locates to the right of B means $\frac{\partial \bar{y}}{\partial p_d^G}$ is positive, which ensures that the equilibrium is unique.

Alternatively, if the benefit of avoidance becomes larger as the risk of infection rises, the NB_a curve will rotate counter-clockwise as in the panel (b) of Figure 3.11. If the NB_a curve rotates only a little, B moves to B', which is still to the right of the original B. This ensures the uniqueness of the equilibrium. If the NB_a rotates substantially, B moves to B", which is to the left of the original B. In this case, whether the vaccination bracket shrinks or expands is not clear. This can also be seen in Equation (3.31) where $\frac{dp_d^I}{dp_d^G}$ can be positive or negative if $\frac{\partial \bar{y}}{\partial p_d^G}$ is negative. Therefore, in this case, there is a possibility of multiple equilibria.

Notice that in the first case, a rise in the risk of infection reduces the benefit of avoidance, which generates the possibility of fatalism. In fact, the fraction of agents who use the avoidance measure decreases in spite of the higher risk of infection. It may seem surprising that in the present context, such a fatalistic behaviour does not generate a negative feedback of more infection and opens up the possibility of multiple equilibria. This is because the agent does not choose between avoiding and not avoiding, but between vaccinating and avoiding, both of which reduce the risk of infection. In response to a higher risk of infection, the agent stops using the avoidance measure, but instead starts using vaccination, which is more effective in reducing the risk of infection for the agent and for the population.

3.8 Conclusion

Despite the overwhelming evidence of the benefits of vaccination, vaccination rates are below the level that achieves herd immunity for many diseases in many countries. Moreover, increasing evidence suggests that people with high socioeconomic status choose not to vaccinate. This paper aimed to understand these vaccination choices and their public health implications. To do so, I built a simple model where many agents who differ in their income try to free ride on other agents' vaccination decisions. The model is highly stylized but is able to identify the conditions under which both low and high income parents do not vaccinate. Moreover, the model could link such individual vaccination decisions to the change in the equilibrium vaccination rate at the population level.

The model explains that low-income parents do not vaccinate because of the common monetary cost of vaccination. The common cost creates two groups of low income parents; one group cannot afford vaccination while the other group chooses not to vaccinate. In contrast, high-income parents may not vaccinate due to the opportunity cost of illness; if they have access to alternative options that effectively reduce the opportunity cost of infection, they will choose not to vaccinate. Given these individual level decisions, the vaccination rate at the population may initially rise but eventually fall once everyone in the population obtains sufficiently high income. This is the first theoretical explanation for the Vaccination Kuznets Curve that I reported in Sakai (2016).

The model has important public policy implications. Given the positive externality involved in vaccination, a classical policy prescription is to lower the cost of vaccination by subsidies. The model in this paper, however, clarifies that such a policy is limited in its ability to raise the vaccination rate. Even if the government successfully lowers the cost of vaccination to zero, there is still a group of high income parents who do not vaccinate, because it is the opportunity cost that drives their vaccination choices. Thus, to mitigate the non-vaccination problem at the high income end, different policy prescriptions are required.

In this regard, it is important to continue our quest for safer vaccines that entails even milder side effects with a lower probability. This will reduce the opportunity cost of vaccination and shrink the non-vaccination at both low and high income ends. In fact, the model suggests that if side effects are completely eliminated, the non-vaccination at the high income end disappears. Alternatively, it is also important to disseminate accurate information about how effective these substitutes for vaccination are. If parents overestimate the effect of alternative measures to protect their children, they may choose not to vaccinate their children. This possibility seems to be underemphasised in policy circles.[21]

This paper provides the first theoretical analysis about why high income parents choose not to vaccinate their children. The model not only provides an explanation about individual level behaviour, but also generates an alarming prediction that the vaccination rate may decrease with economic development. This fall in the vaccination rate raises the risk that infectious pathogens may spread into the population. In fact, recent outbreaks of measles and whooping cough in many parts of the world may be a sign that such a scenario is becoming reality.

[21] Reich (2014) uses an interview survey and finds that the mothers who do not vaccinate their children think they can reduce the risk of disease with avoidance measures.

3.9 Appendix

3.9.1 Proof of Proposition 1

Define the net benefit of vaccination $J(y) = u_v(y) - u_{nv}(y)$. Then, for $0 < y < \tilde{y}$,

$$J'(y) = p_d D - p_s S > 0 \qquad (\because \text{Condition (3.13)}) \tag{3.32}$$

$$J(0) = -c_v < 0 \qquad (\because \text{Condition (3.10)}) \tag{3.33}$$

$$J(\tilde{y}) = (p_d D - p_s S)\frac{c_m}{D-d} - c_v > 0 \qquad (\because \text{Condition (3.13)}) \tag{3.34}$$

Therefore, there is a unique level of income $\underline{y}$ such that $u_v(y) < u_{nv}(y)$ for $0 < y \leq \underline{y}$ and $u_v(y) > u_{nv}(y)$ for $\underline{y} < y < \tilde{y}$. Alternatively, for $\tilde{y} < y \leq y_{max}$,

$$J'(y) = p_d d - p_s S < 0 \qquad (\because \text{Conditions (3.12),(3.13)}) \tag{3.35}$$

$$J(\tilde{y}) = (p_d d - p_s S)\frac{c_m}{D-d} + (p_d c_m - c_v) > 0 \qquad (\because \text{Condition (3.13)}) \tag{3.36}$$

$$J(y_{max}) = (p_d d - p_s S) y_{max} + (p_d c_m - c_v) < 0 \qquad (\because \text{Condition (3.12)}) \tag{3.37}$$

Therefore, there is a unique level of income $\bar{y}$ such that $u_v(y) > u_{nv}(y)$ for $\tilde{y} < y \leq \bar{y}$ and $u_v(y) < u_{nv}(y)$ for $\bar{y} < y < y_{max}$.

3.9.2 Proof of Proposition 2

To find non-vaccination at the low income end, it is sufficient if the utility with vaccination is lower than that without vaccination at $y = 0$. This is the case if $c_v > 0$ because $u_v(0) = u(-c_v) < u(0) = u_{nv}(0)$.

To find non-vaccination at the high income end, it is sufficient if the expected utility from vaccination is smaller than that from non-vaccination at $y = y_{max}$ (i.e., $u_{nv}(y_{max}) > u_v(y_{max})$). On the one hand, using Jensen's inequality, $u_v = p_s u((1-S)y_{max} - c_v) + (1 - p_s)u(y_{max} - c_v) < u(p_s((1-S)y_{max} - c_v) + (1-p_s)(y_{max} - c_v)) = u((1 - p_s S)y_{max} - c_v)$. On the other hand, $u_{nv} = p_d u((1-d)y_{max} - c_m) + (1-p_d)u(y_{max}) > u((1-d)y_{max} - c_m)$. Therefore, it is sufficient if $p_s S > d$ and $(p_s S - d) * y_{max} > c_m - c_v$.

To find an income level at which the agent vaccinates, it is sufficient if the expected utility from vaccination is greater than that from non-vaccination at $y = \tilde{y}$, the income level at which the agent starts using medical care. On the one hand, $u_v = p_s u((1-S)y - c_v) + (1-p_s)u(y-c_v) > u((1-S)y - c_v)$. On the other hand, using Jensen's inequality, $u_{nv} = p_d u((1-D)y) + (1-p_d)u(y) < u(p_d(1-D) + (1-p_d))y) = u((1-p_d D)y)$. Therefore, it is sufficient if $(1-S)\tilde{y} - c_v > (1-p_d D)\tilde{y}$. As $\tilde{y} = \frac{c_m}{D-d}$, (3.17) result.

3.9.3 Sufficient conditions

The main text finds three conditions that generate non-vaccination at both low and high income ends. The conditions are, however, not provided in terms of the primitives in the model because the risk of infection p_d is endogenous. This section examines a set of sufficient conditions for the risk neutral case. A set of sufficient conditions for the risk averse case can be found in the same way. One way to proceed is to introduce an assumption about the form of the income distribution to solve for p_d. Instead, here I keep the general income distribution and derive a set of sufficient conditions. Notice that p_d is bounded between $p_d(0)$ and $p_d(1)$, which are the risks of infection when the vaccination rate is 0 and 1, respectively. Therefore, a set of sufficient conditions can be obtained by replacing p_d with $p_d(0)$ and $p_d(1)$:

$$c_v > 0 \tag{3.38}$$

$$(p_s S - p_d(0)d) * y_{max} > p_d(0)c_m - c_v \tag{3.39}$$

$$\frac{p_d(1)D - p_s S}{c_v} > \frac{D-d}{c_m} \tag{3.40}$$

Condition (3.39) states that the agent prefers medical care when the income is highest in the population and the vaccination rate is zero. If the risk of infection is high, the benefit of vaccination becomes larger. Condition (3.39) requires that medical care is still a preferable option even if the risk is highest. Alternatively, Condition (3.40) means that even if everyone else is vaccinated and the risk is minimal, the vaccination is still more cost effective than medical care. Notice that condition (3.40) does not hold if $p_d(1) = 0$. In general, however,

$p_d(1) > 0$ either because there is a risk of importing the virus from other populations or because non-human reservoirs exist.

Condition (3.40) implies $p_d(1)D - p_sS > 0$, which means the the expected time loss from side effects is smaller than that from infection, even if everyone else is vaccinated. Simply put, this means that even if the risk of infection is minimal, the vaccination is still valuable. Also, Conditions (3.39) and (3.40) together further imply that $p_sS - p_d(0)d > 0$, which means the expected time loss from side effects is larger than that from infection if medical care is used, even if no one is vaccinated. In other words, this condition means that even if the risk of infection is maximal, medical care still dominates the vaccination.

Bibliography

Atwell, E. J., Otterloo, V. J., Zipprich, J., Winter, K., Harriman, K., Salmon, A. D., Halsey, A. N., & Omer, B. S. (2013). Nonmedical vaccine exemptions and pertussis in california, 2010. *Pediatrics*, *132*, 624–630.

Auld, C. M. (2003). Choices, beliefs, and infectious disease dynamics. *Choices, beliefs, and infectious disease dynamics*, *22*, 361–377.

Auld, C. M. (2006). Estimating behavioral response to the aids epidemic. *Contributions in Economic Analysis & Policy*, *5*, 1–29.

Barrett, S. & Hoel, M. (2007). Optimal disease eradication. *Environment and Development Economics*, *12*, 627–652.

Brito, L. D., Sheshinski, E., & Intriligator, D. M. (1991). Externalities and compulsary vaccinations. *Journal of Public Economics*, *45*, 69–90.

Chen, F. & Toxvaerd, F. (2014). The economics of vaccination. *Journal of Theoretical Biology*, *363*, 105–117.

Francis, J. P. (1997). Dynamic epidemiology and the market for vaccinations. *Journal of Public Economics*, *63*, 383–406.

Gersovitz, M. & Hammer, S. J. (2003). Infectious diseases, public policy, and the marriage of economics and epidemiology. *The world bank research observer*, *18*, 129–157.

Gersovitz, M. & Hammer, S. J. (2004). The economical control of infectious diseases. *The Economic Journal*, (492), 1–27.

Goldman, M. S. & Lightwood, J. (2002). Cost optimization in the sis model of infectious disease with treatment. *Topics in Economic Analysis & Policy*, *2*.

Klevens, M. R. & Luman, T. E. (2001). Us children living in and near poverty: risk of vaccine-preventable diseases. *American Journal of Preventive Medicine*, *20*, 41–46.

Kremer, M. (1996). Integrating behavioral choice into epidemiological models of aids. *The Quarterly Journal of Economics*, *111*, 549–573.

Kureishi, W. (2009). Partial vaccination programs and the eradication of infectious diseases. *Economics Bulletin*, *29*, 2758–2769.

Molinari, M. N.-A., Kolasa, M., Messonnier, L. M., & Schieber, A. R. (2007). Out-of-pocket costs of childhood immunizations: a comparison by type of insurance plan. *Pediatrics*, *120*(5), e1148 –e1156.

Oster, E. (2016). Does disease cause vaccination? disease outbreaks and vaccination response. *NBER Working Paper No. 22464*.

Reich, A. J. (2014). Neoliberal mothering and vaccine refusal imagined gated communities and the privilege of choice. *Gender & Society*, 0891243214532711–0891243214532711.

Rowthorn, R. B. & Toxvaerd, F. (2012). The optimal control of infectious diseases via prevention and treatment. *CEPR Discussion Paper No. DP8925*.

Sakai, Y. (2016). The vaccination kuznets curve: Rise and fall of vaccination rates with income. *University of Calgary, Graduate Student Working Paper Series*, *01-2016*.

Smith, J. P., Chu, Y. S., & Barker, E. L. (2004). Children who have received no vaccines: who are they and where do they live? *Pediatrics*, *114*, 187–195.

Smith, J. P., Humiston, G. S., Marcuse, K. E., Zhao, Z., Dorell, G. C., Howes, C., & Hibbs, B. (2011). Parental delay or refusal of vaccine doses, childhood vaccination coverage at 24 months of age, and the health belief model. *Public Health Reports (Washington, D.C.: 1974)*, *126 Suppl 2*, 135–146.

Toxvaerd, F. (2010a). Infection, acquired immunity and externalities in treatment. *CEPR Discussion Paper No. DP8111*.

Toxvaerd, F. (2010b). Recurrent infection and externalities in prevention. *CEPR Discussion Paper No. DP8112*.

Wei, F., Mullooly, P. J., Goodman, M., McCarty, C. M., Hanson, M. A., Crane, B., & Nordin, D. J. (2009). Identification and characteristics of vaccine refusers. *BMC Pediatrics*, *9*, 18–18.

Wiemer, C. (1987). Optimal disease control through combined use of preventive and curative measures. *Journal of Development Economics*, *25*, 301–319.

Wu, C. A., Wisler-Sher, J. D., Griswold, K., Colson, E., Shapiro, D. E., Holmboe, S. E., & Benin, L. A. (2008). Postpartum mothers' attitudes, knowledge, and trust regarding vaccination. *Maternal and Child Health Journal*, *12*, 766–773.

Xu, X. (1999). Technological improvements in vaccine efficacy and individual incentive to vaccinate. *Economics Letters*, *65*, 359–364.

Yang, T. Y., Delamater, L. P., Leslie, F. T., & Mello, M. M. (2016). Sociodemographic predictors of vaccination exemptions on the basis of personal belief in california. *American Journal of Public Health*, *106*, 172–177.