Strategic Vaccination Behavior and the Public Goods Dilemma using a Game Theory Model with Measles Data

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Abstract

Vaccination is a powerful public health tool (Fine et al., 2011). Still, individual choices to vaccinate often depend on the level of protection they believe others are providing. It directly links empirical measles trends to a game-theoretic tipping point for vaccination. The analysis began by examining global measles data to understand how vaccination rates impact disease cases (Ritchie, Roser, & Ortiz-Ospina, n.d.). A logistic regression model captured this relationship, showing a sharp decline in cases as coverage increased. This curve was then transformed into a benefit function (normalized between 0 and 1), which quantifies the level of indirect protection an individual receives based on how many others are vaccinated. Using this benefit function, individual decision making was modeled as a public goods game (Chaudhuri, 2011). Utility functions were derived for both strategies, and simulations were run to find the tipping point: the point where the expected benefit of free riding equals that of vaccinating (Bauch & Earn, 2004; Betsch et al., 2013).

It was found that when about 82.0 percent of the population is vaccinated, individuals become indifferent between the two choices at a cost of disease (d) of 10. To test the robustness of this result, sensitivity tests were conducted by varying the perceived cost of disease (d), using values of 5, 10, 15, and 20. Higher values of d shifted the tipping point to the right. Lower values of d had the opposite effect, making people stop vaccinating at lower coverage levels. Policymakers can use this model to guide strategies that reduce free riding and promote public health.

Introduction

Vaccination is among the most effective tools in preventing the spread of infectious diseases (Fine et al., 2011). Beyond individual protection, vaccines contribute to herd immunity, where a high level of community-wide coverage protects even those who are unvaccinated (Fine et al., 2011). However, as vaccination rates increase, individuals may begin to rely on the immunity of others, perceiving less need to vaccinate themselves (Bauch & Earn, 2004; Geoffard & Philipson, 1997). This tendency to benefit from public health measures without contributing to them is known as free riding (Geoffard & Philipson, 1997). The rise of vaccine hesitancy in some populations has made it increasingly important to understand how personal decisions are shaped by perceptions of risk and collective protection (Betsch et al., 2013; Brewer et al., 2007). This problem presents a fundamental conflict between individual incentives and collective well-being. While widespread vaccination reduces disease transmission, individuals may weigh the small cost or risk of vaccination against their perceived safety due to others' participation. In such cases, people may opt out, assuming others will maintain community protection. This creates a classic social dilemma: if too many free ride, the population loses herd immunity, and everyone becomes more vulnerable (Fine et al., 2011). Understanding this behavioral tipping point is critical for anticipating and addressing drops in vaccine uptake (Feng et al., 2018).

To explore this issue, the study draws on real-world data from global measles outbreaks (Ritchie, Roser, & Ortiz-Ospina, n.d.). A logistic regression model is used to capture how disease incidence declines as vaccination rates increase. The resulting curve, which exhibits the expected saturation effect of herd immunity, is normalized into a benefit function that describes the protection an individual receives based on the global vaccination coverage. This allows for a quantitative link between community immunity and perceived personal benefit, setting the foundation for strategic modeling. Previous vaccination-game studies often used assumed benefit functions or fixed payoffs. In this work the benefit curve is fitted to real-world measles data using a logistic regression model. This grounds the game-theoretic threshold condition in observed epidemiological patterns. The model also allows clear measurement of how the threshold changes when disease severity (d) is varied. Individual decision making is then analyzed through the lens of game theory (Bauch & Earn, 2004). Specifically, the scenario is modeled as a Public Goods Game (Chaudhuri, 2011), where vaccination incurs a cost (paying for the vaccine) but contributes to a shared public benefit (herd immunity) as well as the private benefit of the vaccine protecting the user. The payoff matrix is as follows:

Action	Payoff Expression
Vaccinate	u - c
Not Vaccinate	u - d(1 - b(x))

Table 1. Payoff variable definitions used in the game-theoretic model. *u* denotes the utility of remaining healthy. *c* represents the cost associated with vaccination. *d* refers to the cost incurred from contracting the disease. *b(x)* indicates the level of indirect protection from herd immunity at a given vaccination coverage *x*.

In this setup, a Nash equilibrium arises where each individual's decision is optimal given the choices of others (Bauch & Earn, 2004). As vaccination coverage increases and b(x) rises, the incentive to free ride grows. The tipping point is the critical value of x at which both strategies yield equal utility, beyond which rational individuals may opt out of vaccination.

The primary objective of this study is to identify this tipping point using simulation. By comparing the utility functions for vaccinating and not vaccinating across different levels of coverage, the point of indifference is determined. This value provides a measurable threshold for when free riding becomes individually rational. A secondary objective is to analyze how this threshold changes under different assumptions about disease severity. By varying the parameter d, the model reveals how perceptions of disease impact vaccination behavior. Together, these observations offer a mathematical and behavioral framework for examining or devising public health strategies aimed at maximizing community-wide immunity.

Methods

Data Collection and Alignment

To explore how disease incidence relates to vaccination behavior, global data on measles cases and vaccination rates were collected from Our World in Data. The measles case data represented weekly counts, while the vaccination data indicated cumulative global vaccination percentages over time. Since these datasets differed in both resolution and aggregation type, a preprocessing step was used for standardization. Both datasets were aligned to a monthly timescale allowing for a consistent and fair comparison. Vaccination values were mapped to the nearest monthly measles data point to standardize the timeline.

Regression Modeling

Once standardized, the data was used to model the relationship between vaccination coverage and number of measles cases. Three regression models were tested: linear, quadratic, and logistic. Although the quadratic model achieved the highest R^2 value, the logistic model was selected because it better reflects real-world epidemic dynamics. The linear model had an acceptable fit but would have been ill-suited for use in population-based modeling. Logistic models are known to capture biological behavior. In this case, disease reduction accelerated with early increases in vaccination but plateaued as saturation was approached. The final logistic function modeled the expected number of measles cases as a function of vaccination coverage. It took the form:

$$\text{cases}(x) = L / [1 + e^{(k*(x-x_0))}]$$

The parameters were estimated as follows: L - 1804.15, representing the upper limit of measles cases. In this formulation, x represents vaccination coverage in percent (0–100), and cases are expressed per 100,000 population. The steepness parameter k - 0.0412, and the midpoint x_0 was determined to be 15.70. This logistic function effectively captured the observed decline in case counts with rising vaccination coverage.

Benefit Function Derivation

To make the case model usable for strategic decision making it was transformed into a benefit function ‘b(x)’. This function describes how much protection a person receives from herd immunity at any given population coverage level. The function was normalized so that its values ranged from 0 to 1 using the equation:

$$b(x) = 1 - (\text{cases}(x) - y_{min}) / (y_{max} - y_{min})$$

‘b(x)’ approaches 1 as vaccination rates increase and case counts fall. This function represents the fraction of maximum protection an unvaccinated individual receives at any given x. As x increased, b(x) increased, hinting towards greater indirect protection.

Game Theory Modeling

With the benefit function established a game-theoretic model was used to understand individual vaccination decisions. The situation was structured as a two-player Public Goods Game, where individuals could either choose to vaccinate or remain unvaccinated. Vaccinating provides certain protection but involves a cost. Not vaccinating is free, but exposes the individual to infection depending on how many others vaccinate. The expected utility for each strategy was calculated as follows: for someone who vaccinates the payoff is 'u-c'. For someone who does not vaccinate, the expected payoff is 'u-[d*(1-b(x))]'. Here, 'u' represents the utility from remaining healthy and is fixed at 1. These are dimensionless utility units chosen for scenario analysis, with c representing a small fixed cost of vaccination and d representing a range of perceived disease severity values. The cost of vaccination (c) is fixed at 0.5. The cost of getting sick (d) is initially set to 10. These equations represent two strategic options under uncertainty. A vaccinated person pays a known cost in exchange for guaranteed immunity. An unvaccinated person risks incurring a larger cost that relies on community vaccination behavior. The central idea is that as more people vaccinate, b(x) increases, which reduces the chance of infection and increases the payoff for the unvaccinated population. This approach reflects core logic from public goods games. Individuals weigh private costs against a benefit that increases with group participation. The model enables prediction of the tipping point: the value of x at which the utility of vaccinating equals the utility of not vaccinating. (Figure 1)

Figure 1

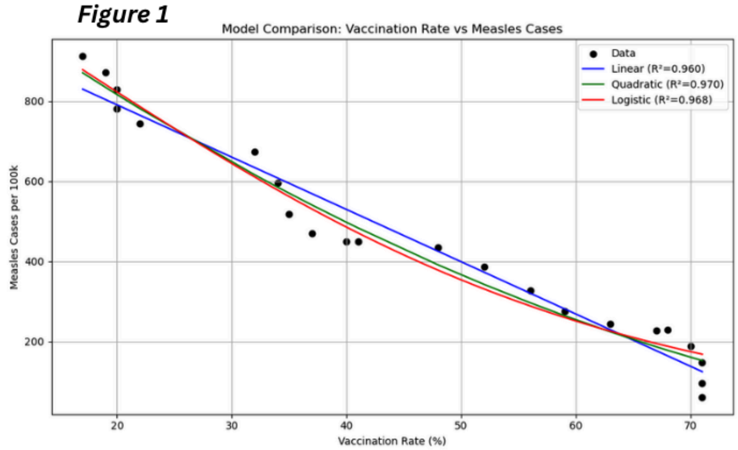

Figure 1. Model Comparison: Vaccination Rate vs Measles Cases. A scatter plot of real-world measles case data per 100,000 population compared against national vaccination coverage. Three regression models are fitted to the data: linear (blue), quadratic (green), and logistic (red). The quadratic model yields the highest R^2 (0.970), the logistic model (0.968).

Tipping Point Simulation and Sensitivity Analysis

To identify this tipping point the difference between the two utility equations was computed across a range of vaccination coverage values from 0 to 100. The point where the two payoffs came closest (intersected each other) was recorded as the tipping point. For a disease cost d = 10, the simulation showed that individuals become indifferent between vaccinating and not vaccinating at approximately 82.0% of the population vaccinated. To test how sensitive this result was to assumptions about disease severity, the parameter d was tested using multiple values. Further simulations were run for d at values of [5, 10, 15, 20]. The tipping point was recalculated using the same method for each value of d. Results showed that the tipping point moved to the right as d increased. In other words, when the disease was perceived as more severe, individuals continued choosing to vaccinate even when a large portion of the population was already vaccinated to minimize risks. On the other hand, when the disease was perceived as less severe, people were willing to rely on herd immunity earlier, leading to a lower tipping point. The entire analysis was implemented in Python using NumPy and Matplotlib. Logistic regression was performed using SciPy optimization methods. The benefit function was derived directly from the fitted curve and used to compute the expected utilities for both strategies. Plots were generated for each scenario to visualize the tipping point dynamics.

Results

Simulation Setup and Utility Framework

To evaluate how individual vaccination decisions shift under varying disease severities, we simulated utility outcomes across a range of vaccination coverage levels using the fitted logistic model. The simulation computed utilities under the public goods framework for two choices, vaccinate or not vaccinate. These utilities were defined respectively as: U_vaccine = u - c, and U_no vaccine = u - d(1 - b(x)), where b(x) denotes the benefit derived (from the logistic curve modeling disease incidence reduction) as vaccination coverage x changes. All simulations fixed u = [1], c = [0.5], and varied d, the perceived disease cost, to assess behavioral responses to disease severity. The logistic model used to generate b(x) was fit to real-world measles case data obtained from Our World in Data, yielding the equation b(x) = 1 - (cases(x) - y_min) / (y_max - y_min), where cases(x) is a decreasing logistic function of vaccination rate x. The model exhibited a strong fit with $R^2 = 0.968$, confirming its validity for utility derivation. The regression comparison showed that all three models, linear, quadratic, and logistic, fit the measles data with high accuracy. All had R^2 values above 0.96. The quadratic model had the highest R^2 value at 0.970, followed by the logistic model at 0.968, and then the linear model at 0.960. Despite the quadratic model having the best statistical fit, the logistic model was chosen for downstream analysis because it better reflects disease transmission. The logistic curve captures the diminishing marginal returns of increasing vaccination coverage, which mirrors how herd immunity naturally behaves. This theoretical alignment makes the logistic model a more appropriate basis for constructing the benefit function used in the game-theoretic simulations.

Tipping Point Identification and Sensitivity Analysis

The baseline simulation was conducted at d = 10, representing a moderate perceived disease burden. At this level, the tipping point (the minimum percentage of the population that must be vaccinated for an individual to rationally choose vaccination) was found to occur at approximately 82.0% (Figure 3b). This value was determined by numerically solving the point of intersection between the constant utility curve for vaccinating and the declining utility curve for not vaccinating. Specifically, the solution satisfies the equation u - c = u - d(1 - b(x)), simplifying to b(x) = 1 - c/d. To test the robustness of this finding, a sensitivity analysis was performed by varying d while keeping all other parameters constant. The resulting tipping points showed a clear and systematic trend. When d = 5, representing a less severe disease, the tipping point dropped to approximately 71.1% (Figure 2). At d = 15, it increased to around 86.8% (Figure 3c). Finally, for d = 20, simulating an extremely severe disease, the tipping point rose to 89.4% (Table 2)(Figure 3d). These results confirm that greater disease severity raises the vaccination threshold required for rational uptake, as the cost of being unvaccinated becomes more significant.

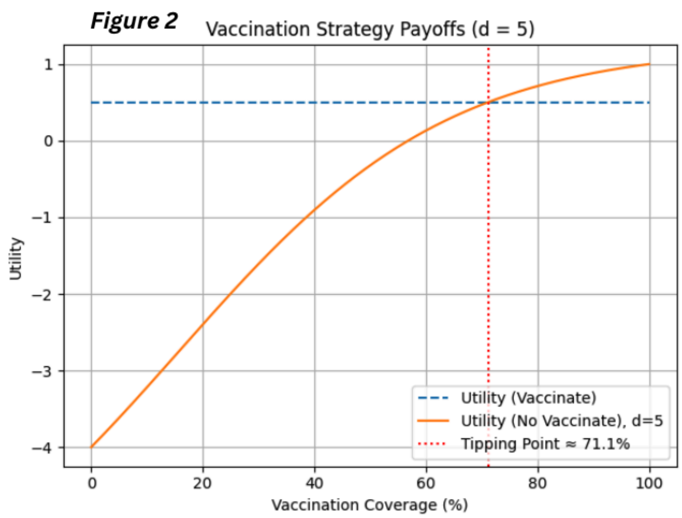

Figure 2. Utility Comparison for Vaccination Strategies (d = 5). Simulated utility curves under a public goods framework, where individuals choose to vaccinate or free ride. The horizontal blue line represents the constant utility of vaccination. The orange curve shows the decreasing utility of not vaccinating as coverage increases. The red dashed vertical line indicates the tipping point at approximately 71.1 percent coverage, where the utilities intersect and rational individuals begin to favor vaccination.

S.No	d value	Tipping Point (%)
1	5	71.1
2	10	82.0
3	15	86.8

4	20	89.4

Table 2: Tipping point vaccination coverage by disease severity parameter d

Visualization and Interpretation

Figure 3 graphically depicts the utility functions for each scenario. In each plot, the flat horizontal line represents the utility of choosing to vaccinate, while the curved line corresponds to the utility of not vaccinating as a function of the vaccination rate in the population. The red vertical line indicates the tipping point (the intersection between the two curves) where the rational decision shifts from opting out to opting in. Figure 3a shows the outcome for d = 5, a low severity condition, where the tipping point occurs earlier in the vaccination curve. In Figure 3b, the tipping point shifts rightward under d = 10. This shift continues progressively in Figures 3c and 3d for d = 15 and d = 20, respectively. Each figure visually depicts the theoretical trend observed: as the perceived cost of contracting the disease increases individuals require a higher level of population immunity before they are willing to risk skipping vaccination. Even at high levels of coverage, the cost of infection remains large enough under severe conditions (high d values) to motivate continued vaccination. This behavioral shift is explained by the shape of the unvaccinated utility curve. As more people vaccinate, the infection risk (encoded in 1 - b(x)) declines, flattening the curve. However, with higher d, even this reduced risk leads to a large enough penalty to sustain the utility of vaccination above that of free-riding. In this situation the intersection moves rightward, not because the benefit of not vaccinating increases, but because its cost remains intolerably high unless the population is nearly fully immunized. These results provide quantitative evidence of how disease severity influences strategic vaccination decisions. The consistent rightward shift in tipping points with increasing d highlights the fragility of herd immunity in the face of low perceived risk. In contexts where the disease is viewed as mild, large segments of the population may rationally choose not to vaccinate unless coverage is already very high. When the perceived threat is severe, individuals will opt for protection even in largely vaccinated populations.

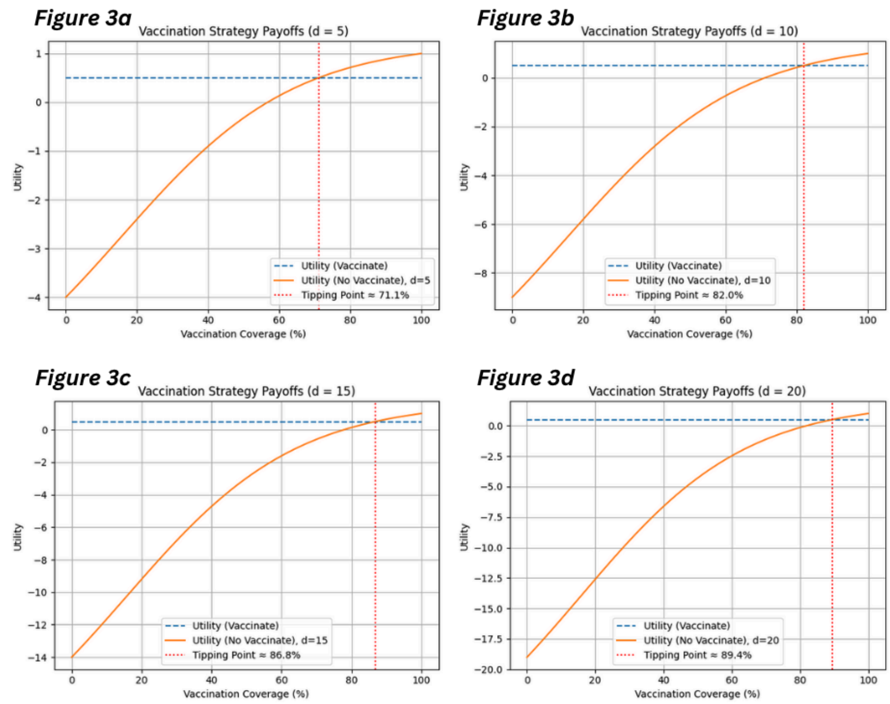

Figure 3a–3d. Effect of Disease Severity on Vaccination Tipping Points. Each panel shows utility simulations for different disease severity levels: 3a: d = 5, tipping point ≈ 71.1%; 3b: d = 10, tipping point ≈ 82.0%; 3c: d = 15, tipping point ≈ 86.8%; 3d: d = 20, tipping point ≈ 89.4%. Across all panels, the flat blue line represents the constant utility of vaccination, while the curved orange line represents the utility of not vaccinating. As disease severity increases, the orange curve drops lower and intersects the blue line later, shifting the tipping point to the right and indicating greater incentive to vaccinate.

Discussion

In a standard experimental setup, each player receives a private amount of tokens and secretly decides how many to contribute to a public pot. The total contributions are multiplied by a factor of 2 and redistributed equally among all players, regardless of individual contribution. This interplay of private sacrifice and shared benefit creates a tension between cooperation and free riding, and is known within game theory as the public goods game (Chaudhuri, 2011). Since each person gains more by withholding tokens while still enjoying the collective payoff, the optimal strategy is to contribute as few tokens as possible. This setup is directly analogous to vaccination decisions (Bauch & Earn, 2004). Individuals decide whether to incur a personal cost by vaccinating or rely on the contributions of others through herd immunity. When perceived disease risk is low, many rational actors free ride. When risk is high, the incentive to cooperate increases. The results presented above illustrate a clear relationship between perceived disease severity and rational vaccination behavior. As the cost of infection increases, individuals require a higher level of collective immunity before they are willing to free ride. This aligns with public goods theory in which cooperation depends on overall participation (Betsch et al., 2013). In the context of vaccination, this translates into a tipping point in coverage at which rational actors shift from free riding to cooperating. The simulations reveal that this tipping point is dynamic and shifts as a function of perceived threat (Feng et al., 2018). In scenarios of severe disease, individuals will still vaccinate even when herd immunity is nearly reached. Under mild disease conditions, rational actors tend to delay vaccination as long as possible. These dynamics carry important public health policy implications. In real-world settings, perceived threat often has more impact on uptake than official case numbers (Brewer et al., 2007). If individuals believe the disease is mild, even low coverage may not appear sufficient to warrant vaccination. Conversely, if the threat is seen as high, individuals may vaccinate even in a mostly immunized population. This suggests risk communication strategies could effectively influence the implicit severity parameter d. Through communication and messaging, behavior may shift in populations.

The model provides insight but rests on idealized assumptions. It assumes fully rational behavior. In reality, people may deviate due to misinformation, cultural pressures, or distrust (Kabir, 2023). The model uses a uniform cost of vaccination and perceived disease cost. It ignores individual heterogeneity in beliefs, access, or socioeconomic status. It assumes a well-mixed population structure, ignoring network contact patterns, population clustering, or local outbreaks (Fu et al., 2011). It also omits temporal dynamics such as evolving variants, vaccine availability, and shifting public awareness. Finally, the benefit curve b(x) is estimated from real-world data that may suffer from reporting bias such as undercounting (Simons et al., 2012). Such data limitations may distort the true relationship between coverage and disease incidence. These limitations suggest several promising avenues for future work. Allowing vaccination cost and disease perception to vary across individuals would increase realism. Applying the framework to diseases with different epidemiological profiles may reveal how benefit curves shape strategic thresholds. Incorporating agent-based modeling or social influence networks could simulate realistic behavioral dynamics. Extending the framework along these lines would move the model closer to real-world complexity while preserving its theoretical clarity.

Conclusion

This study modeled vaccination decisions as a strategic choice in a public goods game using real-world data on measles incidence and vaccine uptake. A logistic regression curve captured the relationship between population coverage and disease reduction, allowing for the derivation of a benefit function that served as the foundation for utility-based simulations. By comparing the payoffs of vaccinating versus free riding across different levels of disease severity, the model identified a tipping point: the minimum level of vaccine coverage required for rational individuals to choose vaccination. The central finding was that this tipping point is not fixed but increases with the perceived cost of infection. In severe outbreaks, individuals are more likely to vaccinate even at high coverage levels. Whereas for mild diseases, many may skip vaccination (free ride). This sensitivity highlights the strategic interdependence of public health decisions where individual choices are influenced by collective behavior. The study also emphasizes the value of combining epidemiological modeling with game theory to better understand behavioral dynamics. They also suggest that effective public communication, especially framing around disease risk, can shift population behavior in ways similar to increasing perceived disease severity. Even simple game theoretic models can offer powerful guidance for designing more adaptive and resilient public health policies. No human participants, animals, or patient data were involved. Ethics approval and consent were not required for this modeling study.

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