Does Increased Access Increase Equality?
Gender and Child Health Investments in India

Emily Oster*
University of Chicago and NBER

Draft: April 15, 2008

Abstract

Increases in access to social services are often thought to decrease inequality in the level of these services between advantaged and disadvantaged groups. This is an issue in the developing world, where policy-makers often argue that increasing the level of health care, for example, will decrease gender inequality. However, increases in access to services often have empirically ambiguous effects on inequality, increasing it in some cases and decreasing it in others. This paper argues that this is not surprising, and simple economic theory suggests that we should expect a non-monotonic relationship between access and inequality. At low levels of access to investments, there is no investment for either the advantaged or disadvantaged group, producing equality. Increases in access increase investment for the advantaged group first, generating inequality. Further increases in access increase investment in the disadvantaged group, decreasing inequality. I test the predictions of this theory using data on the availability of health camps (or distance to health centers) and gender differences in vaccinations in India. I find strong support for a non-monotonic relationship between access and gender equality.

1 Introduction

It is often suggested that increasing overall access to social services – education or health, for example – will decrease inequality between advantaged and disadvantaged groups in these services. For example, public education was initially designed to provide training to those who could not afford private schooling, using universal access to provide opportunities to the lower classes. More recently, proponents of universal preschool or pre-kindergarten argue that this will increase relative outcomes for lower socioeconomic status groups (O'Connell, 2005; Sawhill, 1999). This link between higher access and lower inequality is salient even when lower inequality is not the primary goal of increasing access. Universal access to Medicare among the elderly is largely motivated by concerns

*Gary Becker, Kerwin Charles, Steve Cicala, Amy Finkelstein, Andrew Francis, Jon Guryan, Matthew Gentzkow, Lawrence Katz, Michael Kremer, Steven Levitt, Kevin Murphy, Jesse Shapiro, Andrei Shleifer, Rebecca Thornton, three anonymous referees and participants in seminars at Harvard University, the University of Chicago, Stanford University, Princeton University and the NBER provided helpful comments. I am grateful for funding from the Belfer Center, Kennedy School of Government. Laura Cervantes provided outstanding research assistance.

about risk sharing and adverse selection, but Medicare is nevertheless also thought to decrease inequality by providing a safety net for the poor. These issues of access and inequality are important throughout the developing world, where the policies of governments and NGOs often aim to improve the circumstances for disadvantaged groups (for example, women or ethnic minorities) *and* to increase overall levels of access.

The assumption behind the higher access-lower inequality link is that increasing overall access to social services will generate relatively more benefits for under-served groups. However, the evidence on the validity of this assumption is mixed. Some work on Medicare has argued that it actually acts as a transfer from the poor to the rich (McClellan and Skinner, 2006); others argue this is not the case (Bhattacharyaa and Lakdawalla, 2006). Evaluations of recent school accountability programs in the spirit of NCLB have found an *increase* in the black-white test score gap after accountability (although they also find a decrease in the hispanic-white gap) (Hanushek and Raymond, 2004 and 2005). Other evaluations of these programs have argued they are most beneficial for students in the middle of the class, not for those at the bottom (Neal and Schanzenbach, 2007). In a historical example, improvements in infant health care in the 1950s seemed to decrease white infant mortality rates, while leaving black infant mortality rates unchanged, effectively increasing the inequality in mortality. However, further improvements in health care in the 1960s lowered relative mortality rates of black infants, increasing equality (Almond et al, 2007; Chay and Greenstone, 2000).

In this paper I argue that this empirically ambiguous relationship between the level of access to social services and inequality is not surprising and, in fact, is what we would expect based on simple economic theory. I show a model relating the level of access to some investment (equivalently, the cost of the investment) to the difference in investment levels across two groups, one of whom faces discrimination or disadvantage. At very low levels of access (very high cost), there is little or no investment in either group, implying equality. As access increases, the more valued group gets access first, generating inequality. After some point, further increases in access will improve the situation of the less valued group, restoring equality. This model therefore predicts that the relationship between access and inequality may be non-monotonic: inequality increases with increases in access from low levels, but decreases with increases in access when starting at a high level.

I test the predictions of this model using data on vaccinations in India, analyzing the effect of changes in the availability of vaccinations on overall vaccination levels for boys (the advantaged group) and girls (the disadvantaged group). This context is well suited to test this theory for several reasons. First, there is clear evidence of gender discrimination in India. Sen (1990,1992) argued that as of 1980, there were 41 million "missing women" in India; more recent evidence suggests very high rates of sex-selective abortion (Jha et al, 2006). There is strong evidence of discrimination against girls in investments ranging from health care to vaccination to food intake (Das Gupta, 1987; Basu, 1989; Griffiths et al., 2000; Borooah, 2004; Pande, 2003; Mishra et al., 2004; Oster, 2008).

Second, vaccinations fit well into the framework of the model because they are an investment with saturation. A child only needs a certain number of vaccines (the World Health Organization recommends eight) and more than that are not useful. This means that we are more likely to see evidence of both the increase in inequality and the decrease predicted by the model, since the advantaged group is more likely to reach investment saturation. Vaccines in India are also an investment for which there are significant gender differences, and these gender differences actually map into a large share of the difference in child survival (Oster, 2008). This suggests that the analysis here may also have direct policy relevance.

Perhaps the strongest argument for testing the theory in this context is that I am able to take advantage of variations in the availability of "health camps" in India. These camps provide simple maternal and child health services, including vaccinations. The number of health camps varies across villages, generating clear variation in the convenience and cost (in terms of travel) of vaccination. Although placement of camps is not random, I argue that it is unrelated to existing vaccination conditions (either the level or the existing gender difference in vaccination) or to demographics like income, education, or average number of children. Consistent with institutional details, camp concentration does vary by state, as well as with village population and distance to health clinics. These are, however, observable variations that can be controlled for. There is significant variation in the number of camps, meaning it may be possible to observe the relationship between inequality and access over a relatively large range of access levels.

In Section 4, I present evidence on the relationship between health camps and gender differences in vaccination, using data from the National Family and Health Survey in India, which collects detailed data on child health as well as village-level data on the availability of health camps in the last year. Consistent with the theory outlined above and described in more detail in Section 2, I find that initial increases in the number of health camps increase the gender imbalance in vaccination (measured either by total vaccinations or whether the child has any vaccinations), but that further increases decrease the imbalance. As further support for the theory, I find that this non-monotonic effect is stronger for families with a stronger reported gender bias. In Section 5, I discuss two alternative tests of the non-monotonic prediction, relying on information on distance to non-camp vaccination sources and regional-level variation in vaccination levels. In both cases I again find evidence for a non-monotonic relationship between the level of vaccinations and the gender differences.

In the final section of the paper I consider whether these non-monotonicities in vaccination map into non-monotonicities in mortality. I use retrospective information on child mortality to construct a panel of death rates over the period from 1982-1993. I find a non-monotonicity in the relationship between increases in vaccination access and the gender imbalance in mortality. In areas that start with low levels of vaccination, excess female mortality increases over time; in areas that start with high levels of vaccination, excess female mortality decreases over time. This is true only in areas with increases in vaccinations over this period – i.e. those that appear to have had a decrease in vaccination cost.

Together, the results provide strong support for the non-monotonicity predicted by the theory. This result may have policy implications for India and other developing countries that face gender discrimination. policy-makers have argued that increasing the level of development is one of the key factors in ameliorating gender inequality. In 2001, a World Bank report on gender and development begins with the statement that poverty and gender inequality are closely linked: "Large gender disparities in basic human rights, in resources and economic opportunity ... are pervasive around the world ... And these disparities are inextricably linked to poverty," (World Bank, 2001). One of the aspects of development cited as crucial to affecting gender inequality is access to health services (World Bank, 1991; Hill and Upchurch, 1995). It has been argued that increasing the level of health care will benefit women and reduce gender inequality (Grown, Gupta and Pande, 2005), although the link between development and inequality is not limited to health care (see, for example, Duflo, 2005). This argument is particularly salient in India, where poverty is often linked to gender ratios and excess female mortality by region (World Bank, 1991; Chatterjee, 1990). The results here suggest *how* interventions are introduced to developing areas may be meaningful. A program like the health camps analyzed here, which is not targeted to decrease gender inequality, may actually have the opposite effect: simply increasing access is not sufficient. Programs that are targeted to affect gender inequality may be necessary, although there are clear tradeoffs; for example, targeting gender inequality may be inconsistent with the aim of decreasing other forms of inequality.

The rest of the paper is organized as follows. Section 2 discusses the theoretical framework, both in general and with a specific application to investments by parents in the health of children. Section 3 describes the National Family and Health Survey data. Section 4 presents the results on health camps and inequality, and Section 5 shows the relationship between other measures of access and inequality. Finally, Section 6 shows the test for non-monotonicities in mortality, and Section 7 concludes.

2 Theory of Discriminatory Investment

This section presents a simple model of discriminatory investments. The question of interest is how changes in access to investments (health services, education, etc) will affect the difference in the level of those investments between an advantaged and disadvantaged group. In the first subsection I outline the basic model of a discrete investment, without being explicit about the type of investment or the decision maker involved. In the second subsection I discuss, more informally, generalizing the model to the case with substitutes and to continuous investments. The third subsection explicitly discusses the specific case of vaccinations in a world with gender bias, which is the primary focus of the empirical work.

2.1 Baseline Model of Discriminatory Investments

Individuals in the model are of two types, advantaged and disadvantaged, with measure 1 of each type. There is a social planner who has access to some investment that would be beneficial to both types, and he makes decisions about investment for each individual. The investment is provided by some outside entity (for example, the government) at a cost of $v + \varepsilon_i$ for an individual i, where $\varepsilon \sim N\left(0, \sigma^2\right)$. This cost is not systematically different across the two types. In the model, the investment is assumed to be discrete.[1]

The social planner values the investment differently for the two types. Denote the value of the investment for the advantaged group Λ_A and for the disadvantaged group Λ_D. There are many reasons why these values might differ, and those reasons are likely to be different across different contexts. For this general model, I will simply assume that these values differ.

The investment will be chosen for the advantaged and disadvantaged groups, respectively, if the following inequalities hold.

$$\Lambda_A - v > \varepsilon_i$$

$$\Lambda_D - v > \varepsilon_i$$

[1] The next subsection discusses the issue of continuous investments.

The share of the advantaged group that gets the investment is, therefore, $F(\Lambda_A - v)$ and the share of the disadvantaged group is $F(\Lambda_D - v)$, where $F(.)$ is the normal distribution. The inequality in the investment is measured by the difference in these shares: $F(\Lambda_A - v) - F(\Lambda_D - v)$. The analysis focuses on the change in this quantity as v changes: as the average cost decreases, how does the inequality change?

Denote the difference in the share with the investment in each group as Θ. Under the assumption of normally distributed costs, this difference is simply

$$\Theta = \int_{\Lambda_D - v}^{\Lambda_A - v} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-(x)^2}{2\sigma^2}\right) dx$$

Integrating out, and differentiating with respect to v implies that

$$\frac{d\Theta}{dv} = \frac{1}{\sqrt{2\pi\sigma^2}} \left(-\exp\left(\frac{-(\Lambda_A - v)^2}{2\sigma^2}\right) + \exp\left(\frac{-(\Lambda_D - v)^2}{2\sigma^2}\right)\right)$$

The sign of this differential changes based on v. The result is summarized in Proposition 1.

Proposition 1. *When investment costs are high on average, decreases in the cost result in increased bias towards the advantaged group. As average investment costs decrease, the sign of this effect switches and further decreases result in decreases in inequality.*

Proof. We begin by restating the proposition as follows: There exists v^* such that when $v^* < v < \infty$, $\frac{d\Theta}{dv} < 0$ and when $v = v^*$, $\frac{d\Theta}{dv} = 0$ and when $0 \leq v < v^*$, $\frac{d\Theta}{dv} > 0$. Further, this $v^* = \frac{\Lambda_A + \Lambda_D}{2}$. Given this, the proof is straightforward.

Note that the sign of $\frac{d\Theta}{dv}$ is the same as the sign of $(\Lambda_A - v)^2 - (\Lambda_D - v)^2$. If this is negative, the differential is negative, and if it is positive, the differential is positive. We will therefore focus on conditions to sign that object. In particular, we will focus on signing it in three cases: when $v > \frac{\Lambda_A + \Lambda_D}{2}$, when $v = \frac{\Lambda_A + \Lambda_D}{2}$ and when $v < \frac{\Lambda_A + \Lambda_D}{2}$

1. $v > \frac{\Lambda_A + \Lambda_D}{2}$. Rearranging, this holds when $-(\Lambda_D - v) > \Lambda_A - v$. Squaring both sides, we find $(\Lambda_D - v)^2 > (\Lambda_A - v)^2$, which implies that $(\Lambda_A - v)^2 - (\Lambda_D - v)^2 < 0$, so $\frac{d\Theta}{dv} < 0$.

2. $v < \frac{\Lambda_A + \Lambda_D}{2}$. Rearranging, this holds when $-(\Lambda_D - v) < \Lambda_A - v$. Squaring both sides, we find $(\Lambda_D - v)^2 < (\Lambda_A - v)^2$, which implies that $(\Lambda_A - v)^2 - (\Lambda_D - v)^2 > 0$, so $\frac{d\Theta}{dv} > 0$.

3. $v = \frac{\Lambda_A + \Lambda_D}{2}$. Rearranging, this holds when $-(\Lambda_D - v) = \Lambda_A - v$. Squaring both sides, we find $(\Lambda_D - v)^2 = (\Lambda_A - v)^2$, which implies that $(\Lambda_A - v)^2 - (\Lambda_D - v)^2 = 0$, so $\frac{d\Theta}{dv} = 0$.

□

The proposition suggests that, beginning in a situation with very high investment costs (hence, limited investments), increases in access will make the disadvantaged group relatively worse off. Further increases, however, are predicted to decrease inequality.

To see the graphical intuition behind the result, consider Figure 1. This figure graphs two possible cost distributions with different levels of v; the dotted line represents a distribution with better access to the health investment (lower v). The cutoffs D_1, A_1 and D_2, A_2 represent two sets of investment cutoffs (D_x is the cutoff for the disadvantaged group, A_x for the advantaged group). The mass of the distribution under the cutoff receives the investment, so the D_1, A_1 cutoffs represent a world with overall higher investment levels. Consider what happens to the difference in investments when we move from the solid to the dotted distribution, which represents a decrease in v. For the case of D_2, A_2, this movement causes a greater increase in the share receiving the investment for the advantaged group than for the disadvantaged group because both lines are on the increasing part of the distribution. In contrast for the case of D_1, A_1, the increase causes a greater improvement for the disadvantaged group because both lines are on the decreasing part of the distribution. It is this intuition that is central to the result.

In Appendix A, I discuss the specific generalizability of this result to other cost functions. Although it will not be true for all cost distributions, the intuition in Figure 1 is robust. In particular, the fact that $\frac{d\Theta}{dv}$ is negative at high values of v and positive at low values will be true in general for any single peaked distributions (although it will hold for other distributions, as well).

In addition to this basic prediction of a non-monotonicity, the model also makes a prediction about how this relationship will vary as the magnitude of the difference in values across groups varies, summarized in Proposition 2.

Proposition 2. *When the relative value of the advantaged group is higher, the amplitude of the* $\frac{d\Theta}{dv}$ *function will be larger, so we expect a larger (in magnitude) relationship between access and inequality.*

Proof. The amplitude is determined by the maximum value (in absolute value terms) attained by the function $\frac{d\Theta}{dv}$. Note that an increase in the value of the advantage group can be represented by an increase in Λ_A, holding Λ_D constant. $\frac{d\Theta}{dv}$ attains its maximum absolute value twice: when $\Lambda_A = v$ and when $\Lambda_D = v$, and this value will be the same in absolute value. At this point, $\frac{d\Theta}{dv} = \frac{1}{\sqrt{2\pi\sigma^2}}\left(1 - exp\left(\frac{-(\Lambda_A-\Lambda_D)^2}{2\sigma^2}\right)\right)$. The derivative of this with respect to Λ_A is $\frac{1}{\sqrt{2\pi\sigma^2}}\left(\exp\left(\frac{-(\Lambda_A-\Lambda_D)^2}{2\sigma^2}\right)\left(\frac{2(\Lambda_A-\Lambda_D)}{2\sigma^2}\right)\right)$, which is positive. So as the relative value of the advantaged group increases, the amplitude of this function increases, and we expect the magnitude of the relationship between access and inequality to be larger. □

The intuition here is, again, relatively straightforward. Referring again to Figure 1, if the cutoffs for the two groups are very close to each other, then when the curve shifts left the increase in area to the left of each cutoff will be similar. If the cutoffs are very far apart, the same curve shift causes very different magnitude increases in the area to the left.

2.2 Generalization of the Theory: Substitutes and Continuous Investments

The theory outlined above embeds a number of assumptions. As I will detail below, in subsection 2.3, I believe that the assumptions are a good fit to the case of vaccinations in India. This subsection discusses the degree to which we expect the basic implications above to continue to hold if we relax the most important of the assumptions above. In particular, I discuss what would happen in the case where there are substitutes for the government provided-investment, and the case where investments are continuous.

Substitutes

The model above assumes that the investment good can only be obtained from some outside entity, at cost $v + \epsilon_i$, and there are no substitutes. In many situations, however, there are likely to be substitutes available. For example, if we think about education, private schools are a substitute for publicly-provided education. Even in the case of vaccines, there are some for which substitutes are available – typhoid can be avoided with a vaccine, but also by boiling water before drinking it.[2]

To model this simply, assume that the investment can be obtained either from the outside entity at a cost of v or from another source at cost t. The outcome is still valued at Λ_A for the advantaged group, and Λ_D for the disadvantaged group. There are three relevant cases.

- **Case 1** $t > \Lambda_A > \Lambda_D$: the cost of obtaining the investment privately is larger than the value of the investment for the advantaged group (and therefore larger for the disadvantaged group as well). In this case, the theory detailed above is unchanged. Since the cost of obtaining the investment privately is so large, its availability is functionally irrelevant, and choices about investment are determined by movements in v.
- **Case 2** $\Lambda_A > \Lambda_D > t$: the cost of obtaining the investment privately is smaller then the value of the investment for the disadvantaged group (and, therefore, also smaller than the advantaged group). In this case, everyone gets the investment regardless of the cost of provision by the outside entity, and the theory outlined above will not hold. Movements in the outside entity cost v will have no meaning, since everyone is already getting the investment even if v is extremely high.
- **Case 3** $\Lambda_A > t > \Lambda_D$: the cost of obtaining the investment privately is less than the value of the investment for the advantaged group, but more than the value for the disadvantaged group. In this case, we would expect the advantaged group to get the investment even if v is very high, and only the disadvantaged group investment level would be determined by changes in v. In other words, in this case we would not see a non-monotonicity: decreases in v would only decrease inequality, since they will only affect the level of investment for the disadvantaged group.

[2] I am grateful to an anonymous referee for suggesting this example.

These cases suggest that the introduction of substitutes may or may not affect the possibility that we see a non-monotonicity in the relationship between inequality and changes in v. If the cost of obtaining the investment privately is very high, we would still expect to see this type of relationship; however, if the cost is lower than the benefits, even if it is only lower than the benefits to the advantaged group, the result will break down. It is worth noting that Case 2 is unlikely to come up when thinking about investments that an outside entity like the government might provide: if everyone already gets some investment privately, there is little incentive to provide another version of it.

In any given situation, even with substitutes, the applicability of this non-monotonicity then comes down to how costly a private investment is. There are some circumstances in which Case 3 is clearly applicable. One clear example is boiling water and the typhoid vaccine. Boiling water is expensive, but it is probably not prohibitively expensive, and it could well be the case that the cost is low enough that it makes sense to do it for the advantaged group, but too high for the disadvantaged group. In other situations, we are more clearly in Case 1; for example, when public education was initially introduced, private education was extremely expensive, and accessible only to a very small number of people. For most of the population – advantaged or disadvantaged – this alterative was not an option. Of course, there are a variety of situations in which there simply are no substitutes for some investment – for example, food – in which case this issue is moot.

Continuous Investments

A second key assumption in the model is that the investment is discrete. Obviously, many investments are continuous, and it is interesting to consider to what extent the results above go through in that case.

Again, we focus on a very simple model that incorporates this feature. We assume that the social planner chooses a level of investment n, and the value of this is $\Lambda_X f(n)$, where $X \in A, D$ and $f'(n) \geq 0$. Each unit of n costs v, and, as is implicit in the discrete model, we assume that the social planner has an additive utility function over consumption of some other good c, which has a price of 1 and $\Lambda_X f(n)$; the total budget is Y. The social planner solves the below maximization.

$$max_n c + \Lambda_X f(n)$$

$$\text{s.t. } c + nv = Y$$

The solution is simple: at the optimum n^*, $\Lambda_X f'(n^*_X) = v$. The question of interest is how the difference in investment levels across the two groups varies with v. In particular, what is the sign of $\frac{d(n_A^* - n_D^*)}{dv}$.

It is clear that this will vary depending on the characteristics of $f(n)$. Below I consider three cases: the case with a possibility of saturation of n, the case where $f(n)$ is linear, and a general case where $f(n)$ is a differentiable, non-linear function.

- **Saturation** Allow $f(n)$ to have a general functional form but assume that $n \in [0, \bar{n}]$ – that is, it is not possible to purchase more than $\bar{n}$ of the investment. As before, non-monotonicity requires that there is some region with high v over which decreases in v generate more inequality, and some region with lower v in which decreases in v generate less inequality.

  - **Case 1: Increase in Inequality** Begin with a sufficiently high value of v such that $v > \Lambda_A f'(0) > \Lambda_D f'(0)$, so there is no investment for either group, implying equality. As v decreases, there will be some point at which $\Lambda_A f'(0) > v > \Lambda_D f'(0)$, in which case $n_A^* > 0$ but $n_D^* = 0$, generating inequality.
  - **Case 2: Decrease in Inequality** Begin with a lower value of v such that $\Lambda_A f'(\bar{n}) > v > \Lambda_D f'(\bar{n})$. With this value of v, $n_A^* = \bar{n}$ but $n_D^* < \bar{n}$. Since n cannot increase above $\bar{n}$, at this point further decreases in v will not affect the investment for the advantaged group, but will increase investment for the disadvantaged group, until $n_D^* = \bar{n}$; over this range, inequality will be decreasing.

  This indicates that there will be some non-monotonicity in the relationship between cost and inequality. In contrast to the simple normally-distributed discrete case above, exactly the shape we would expect this relationship to take outside of these two end points is ambiguous, and depends on the functional form of $f(n)$. This is similar to the version of the model outlined in Appendix A for the discrete case with a general functional form for the distribution of $F(\epsilon)$: we know there will be some non-monotonicity, but the shape of the function between the endpoints is not defined without knowing the functional form of $f(n)$.

- **$f(n)$ linear** If $f(n)$ is linear, we have a corner solution. In this case, $f'(n)$ will simply be equal to some constant; denote this ϕ. If $\phi\Lambda_X > v$ then the social planner will choose to devote all of the available resources to this investment, and we will have $n_X^* = \frac{Y}{v}$. If $\phi\Lambda_X < v$ the social planner chooses to spend nothing on this investment and $n_X^* = 0$. Again, non-monotonicity requires that there is some region with high v over which decreases in v generate more inequality, and some region with lower v in which decreases in v generate less inequality.

  - **Case 1: Increase in Inequality** Begin with a sufficiently high value of v such that $v > \phi\Lambda_A > \phi\Lambda_D$, and $n_A^* = n_D^* = 0$, which implies equality – no investment for either type. As v decreases, since $\Lambda_A > \Lambda_D$, there will be a point at which $\phi\Lambda_A > v > \phi\Lambda_D$, and $n_A^* = \frac{Y}{v}$, $n_D^* = 0$, generating inequality.
  - **Case 2: Decrease in Inequality** Begin with a lower value of v such that $\phi\Lambda_A > v > \phi\Lambda_D$. As v decreases further, eventually it will reach levels such that $\phi\Lambda_A > \phi\Lambda_D > v$, where $n_A^* = n_D^* = \frac{Y}{v}$, and equality will be restored.

  As in the case of saturation, in this model the basic intuition behind the non-monotonicity is retained in the case of a linear $f(n)$ function. There is at least some region in which inequality will get worse with decreases in v and some region in which it will get better.

- $f(n)$ **is Differentiable** In this case, if we are not in a corner solution, we can totally differentiate to explicitly solve for $\frac{d(n_A^* - n_D^*)}{dv}$. We find

$$\frac{d(n_A^* - n_D^*)}{dv} = \frac{1}{\Lambda_A f''(n_A^*)} - \frac{1}{\Lambda_D f''(n_D^*)}$$

  The sign of this is ambiguous, as is the way the sign might vary with v. There are situations in which we would expect to see a non-monotonicity (depending on the shape of the function, including the higher-order derivatives nd the magnitude of Λ_A and Λ_D), but there are other functional forms in which we would expect, for example, the movements in inequality to be linear.

The model above is obviously not the only way to incorporate continuous investments. This does give a general sense, however, of how those results would vary. In cases in which we have saturation, in particular, the non-monotonicity seems fairly robust. With continuous investments without saturation it is somewhat ambiguous what we would expect, although there are specific values and functional forms which will yield non-monotonicities even without saturation. In the next subsection I turn specifically to the example of vaccinations.

2.3 An Application to Vaccination by Gender in India

The empirical work in this paper focuses on the case of vaccination in India.[3] In this case, the decision maker is the family, and I assume that each family i is endowed with one child, either a boy or a girl.[4] The value of a living boy child, ϕ_b is greater than the value of a living girl child, ϕ_g. This could be due to simple preference, or it could reflect the fact that the monetary return to daughters is lower. In either case, we can summarize the existence of son preference with this simple difference in values, and this paper is agnostic about the source of the difference.

Parents have the opportunity to invest in the health of their child through vaccination. In general, with the vaccinations used here, there are unlikely to be very strong substitutes. Other than quarantine, it is extremely difficult for parents to avoid exposing their children to the diseases against which they are vaccinated, so in nearly all of these cases vaccination is the only reasonable source of protection. In principle, it is reasonable to think of vaccination in two ways – either as a

[3] In this particular context, there are interesting parallels between this theoretical result and an older literature on wealth and intrahousehold inequality. Kanbur and Haddad (1994), for example, argue that an intrahousehold bargaining framework can predict this type of non-monotonic relationship between wealth and inequality within the household.

[4] For simplicity, I ignore any existing children. Obviously, the number and gender of children that the family already has may influence their utility for each new child. However, the implications described below only require that, on average, the utility from a male child is higher than the utility from a female child. Abstracting away from existing children retains the simplicity of the model. However, an earlier version of this paper discusses a framework in which existing children are explicitly modeled. The central result – the non-monotonicity – holds in that model as well (that version of the paper available from the author).

discrete choice (full vaccination or no vaccination) or as a continuous choice with saturation (choose how many vaccines to get, with a maximum of 8). In practice, a majority of children get either full vaccination or no vaccination, so it seems that, to some extent, this is being treated like a discrete choice. However, in the empirical work I will report results both treating vaccination like a discrete choice (any vaccines versus no vaccines) and treating it as a continuous choice with saturation. Below I briefly outline the theory specific to each formulation.

Importantly, in both cases I assume that the effect of vaccinations is the same for boys and girls. If vaccination is more effective for boys, in particular, then we could get these effects not because of gender bias but because of a larger vaccination benefit. In general, however, there is little evidence that vaccinations are more effective for one gender and, if anything, papers that find a difference in efficacy tend to find that the vaccines to be more effective for girls (Aaby et al, 2002). In other work on this same data (Oster, 2008) I find that the relative value of vaccinations for mortality declines appears to be exactly the same for each gender. This does not, therefore, seem like a significant concern.

Discrete Choice

In this case, the family chooses to either vaccinate or not. Without vaccination, the child will live with probability p. With vaccination, the child lives with probability $\hat{p}$, where $\hat{p} > p$. The value of the vaccination investment for boys is, therefore, $\phi_b(\hat{p} - p)$ and, for girls, $\phi_g(\hat{p} - p)$. Vaccinations are provided by a number of sources, with a cost $v + \varepsilon_i$ for family i, with the variation reflecting the fact that some families live closer to vaccination sources, or may have better access to transportation. The program analyzed here lowers the average cost v by providing additional access to vaccination, often more conveniently located than existing sources. Note that even if we have a model in which each family has multiple children, we still expect the cost of vaccination to act for each child. Because children need vaccines at specific ages, it is not reasonable to take all of your children to be vaccinated at once, so the cost of travel must be paid for each child (or, below, for each vaccine).

Returning to the notation above, denote $\phi_b(\hat{p} - p) = \Lambda_A$ and $\phi_g(\hat{p} - p) = \Lambda_D$. Given this, the problem now maps identically into the basic model in Subsection 2.1, and the propositions are identical. We predict a non-monotonic relationship between access to vaccination and inequality, and this relationship should be larger among families with stronger son preference (higher ϕ_b relative to ϕ_g).

Continuous Choice with Saturation

In this case, the family chooses a number of vaccines n, where $n \in [0, 8]$. Again, without vaccination the child will live with probability p, and with n vaccines, the child lives with probability $p + f(n)p_0$, where $f(0) = 0$ and $p + f(8)p_0 = \hat{p}$, to parallel the above. Each vaccination in this case costs v, as above. In this case, the family chooses n to solve a maximization problem. Specifically, for boys,

$$max_n \phi_b(f(n))p_0 - nv$$

The first order condition indicates that the optimal value of n, n_b^* satisfies $\phi_b f'(n_b^*)p_0 = v$. As noted when discussing the case of continuous investments with saturation in subsection 2.2, the object of interest in this case is $\frac{d(n_b^* - n_g^*)}{dv}$ and the non-monotonicity exists if there is a range of v over which this is positive, and a range over which it is negative. This maps exactly into the case with saturation above, and the discussion there applies here, as well. Intuitively, in the case with saturation there will be some non-monotonicity, because there will be a range of changes in v for which we move from both groups having no vaccines to the boys having at least one vaccine. On the other end, there will be a range of changes in v for which we move from the boys having all vaccines and the girls having less than all, to a place where both groups have all vaccines. In this sense, the non-monotonicity is retained.

As discussed, this case is more complicated because how inequality moves over the rest of the range of v is dependent on the functional form of $f(n)$. One plausible functional form is strict concavity: the first vaccination is more valuable than the second, and so on. In this case, inequality will (weakly) increase with decreases in v until $v < \phi_b f'(8)p_0$ (that is, until boys have full vaccination) and then decrease after that. This gives us a strict non-monotonicity. As discussed, this will *not* be true with any functional form for $f(n)$, of course, but because of the saturation in any case we will get some range over which inequality is increasing and some range over which it is decreasing.

3 Data

The analysis here is run using individual-level microdata on child health investments in India. I use primarily the second wave of the National Family and Health Survey (NFHS), which covers approximately 90,000 women and was run in 1998-1999. Women are asked about their birth history, including children ever born, dates of birth, if the children are alive, and, if not, when they died. In addition, for children under four, information is collected on vaccination and other health inputs. I will also make some use of the earlier wave of the NFHS, which was run on a similar sample size in 1992-1993.

The primary child investment analyzed is vaccination. There are eight possible vaccinations: three DPT (diphtheria, pertussis, and tetanus) vaccines, three polio vaccines, a measles vaccine, and a BCG (tuberculosis) vaccine. The measure of vaccination is simply the total number of vaccinations reported by the child's mother or on their health card. I will also present results in which the measure of vaccination is whether the child has any vaccinations.

The analysis will also use information on the number of "Family Health and Welfare Camps" held in each village in the previous year, as well as information on distance to other sources of vaccination. The information on camps is drawn from the NFHS village survey (administered to the village head). The information on distance is household-specific and comes from the NFHS household survey.

Summary statistics are shown in Table 1. Panel A describes the basic demographics of children included in the sample. Slightly less than half are girls, with an average age of 1.2 years. The mothers in the sample have approximately 3.5 years of education, and are largely Hindu (75%). The children have, on average, 0.70 older brothers and 0.80 older sisters. The slightly larger number of older sisters is suggestive of a gender-biased stopping rule in which families are more likely to continue child-bearing when they have a female child early. Panel B of Table 1 shows summary statistics on vaccination access and levels. The average child in the sample has slightly more than half of their vaccinations – 4.7 out of 8, and 75% have at least one vaccination. The average number of camps in a village each year is 1.2, although the range is from 0 to 70. It is worth noting that girls have significantly fewer vaccines than boys (4.54 versus 4.79 on average) suggesting at least some gender discrimination in vaccination in the sample.

4 Health Camps and Gender Differences in Vaccination

This section describes the primary test of the theory in this paper, which relies on variation in the availability of vaccination camps across villages. In the first subsection I discuss the placement of vaccination camps. The second subsection presents results.

4.1 Placement of Health Camps

Beginning in the mid-1990s, the National Health and Welfare Ministry in India began a new phase of the overall campaign to bring better health care to India – the Reproductive and Child Health Programme (RCH) (Indian Ministry of Health and Family Welfare, 1998). One of the primary elements of this campaign is greater outreach to remote and poorly served regions. This outreach comes primarily in the form of establishing Primary Health Centers (PHC) and Community Health Centers (CHC) to serve relatively small population areas. These centers, in turn, can run RCH camps, either in their own location or in even more remote areas. In contrast to the PHC and CHC, the camps are mobile and temporary, usually lasting only one or two days, and offer only very basic health services (for a general discussion of these camps, see Mavalankar and Sinha, 1999).

There are two obvious concerns in identifying the effects in the paper based on variations in number of camps. First and foremost, there is the concern that the camps are targeted to areas based on existing vaccination conditions. A second, related, concern is that there could be selective migration to areas with many vaccination camps by individuals who have the most need for them (Rosenzweig and Wolpin, 1988). In this context, the latter issue is less likely to be a big deal because there is no reason to think that the same number of camps will be available in future years. So it is unlikely that people will choose migration decisions based on this year's camp placement. The former issue is more of a concern. Both concerns, however, are addressed by the discussion in this section on the correlates of camp placement.

There appears to be no systematic scheme for camp placement. The RCH programme is run at the state level, suggesting that there may well be variations across states in the number of camps. In addition, since the camps were based out of PHCs and CHCs and travel is expensive, we may expect areas closer to these clinics to have more camps. Finally, village population and village area may also have a role, since the benefit of a camp is likely to be larger in bigger villages. Given these concerns, all regressions will allow for the effect of gender to differ between states and will include interactions between gender and village area, village population and distance to other sources of health care.

However, it is also important to consider whether empirical placement of the camps appears to be non-random beyond these controls. For example, are there more camps in richer or more well-educated areas, or areas with more children? To test for this, in Table 2, I regress the number of camps by village on some simple village characteristics (income, maternal education and age, village population, and ideal sex ratio) from the 1998 survey.[5]

In the first column, I simply show the regression on village population, village area, distance to another source, and state fixed effects (the coefficients on state are not shown, but the test that they are all equal is reported). As suspected, all four of these parameters matter – there are more camps in larger villages and in those villages closer to a PHC or CHC, and we can reject the equality of the coefficients for each state with high confidence. Column 2 of Table 2 includes a set of additional demographic controls. None of these additional controls are significant; placement does not seem to be related to education, income, age, religion, or number of children. This is also true if we do not condition on state, village size, and distance (results available from the author).

A more specific concern is that camp placement might be correlated with initial vaccination conditions. It is not possible to examine this possibility using the 1998 data alone since we expect the number of camps to affect vaccination levels. To test for a relationship between vaccination camp placement and pre-existing gender differentials in vaccinations, I take advantage of the 1992 wave of the survey. Figure 2 shows the relationship between the average number of camps (at the district level) and vaccinations rates for the district in 1992. Although the sample sizes are small as we increase the number of camps (so the data is somewhat noisy), the general picture does not suggest either a strong linear or non-monotonic relationship between number of camps and gender difference in vaccination. Table 3 estimates this relationship between the average number of camps (at the district level) and gender difference in vaccination rates for the district in 1992. Column 1 includes the gender difference in vaccination and average vaccinations linearly; column 2 includes a quadratic in each. This regression shows no relationship between the gender differences in vaccination and camp placement. This suggests that although there are important district-specific drivers of the number of camps (as in Table 2), these do not seem to be related to gender imbalances in vaccination.

This discussion should provide some confidence that, although placement of these camps is by no means completely exogenous, the primary drivers of the placement can be observed and controlled for. It is also the case that, even if these camps *were* placed endogenously (for example, targeting areas with low vaccination levels), the endogenaity would have to be of a particular form in order to induce the non-linear results seen here. Targeted camp placement could drive the results only if areas with high male preference were targeted to receive a few camps, while areas with low male preference were targeted to receive either no camps or many camps. It is obviously not possible

[5] In this case, and throughout this section, the number of camps is top-coded at ten. Ninety-eight percent of villages have ten or fewer camps, and the top-coding avoids allowing outliers to drive the results.

to rule this out, but it would need to be generated by quite unusual decision making.

4.2 Results on Camps and Gender Inequality

The central question in this section is how the gender imbalance in vaccination is related to the number of health camps. The basic result can be seen in Figure 3, which reports the gender difference in average number of vaccinations for children six months to two years, graphed against the number of vaccination camps in the previous year, as well as the average number of vaccinations for each gender.[6] The graph shows two measures of the gender difference. The first line (the black squares) just shows the raw differences in number of vaccines. This points to a non-monotonic relationship. In particular, moving from zero or one camp to two camps causes a large increase in the gender difference. Above two camps girls begin to gain. The adjusted line (the black triangles) shows these differences once the measure of vaccines is adjusted for a variety of covariances – child age, mother's education and income and village characteristics.[7] Even once these adjustments are made, the non-monotonicity remains.

In terms of levels, the figure suggests that moving from zero camps to five camps increases the number of vaccinations on average, although vaccinations are slightly lower in the group with the most camps.[8] This decline may be related to camp placement. Perhaps areas with very low levels of vaccinations were targeted to receive a larger number of camps. Even if this is the case, however, and placement is related to pre-existing levels of vaccinations, it may not be a problem for the work here. I am focusing here on the *interaction* between gender and number of camps, so the relationship in levels is not a central issue.

Table 4 explores the relationship between camps and gender imbalance in vaccination in a regression context with controls. I control for standard demographics and family characteristics. In addition, all regressions include state fixed effects and interactions between state and gender dummies, as well as interactions between gender and quadratics in village population, village area and distance to the nearest PHC or CHC.[9] All standard errors are clustered at the village level.

[6] I restrict to children in this age group since they are the ones who would have needed vaccinations in the previous year. Consistent with this, the results are less strong for older children.

[7] To do this adjustment the measure of vaccines is regressed on these controls, and the predicted residuals for boys and girls are subtracted to get the gender difference.

[8] For girls, moving from one to two camps actually is slightly negative in terms of the average number of vaccinations. This is likely due to the relatively small sample of villages; this difference is not statistically significant.

[9] The regressions in Table 4 use as the dependent variable the number of vaccination camps, rather than (for example) number of camps per area or per capita. However, I note that by controlling for area and village population flexibly among the independent variables, we are implicitly considering camps per capita or per area, but with a more flexible functional form.

Column 1 assumes that the relationship between vaccination camps and gender imbalance is quadratic and estimates the coefficient on the interaction between girl and number of camps and the interaction between girl and the number of camps squared (as before, the number of camps is top-coded at ten). The coefficient estimates do point to a non-monotonic relationship. The linear interaction term is negative (increases in vaccination camps increase discrimination), but the squared term is positive. In this table, as in the following ones, for simplicity I show only the coefficients on the variables of interest. However, Appendix W.1 (available on the author's web-site) shows the complete regressions in all cases.

Despite the evidence in the previous subsection that the placement of camps is unrelated to village-level socioeconomic status, there may still be concerns about these issues. Column 2 of Table 4 therefore replicates Column 1 but also includes controls for the interaction between gender and income, gender and income squared, and gender and education (linear and squared), as well as the existing controls for gender interactions with village population and distance. If the result on vaccination camps is being driven by some non-linear interaction of gender and another control, this specification should identify it. In fact, the coefficients in Column 2 are extremely similar to Column 1, suggesting that any correlations here make virtually no difference to the results.

Finally, in Column 3 of Table 4, I explore the relationship between camps and vaccination in a less parametric way. In this case, I include dummy variables for number of camps (1,2,3,4,5 and 6 or more – 0 is the excluded category) and number interacted with gender. This allows us to see exactly what is driving the results in Columns 1 and 2. The results are similar to what we would expect based on Figure 3. The only significant interactions are between gender and two or three camps; in areas with two to three camps the inequality is significantly worse than in areas with none. However, despite the lack of significance on the other coefficients, we see a pattern that mimics Figure 3: the coefficient on two camps and three camps is large and negative, and then we see less negative coefficients on interactions with more than three camps.

Table 5 replicates Table 4 but uses as the dependent variable a binary measure of whether the child has any vaccinations. The results mimic Table 4: we see evidence of a non-monotonic relationship, both when looking at the interaction with continuous number of camps (Columns 1 and 2) and in the interaction with number of camps measured discretely (Column 3).

Proposition 2 in the Section 2 suggests that the non-linear effect identified above should be stronger in areas with stronger son preference. To test this, I divide the sample based on each woman's reported ideal sex ratio and replicate the regression in Column 1 of Table 4 for each half of the sample. The hypothesis is that the magnitude of the coefficients should be larger for the set of women who report wanting a greater ratio of boys to girls.[10] I define women as having a preference for boys if they report wanting more boys than girls; the alternative is desiring equal numbers or more girls.

These regressions are shown in Table 6. Columns 1 and 2 focus on total vaccinations as the measure of vaccines; Columns 3 and 4 focus on whether the child has any vaccines. Columns 1 and 3 include women who do not report wanting a male-biased sex ratio among children; Columns 2 and 4 include those who do. In Column 1, neither of the two interactions between gender and camps is significant. In Column 2, however, the interactions are more significant and much larger.[11] The contrast suggests that, as predicted, this relationship holds more consistently for families with more gender-biased preferences. Columns 3 and 4 show a similar pattern: no significant relationship for families in which the mother does not report wanting more boys, but a non-monotonic relationship in families that do.

Table 6 bolsters the conclusions in Table 4 and Table 5. The effect of vaccination camps is largest for families with stronger male-biased preferences. Another obvious test would be to explore whether the inequality-access relationship holds less strongly for families where there are two children of opposite gender close in age. Intuitively, in families where a female child needs vaccination at the same time as a male child, the relationship between access and inequality may be muted since there is a high fixed cost to travel. Unfortunately, the sample sizes are too limited (given the necessary closeness in age – a year or less) to test this hypothesis.

5 Other Determinants of Vaccination Access

A significant advantage of the analysis above is that vaccination camps are likely to operate in large part as shocks to the availability of vaccination in the village. This makes them less obviously correlated with existing conditions. In addition, their discrete nature makes the exploration of non-monotonic effects relatively straightforward. The theoretical framework, however, is not specific to vaccination camps (or even to vaccination). In general, we expect discrimination to be non-monotonic in any measure of access. This section considers two alternative proxies for access to

[10] Obviously, reported ideal number of male and female children is not a perfect measure of gender preferences. However, it should provide some proxy. In addition, it is certainly the case that the gender inequality in vaccination is larger for families where parents report wanting more male children (results available from the author). I have run similar regressions dividing the sample based on the average ideal gender ratio in the area the individual lives in, rather than *their* reported gender ratio, and the results are similar.

[11] These are not wildly statistically precise, likely due to the smaller sample size.

vaccination and aims to demonstrate, among other things, that the results are not driven by the use of health camps as the shifter of access.

I first proxy for access using the reported distance from the nearest Primary Health Center, Community Health Center, or Government Hospital, as reported in the village survey in the 1998 NFHS. Approximately 50 percent of women report this as their source of immunization, so it seems to be a good proxy for access. Of course, access to these centers has other implications and may be correlated with unobservables. However, there is no obviously apparent bias that would produce a non-monotonic relationship in gender imbalance.

Figure 4 mimics Figure 3, this time considering the relationship between distance to the nearest source (5 groups) and vaccination gender differences. Again, as with vaccination camps, we see a non-monotonic relationship. As the distance increases, vaccination levels decrease for both boys and girls, but the difference increases and then decreases.

Table 7 shows the relationship between total vaccinations and gender, interacted with both distance and distance squared. In this case, we measure vaccinations for all children over the age of six months. Unlike in the measure of health camps, we do not need to focus only on children who were vaccinated in the last year, since the distance to the nearest source will be constant across years. In this case, the theory would predict the interaction with distance to be negative and with distance squared to be positive.[12] A sizable fraction of people report having a health facility in their village. These are coded as zero distance, although this may not be strictly correct.

In Column 1 of Table 7, I show the regression with all observations; in Column 2, I restrict to people who report a non-zero distance to avoid any issues with the in-village measure. The coefficients have the expected sign, although they are much more significant in the second column, when I leave out people who have a health facility in their village. This may reflect the fact that there is variation in distance even within the village which is not measured. Columns 3 and 4 of Table 7 split the entire sample based on gender preferences (as was done in Table 6). Column 3 shows the regression for women who report wanting more girls or wanting equality; Column 4 shows the regression for women who report wanting more boys. Again, as expected, the results are much stronger for those with a male-biased preference.

As a second test, I consider the cross-regional relationship between the level of vaccination and the gender difference in vaccination. In this case, the level of vaccination is the proxy for

[12]These predicted interactions have the opposite sign from the interactions on number of camps because increases in the number of camps imply increases in access and increases in distance imply decreases in access.

vaccination access. Even more than the analysis with Primary and Community Health Centers, this is subject to bias. However, it *does* provide the only opportunity to consider this relationship outside of rural villages.

I take advantage of the cluster design of the NFHS (a cluster, in this case, is a collection of on average 750 households in the same area). I aggregate the data to the cluster level and calculate the average number of vaccinations and the difference between this average for boys and girls. This regression will be run using the 1992 and 1998 data together; since I do not rely on the village-level information (either about camps or distance) I can use the 1992 survey as well.

The primary regression will consider the shape of the relationship between the level of vaccinations and the gender difference in vaccination. The results are shown in Table 8, where the dependent variable is the gender difference in average number of vaccines received; Column 1 considers a monotonic relationship between the level and the difference, and Column 2 considers a non-monotonic relationship. The results seem consistent with a nonlinear relationship: in Column 2 both the average and the average squared are significant and have the expected sign. The number of vaccinations ranges from zero to eight. The magnitude of the coefficients suggests that the gender imbalance is increasing up to an average of six vaccinations and decreasing thereafter.[13]

6 Non-Monotonicities in Mortality over Time

The evidence above suggests that there are non-monotonicities in child health investments and gender inequality. Although this maybe interesting on its own, this is likely to be more important if these non-monotonicities map into non-monotonicity in mortality. The ultimate outcome of interest here is not vaccinations *per se* but mortality, for which vaccinations may be an important input.

Even without looking directly at data on mortality, existing evidence on the connection between vaccination and mortality rates among children does suggest that changes in vaccination will map into changes in mortality. If getting vaccinated decreases mortality in the developing world (as we know that it does – see, among a huge additional literature – Aaby et al, 2002; Clemens et al, 1988; Koenig et al, 1990) then any changes in vaccination are likely to map fairly directly into changes in mortality.[14] However, this link is not necessarily sufficient. In particular, if the

[13] This result is in contrast to the results in Pande and Yazbeck (2003), who argue that gender differences in immunization across states do not seem to be related to state immunization levels. This may underscore the importance of considering the regional relationship at a less aggregated level.

[14] Note that this evidence means that even if there are, for example, compensating differences in behavior (I vaccinate the boys, but give the girls more food) the link will still hold. Data from the field on the effectiveness of vaccinations means that we can be confident that, even in the real world situations in which these vaccinations are given, we still see

effectiveness of vaccinations differs by gender, for example, this may break down. One clue that this is probably not the case comes from earlier work that I have done (Oster, 2008), which shows that differences in vaccination rates by gender explain about 30% of the gender differences in mortality in childhood. This suggests that, empirically, girls do suffer significantly from lack of vaccination.

Ultimately, however, the best way to see whether the changes in vaccinations map into non-monotonicities in mortality is to look in the data. Ideally, we would like to have a relatively long time-series in which child mortality by gender is observed. These type of data are not generally available. It is possible, however, to create a short time series using retrospective reports on child mortality in the two survey waves of the NFHS. I consider the mortality outcomes for children born between five and ten years before each survey year (1992 and 1998). This effectively creates a time series of child death rates from 1982 through 1993. The outcome of interest is death between 18 months and five years. I do not consider very early life mortality, since it will be generally unaffected by investments like vaccinations.

The theory would suggest that, to the extent that the cost of vaccinations decreased over this period, the gender imbalance in mortality should go up in areas where the initial level of vaccination was low, and down in areas where the initial level of vaccination was high. Obviously, if we had a very long time series, it would be possible to look for non-monotonic changes *within* a given area over time. With such a short time series, however, it is necessary to use cross-sectional variations in initial levels. I use state-level variation in vaccination levels as the initial condition, and estimate the following equation:

$$\begin{aligned} Dead_{is} &= \alpha + \beta_1(girl_{is}) + \beta_2(girl_{is} \times birthdate_{is} \times vaccines92_s) \\ &\quad + \beta_3(girl_{is} \times birthdate_{is} \times vaccines92_s^2) + \mathbf{\Phi X_{is}} + \epsilon_{is} \end{aligned}$$

where i indexes the individual and s indexes the state of residence, and $vaccines92_s$ is the level of vaccination in that state in 1992. The controls here ($\mathbf{X_{is}}$) include standard demographics *plus* all of the appropriate interactions between gender, birthdate and vaccinations so we can consistently estimate the triple interactions. As in the earlier regressions, if there is a non-monotonicity in inequality here, we expect to see that $\beta_2 > 0$ and $\beta_3 < 0$. That is, inequality is increasing over time in areas that start with low levels of vaccines, but decreasing in areas that start with high levels of vaccines.

One important wrinkle in this analysis lies in the fact that, as stated above, this should

a link between vaccination and lower mortality.

hold only if the cost of vaccinations decreased over this period. It is difficult to measure costs of vaccination directly. However, we do observe that in nearly all states the average level of vaccination increases over this period (by an average of 0.30 vaccinations). There is no reason to think that the benefits of vaccination have been increasing, so the increase in level of vaccine is very likely to have been driven by a decrease in cost. It is worth noting that there are a few states for which the level of vaccination actually has not increased over this period, which potentially provide an additional test. When presenting the results I will show estimates for all of the states together, and then divide the sample based on whether the vaccination levels increased to test whether this relationship shows up only in areas where vaccination levels have gone up. The theory would suggest that we should only see this effect for states which saw an increase in vaccination rates over this period.[15]

Table 9 shows the primary results on mortality.[16] In Column 1, I include all states. We see evidence of the non-monotonicity in mortality: the coefficient on the interaction between gender, time and initial vaccination levels is positive and significant, whereas the coefficient on the interaction between gender, time and initial vaccination level squared is negative and significant. Columns 2 and 3 divide the sample based on whether the state saw an increase in vaccination – our indicator for a decrease in cost – during this period. In Column 2, limited to the states in which we see vaccination increases, the coefficients have the expected sign and remain significant. However, in Column 3 the coefficients are not significant, and do not have the expected sign. This is what we would expect given the theory. If there is no decrease in cost, we do not expect to see any non-monotonic variation in mortality over time.

As in the case of vaccinations, here I also divide the sample based on gender preferences and re-estimate the regressions based on the reported ideal child gender ratio. Column 1 of Table 10 includes only people who report wanting more girls or equal numbers of boy and girl children, and Column 2 includes those who report wanting more boys. As in the regressions on vaccination, we see here that the non-monotonicity is much stronger and more significant for those individuals who express stronger male-biased gender preferences. Overall, the evidence in Tables 9 and 10 points to the conclusion that the non-monotonicities in vaccination are reflected in non-monotonicities in mortality.

[15] Related to this, I define vaccinations here based on vaccinations marked on a vaccination card only, not reported by the mother. This will combine changes in vaccination with changes in official sources of vaccination (i.e. those that will reliably require a card), and the hope is that it captures changes in costs more completely.

[16] The coefficients reported are marginal effects from a probit model; since death is a relatively unusual event, an OLS specification is not appropriate.

7 Conclusion

Increased access to social services is often though to decrease inequality, but in reality the effect of these increases is empirically ambiguous in many contexts. The results in this paper – both theoretical and empirical – suggest that this is not surprising, and that the relationship between access to services and inequality may be non-monotonic in a world with discrimination. Improvements in access may increase inequality initially, with further improvements decreasing it.

In the case analyzed here, I find non-monotonicities in the relationship between access to vaccination and gender differences in vaccination rates. From a policy perspective, the non-monotonicity would suggest that if policymakers care directly about the sex ratio, interventions to increase access to health inputs should focus on saturating one area rather than introducing the inputs in a more limited way in all areas. Depending on the magnitude of the effect of vaccinations on mortality, saturating one area versus providing some vaccination to all areas could make a reasonable difference in the gender imbalance in mortality.

It is worth keeping in mind, however, that the goal of gender equality may be at odds with the goal of achieving other forms of equality. In the example above, saturating one area with vaccinations and ignoring another area generates *regional* inequality in health outcomes, even if it serves to improve the gender balance. Ultimately, this is a tradeoff for policy-makers to consider when making choices about the distribution of health services.

Finally, as alluded to in the introduction, the theoretical framework here may help explain a variety of patterns in inequality, not just those in India. To the extent that this is more broadly applicable, it may argue for targeted interventions (Head Start rather than universal preschool, for example) that specifically focus on individuals in disadvantaged groups.

Appendix A: General Theoretical Results

This appendix discusses the general form of the result in Section 2. As there, I note that the conditions for vaccinations for the advantaged and disadvantaged groups are:

$$\begin{aligned} \Lambda_A - v &> \varepsilon_i \\ \Lambda_D - v &> \varepsilon_i \end{aligned}$$

and that the difference of interest is $F(\Lambda_A - v) - F(\Lambda_D - v)$. In the text I focus on the case where $F(.)$ is normal and show results indicating that at high v this difference will increase with decreases in v, and at low v the difference will decrease with decreases in v. Here, I discuss what must generally be true about the distribution for this to hold.

This difference Θ can be represented

$$\Theta = \int_{\Lambda_D}^{\Lambda_A} f(x - v)\, dx$$

Differentiating this with respect to v yields:

$$\frac{d\Theta}{dv} = -\int_{\Lambda_D}^{\Lambda_A} f'(x - v)\, dx$$

In order for this to be negative at high v and positive at low v, I simply require that $f(.)$ be increasing in the left tail, and decreasing in the right tail. Any single-peaked distribution will have this property.

In contrast to the case of the normal, which is decreasing everywhere in v, I will not be able to prove this generally. However, the intuition that the disadvantaged group become relatively worse off with decreases in v at high v and relatively better off with decreases in v at low v will be true for a wide class of distributions.

References

Aaby, P, H Jensen, ML Garly, C Bale, C Martins, and I Lisse, "Vaccinations and child survival in a war situation with high mortality: effect of gender," *Vaccine*, 2002, *21* (1-2), 15–20.

Almond, Doug, Ken Chay, and Michael Greenstone, "Civil Rights, the War on Poverty, and Black-White Convergence in Infant Mortality in Mississippi," 2007. Mimeo, Columbia Univeristy.

Basu, Alaka, "Is Discrimination in Food Really Necessary for Explaining Sex Differentials in Childhood Mortality?," *Population Studies*, 1989, *43* (2), 193–210.

Bhattacharyaa, Jay and Darius Lakdawalla, "Does Medicare benefit the poor?," *Journal of Public Economics*, 2006, *90*, 277–292.

Borooah, Vani, "Gender bias among children in India in their diet and immunisation against disease," *Social Science and Medicine*, 2004, *58*, 1719–1731.

Chatterjeee, Meera, "Indian Women: Health and Productivity," *Policy, Research and External Affairs Working Paper Series*, 1990, (442).

Chay, Ken and Michael Greenstone, "The Convergence in Black-White Infant Mortality Rates during the 1960s," *American Economic Review*, 2000, *90* (2), 326–332.

Clemens, JD, BF Stanton, J Chakraborty, S Chowdhury, MR Rao, M Ali, S Zimicki, and B Wojtyniak, "Measles vaccination and childhood mortality in rural Bangladesh," *American Journal of Epidemiology*, 1988, *128* (6), 1330–1339.

Das Gupta, Monica, "Selective Discrimination Against Female Children in Rural Punjab, India," *Population and Development Review*, 1987, *13* (1), 77–100.

Duflo, Esther, "Gender Equality in Development," 2005. MIT Working Paper.

Griffiths, Paula, Zoe Matthews, and Andrew Hinde, "Understanding the Sex Ratio in India: A Simulation Approach," *Demography*, 2000, *37* (4), 477–488.

Grown, Caren, Geeta Rao Gupta, and Rohini Pande, "Taking Action to Improve Women's Health Through Gender Equality and Women's Empowerment," *The Lancet*, 2005, *365*, 541–543.

Hanushek, Eric and Margret Raymond, "The Effect of School Accountability Systems on the Level and Distribution of Student Achievement," *Journal of the European Economic Association*, 2004, *2* (2-3), 406–415.

____ **and** ____ , "Does School Accountability Lead to Improved Student Performance," *Journal of Policy Analysis and Management*, 2005, *24* (2), 297–327.

Hill, Kenneth and Dawn Upchurch, "Gender Differences in Child Health: Evidence from Demographic and Health Surveys," *Population and Development Review*, 1995, *21* (1), 127–151.

Indian Ministry of Health and Family Welfare, *Annual Report*, New Delhi, India: Govt. of India, Ministry of Health and Family Welfare, 1998.

Jha, Prabhat, Rajesh Kumar, Priya Vasa, Neeraj Dhingra, Deva Thiruchelvam, and Rahim Moineddin, "Low male-to-female sex ratio of children born in India: National Survey of 1.1 Million Households," *Lancet*, 2006, *367*, 211–218.

Kanbur, Ravi and Lawrence Haddad, "Are Better Off Households More Unequal or Less Unequal," *Oxford Economic Papers*, 1994, *46*, 455–468.

Koenig, MA, MA Khan, B Wojtyniak, JD Clemens, J Chakraborty, V Fauveau, JF Phillips, J Akbar, and US Barua, "Impact of measles vaccination on childhood mortality in rural Bangladesh," *Bulletin of the World Health Organization*, 1990, *68* (4), 441–447.

Mavalankar, D.V. and Harshit Sinha, "Reproductive Health Camps: An Innovative Approach to Integrating Reproductive Health Intervention into Primary Health Care," 1999. Indian Institute of Management Working Paper.

McClellan, Mark and Johnathan Skinner, "The Incidence of Medicare," *Journal of Public Economics*, 2006, *90*, 257–276.

Mishra, Vinad, T.K. Roy, and Robert Retherford, "Sex Differentials in Childhood Feeding, Health Care, and Nutritional Status in India," *Population and Development Review*, 2004, *30* (2), 269–295.

Neal, Derek and Diane Whitmore Schanzenbach, "Left Behind By Design: Proficiency Counts and Test-Based Accountability," *NBER Working Paper 13293*, 2007.

O'Connell, Jack, "NAACP Universal Preschool Summit, prepared remarks," Online, at http://www.cde.ca.gov/nr/sp/yr05/yr05sp1019.asp 2005.

Oster, Emily, "Proximate Causes of Population Sex Imbalance in India," *Demography,* forthcoming, 2008.

Pande, Rohini, "Selective gender differences in childhood nutrition and immunization in rural India: The role of siblings," *Demography*, 2003, *40* (3), 395–418.

___ **and Abdo Yazbeck**, "Whats in a country average? Wealth,gender,and regional inequalities in immunization in India," *Social Science and Medicine*, 2003, *57*, 2075–2088.

Rosenzweig, Mark and Kenneth Wolpin, "Migration Selectivity and the Effects of Public Programs," *Journal of Public Economics*, 1988, *37*, 265–289.

Sawhill, Isabel, "Kids Need an Early Start: Universal preschool education may be the best investment Americans can make in our children's education - and our nation's future," Technical Report, Blueprint, Brookings Institution 1999.

Sen, Amartya, "Missing Women," *British Medical Journal*, 1992, *304*, 587–588.

___ , "More than 100 Million Women are Missing," *New York Review of Books*, December 20, 1990.

Watson, Tara, "Public health investments and the infant mortality gap: Evidence from federal sanitation interventions on U.S. Indian reservations," *Journal of Public Economics*, 2006, *90*, 1537–1560.

World Bank, *Gender and Poverty in India: A World Bank Country Study*, Washington, DC: World Bank, 1991.

——, "Engendering Development," Technical Report, World Bank 2001.

Table 1. ***Summary Statistics***

Panel A: Demographic Variables				
	Mean	**SD**	**Min**	**Max**
Girl (0/1)	0.48	0.50	0	1
Child Age	1.18	0.42	0.5	2
Mom Education	3.57	4.60	0	22
# Durables	1.34	1.35	0	6
Hindu (0/1)	0.74	0.44	0	1
# Older Brothers	0.72	0.98	0	8
# Older Sisters	0.81	1.09	0	8

Panel B: Vaccination Data				
	Mean	**SD**	**Min**	**Max**
Total Vaccinations	4.67	3.28	0	8
Any Vaccinations (0/1)	0.74	0.43	0	1
Total Vaccinations, Girls	4.54	3.32	0	8
Any Vaccinations (0/1), Girls	0.72	0.44	0	1
Total Vaccinations, Boys	4.79	3.26	0	8
Any Vaccinations (0/1), Boys	0.75	0.43	0	1
Share with Measles Vacc	0.37	0.48	0	1
Share with Any Polio Vacc	0.72	0.45	0	1
Share with BCG Vacc	0.65	0.48	0	1
Share with Any DPT Vacc	0.67	0.47	0	1
Number of Villages	2414			
# Camps	1.19	3.90	0	70
Dist (km) Source.	6.85	7.95	0	78
Village Pop	3028	472	0	50000

Notes: This table presents summary statistics for the data used in the paper, from the NFHS. Individual demographic information comes from the household survey data. Information on vaccination camps, distance from vaccination sources and village population comes from the village surveys.

Table 2. *Vaccination Camps and Current Village Characteristics*

	Dependent Variable: Number of Camps	
	(1)	(2)
Explanatory Variables:		
Village Population	.699***	.6864***
	(.139)	(.14)
Village Area (in 100 HA)	.0313***	.0314***
	(.007)	(.007)
Distance to Other Source	−.0134**	−.0131**
	(.006)	(.006)
Ave Mother Educ		−.0188
		(.024)
Ave. Mother Age		.0142
		(.021)
Ave. # Durables		.0697
		(.075)
Ave. Ideal Sex Ratio		.082
		(.616)
Ave. # Kids		−.0258
		(.059)
Share Hindu		−.1487
		(.164)
constant	.679***	.477
	(.075)	(.463)
State Fixed Effects	YES	YES
F-Stat, State FE Equal	4.29	4.15
Number of Observations	1878	1878
R^2	.18	.18

Notes: This table estimates whether there is evidence that camp placement is based on current village characteristics. An observation is a village, and the dependent variable is the average number of camps (top coded at 10).
standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3. ***Camps and 1992 District Vaccination Characteristics***

	Dependent Variable: Ave. Number of Camps (by District)	
	(1)	(2)
Explanatory Variables:		
Gender Diff in Vacc, 1992	−.0324	−.033
	(.069)	(.069)
Average Vacc, 1992	−.0873	.0038
	(.061)	(.205)
Gender Diff in Vacc, 1992, Sq.		−.0019
		(.03)
Average Vacc, 1992, Sq.		−.0112
		(.024)
Ave. Income (Durables)	.4453**	.4463
	(.214)	(.214)
Ave. Mother's Educ	−.1373*	−.1329
	(.071)	(.072)
Total Kids	.019	.0179**
	(.117)	(.118)
constant	1.081*	.93
	(.66)	(.74)
State FE	YES	YES
Number of Observations	359	359
R^2	.31	.31

Notes: The table estimates whether there is any evidence for camp placement being based on existing gender differences in vaccination. An observation is a district and the dependent variable is the average number of camps among villages in that district. The independent variable of interest is the difference in vaccination rates across genders in that state in 1992. The regressions are weighted by the number of children in each district.
standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4. *Vaccination Camps and Gender Imbalance in Vaccination*

	Dependent Variable: Number of Vaccinations Child Has		
	(1)	(2)	(3)
Explanatory Variables:			
Girl × # Camps	−.1751**	−.1804***	
	(.069)	(.069)	
Girl × # Camps Sq.	.0171**	.0176**	
	(.008)	(.008)	
# Camps	.1155**	.1162**	
	(.058)	(.057)	
# Camps Sq.	−.0107	−.0111*	
	(.007)	(.007)	
Girl × Camps=1			.1769
			(.212)
Girl × Camps=2			−.4936***
			(.184)
Girl × Camps=3			−.5286**
			(.224)
Girl × Camps=4			−.1503
			(.286)
Girl × Camps=5			.0448
			(.43)
Girl × Camps=6+			−.1405
			(.296)
Child Age	3.2915***	3.2542***	3.2681***
	(.36)	(.359)	(.359)
Child Age Sq.	−.983***	−.9703***	−.9741***
	(.144)	(.144)	(.144)
# Older brothers	−.1475**	−.1576***	−.1492**
	(.061)	(.061)	(.061)
# Older Sisters	−.0334	−.0466	−.0336
	(.059)	(.059)	(.059)
Dummies for # Camps	NO	NO	YES
State Fixed Effects	YES	YES	YES
State-Gender Inter.	YES	YES	YES
Village Pop-Gender Inter.	YES	YES	YES
Village Area-Gender Inter.	YES	YES	YES
Distance-Gender Inter.	YES	YES	YES
Gender-Control Inter.	NO	YES	NO
Number of Observations	8495	8495	8495
R^2	.35	.35	.35

Notes: This table estimates the effect of vaccination camps on the gender imbalance in vaccination. An observation is a child aged six months to two years and the dependent variable is the number of vaccinations the child has received (0-8). # Camps is the number of Family Health and Welfare Camps reported in the village in the previous year – 0, 1, 2, 3, 4, 5 or 6 or more. All interactions between gender and controls include interactions between gender and the control linear and squared. The main effect of *girl* is subsumed in the state-gender interactions. Other controls: maternal age, maternal education, family durable ownership, a dummy for being Hindu, birth order and village size. Full regressions with all controls reported are in Appendix Table W.1.1 (on author's website).
standard errors in parentheses, clustered at the village level. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 5. *Vaccination Camps and Gender Imbalance in Binary Vaccination*

	Dependent Variable: Child has Any Vaccinations (0/1)		
	(1)	(2)	(3)
Explanatory Variables:			
Girl × # Camps	−.0211**	−.0221**	
	(.009)	(.009)	
Girl × # Camps Sq.	.0024**	.0025**	
	(.001)	(.001)	
# Camps	.0179**	.0181**	
	(.008)	(.008)	
# Camps Sq.	−.0017*	−.0018**	
	(.001)	(.001)	
Girl × Camps=1			.0134
			(.033)
Girl × Camps=2			−.0682***
			(.026)
Girl × Camps=3			−.0338
			(.03)
Girl × Camps=4			−.0233
			(.034)
Girl × Camps=5			.0394
			(.045)
Girl × Camps=6+			.0034
			(.038)
Child Age	.1114**	.1069**	.1092**
	(.053)	(.053)	(.053)
Child Age Sq.	−.0328	−.0312	−.032
	(.021)	(.021)	(.021)
# Older brothers	−.0135	−.0148	−.0137
	(.01)	(.01)	(.01)
# Older Sisters	−.0002	−.0018	−.0001
	(.009)	(.009)	(.009)
Dummies for # Camps	NO	NO	YES
State Fixed Effects	YES	YES	YES
State-Gender Inter.	YES	YES	YES
Village Pop-Gender Inter.	YES	YES	YES
Village Area-Gender Inter.	YES	YES	YES
Distance-Gender Inter.	YES	YES	YES
Gender-Control Inter.	NO	YES	NO
Number of Observations	8495	8495	8495
R^2	.15	.15	.15

Notes: This table estimates the effect of vaccination camps on the gender imbalance in vaccination. An observation is a child aged six months to two years and the dependent variable is whether the child has any vaccinations. # Camps is the number of Family Health and Welfare Camps reported in the village in the previous year – 0, 1, 2, 3, 4, 5 or 6 or more. All interactions between gender and controls include interactions between gender and the control linear and squared. The main effect of *girl* is subsumed in the state-gender interactions. Other controls: maternal age, maternal education, family durable ownership, a dummy for being Hindu, birth order and village size. Full regressions with all controls reported are in Appendix Table W.1.2 (on author's website).
standard errors in parentheses, clustered at the village level. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 6. *Effect of Vaccination Camps by Gender Preference*

Dependent Variable:	*Number of Vaccinations Child Has*		*Child has Any Vaccines*	
	(1)	(2)	(3)	(4)
	Ideal: Equal/Girls	**Ideal: More Boys**	**Ideal: Equal/Girls**	**Ideal: More Boys**
Explanatory Variables:				
Girl × # Camps	−.114	−.2246*	−.0103	−.0311*
	(.082)	(.125)	(.011)	(.018)
Girl × # Camps Sq.	.0066	.0268*	.001	.0038**
	(.009)	(.014)	(.001)	(.002)
# Camps	.1088*	.0773	.0148*	.0172
	(.065)	(.087)	(.008)	(.012)
# Camps Squared	−.0076	−.0091	−.0012	−.0017
	(.008)	(.01)	(.001)	(.001)
Child Age	3.0899***	3.6218***	.0086	.2614***
	(.442)	(.566)	(.062)	(.093)
Child Age Sq.	−.8938***	−1.1377***	.0037	−.0878**
	(.177)	(.231)	(.025)	(.037)
# Older Brothers	−.0368	−.2258***	−.0043	−.0179
	(.089)	(.082)	(.013)	(.014)
# Older Sisters	.0825	−.1489*	.0102	−.0105
	(.083)	(.083)	(.012)	(.013)
State Fixed Effects	YES	YES	YES	YES
State-Gender Inter.	YES	YES	YES	YES
Village Pop-Gender Inter.	YES	YES	YES	YES
Village Area-Gender Inter.	YES	YES	YES	YES
Distance-Gender Inter.	YES	YES	YES	YES
Number of Obs.	5023	3472	5023	3472
R^2	.36	.29	.14	.14

Notes: This table estimates the effect of vaccination camps on the gender imbalance in vaccination. An observation is a child aged six months to two years and the dependent variable is either the number of vaccinations the child has received (in Columns 1 and 2) or a dummy for having any vaccines (Columns 3 and 4). # Camps is the number of Family Health and Welfare Camps reported in the village in the previous year. All columns include interactions between gender and state, as well as interactions between gender and village population (linear and squared), gender and village area (linear and squared) and distance to closest CHC or PHC (linear and squared). Columns 1 and 3 includes only women who report wanting equal numbers of boys and girls or more girls; Columns 2 and 4 includes women who report wanting more boys. Other controls: maternal age, maternal education, family income, a dummy for being Hindu, birth order, a quadratic in child age. Full regressions with all controls reported are in Appendix Table W.1.3 (on author's website).

standard errors in parentheses, clustered at the village level

* significant at 10%; ** significant at 5%;*** significant at 1%

Table 7. ***Access to Health Facility and Gender Imbalance in Vaccination***

	Dependent Variable: Number of Vaccinations Child Has			
	(1)	(2)	(3)	(4)
	All	**Not in Village**	**Ideal: Equal/Girls**	**Ideal: Boys**
Explanatory Variables:				
Girl × Dist.	−.0138	−.0283**	.0036	−.0445**
	(.011)	(.013)	(.014)	(.018)
Girl × Dist. Sq.	.0005*	.0008**	.0001	.0013***
	(0)	(0)	(0)	(0)
Distance	−.0222**	−.0221*	−.0268**	−.0132
	(.01)	(.013)	(.012)	(.013)
Dist. Sq.	−.0001	−.0001	.0001	−.0004
	(0)	(0)	(0)	(0)
Child Age	1.9152***	1.8714***	1.9534***	1.8999***
	(.141)	(.16)	(.176)	(.23)
Child Age Sq.	−.4344***	−.4163***	−.4511***	−.4212***
	(.041)	(.047)	(.052)	(.067)
# Older Brothers	−.1038**	−.1185**	−.0084	−.163***
	(.044)	(.049)	(.064)	(.059)
# Older Sisters	.031	.0124	.098*	−.0385
	(.041)	(.046)	(.059)	(.058)
State Fixed Effects	YES	YES	YES	YES
Village Pop-Gender Inter.	YES	YES	YES	YES
Number of Obs.	16,948	13,412	9873	7075
R^2	.33	.32	.34	.27

Notes: This table estimates the effect of distance to a primary health center, a community health center, or a government hospital on the gender imbalance in vaccination. An observation is a child aged six months to four years and the dependent variable is the number of vaccinations the child has received (0-8). Distance is the minimum distance reported in the village survey to either a Primary Health Center, a Community Health Center, or a Government Hospital. Column 1 includes all observations and Column 2 limits to those without one of these health facilities in the village. Column 3 includes all villages, but only people who report wanting equal numbers of boys and girl or more girls; Column 4 includes all villages but only those who report wanting more boys. Other controls: maternal age, maternal education, family income, a dummy for being Hindu, and birth order. Full regressions with all controls reported are in Appendix Table W.1.4 (on author's website).
standard errors in parentheses, clustered at the village level
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8. ***Regional Relationship Between Levels and Difference in Vaccination***

	Dependent Variable: Boy Vacc - Girl Vacc	
	(1)	(2)
Explanatory Variables:		
Average Vacc.	$-.0477^{**}$	$.1414^{**}$
	(.021)	(.068)
Average Vacc. Sq.		$-.0233^{***}$
		(.008)
Ave. Mother Educ.	$-.0102$	$-.0003^{***}$
	(.017)	(.017)
Ave. Income (durables)	$.1091^{**}$	.1058
	(.055)	(.055)
Year	$-.0062$	$-.0067^{*}$
	(.011)	(.011)
Urban Type	$.1132^{***}$	.1152
	(.041)	(.041)
# Older Brothers	.1242	$.1328^{***}$
	(.128)	(.128)
# Older Sisters	$-.164$	$-.1845$
	(.114)	(.115)
constant	12.505	13.162
	(22.723)	(22.707)
Number of Observations	5142	5142
R^2	.01	.01

Notes: This table estimates the relationship between average vaccination level and gender difference in vaccination. An observation is a cluster in the survey. The dependent variable is the vaccination average for boys minus that for girls. The independent variables of interest are the average vaccination level and that variable squared. These are intended to proxy for the cost of these investments.

standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9. ***Changes in Gender Bias in Mortality, 1982-1992***

Dependent Variable: Child Died 18 months - 5 years			
	(1) **All**	(2) **Increase in Vaccinations**	(3) **No Increase in Vaccinations**
Explanatory Variables:			
Girl	86.81**	78.21*	−7.93
	(41.97)	(43.92)	(30.02)
Girl × Birth Yr. × Vacc92	.0505**	.0486**	.0000
	(.023)	(.023)	(.000)
Girl × Birth Yr. × Vacc92 Sq.	−.0128**	−.0121**	−.0028
	(.005)	(.006)	(.004)
Girl × Birth Yr	−.0436**	−.0393*	.0042
	(.021)	(.022)	(.015)
Girl × Vacc92	−100.32**	−96.50**	
	(44.70)	(46.28)	
Girl × Vacc92 Sq.	25.36**	24.08**	5.59
	(10.78)	(10.97)	(8.34)
Birth Year × Vacc92	−.0424***	−.0395**	−.0189
	(.015)	(.016)	(.119)
Birth Year × Vacc92 Sq.	.0075**	.0065*	.0038
	(.003)	(.003)	(.031)
Vacc92	84.29***	78.47**	36.36
	(29.44)	(30.84)	(236.20)
Vacc92 Sq.	−14.81**	−12.91*	−7.28
	(6.73)	(6.95)	(62.50)
Birth Yr.	.0391***	.0451***	−.0018
	(.015)	(.016)	(.101)
Number of Observations	129,138	99,146	29,992

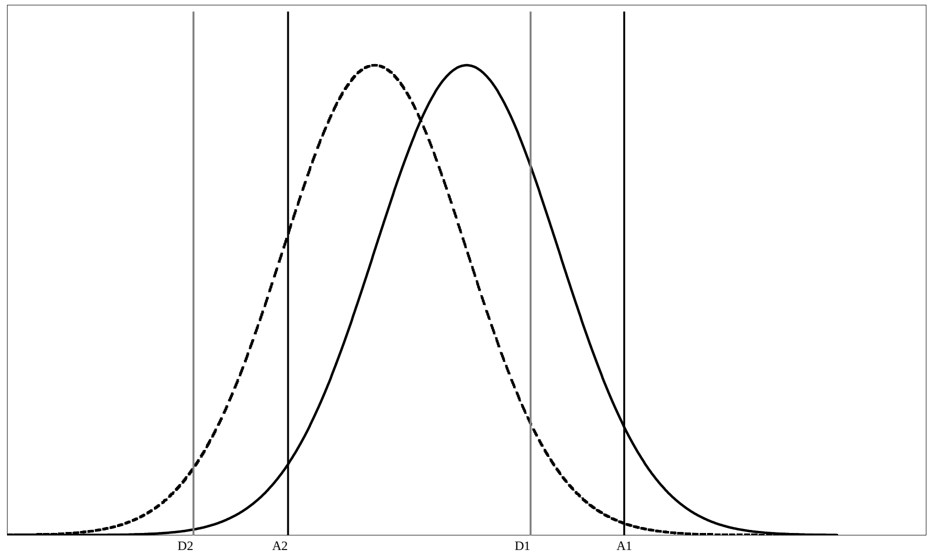
Notes: This table estimates the evolution of gender inequality in mortality over the period from 1982 to 1993, using a created panel based on children of different ages. The coefficient are from a probit model. The dependent variable is an indicator for whether the child died between 18 months and five years, conditional on having reached 18 months. The regression is limited to children born five to ten years before the survey. Column 1 includes all states; Column 2 includes only those with an increase in vaccination rates between surveys and Column 3 includes only those without an increase in vaccination rates between surveys. In Column 3, the interaction between girl and total number of vaccines is dropped due to collinearity in the smaller sample. Other controls: maternal age, maternal education, family income, child age (quadratic), birth order, Hindu and number of older brothers and number of older sisters. Full regressions with all controls reported are in Appendix Table W.1.5(on author's website).
standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 10. ***Changes in Gender Bias in Mortality, 1982-1992, by Son Preference***

	Dependent Variable: Child Died 18 months - 5 years	
	(1)	(2)
	Ideal: Equal/Girls	**Ideal: Boys**
Explanatory Variables:		
Girl	42.40	136.73**
	(59.86)	(62.04)
Girl × Birth Yr. × Vacc92	.0301	.0804**
	(.03)	(.035)
Girl × Birth Yr. × Vacc92 Sq.	−.0079	−.0207**
	(.007)	(.009)
Girl × Birth Yr.	−.0212	−.0687**
	(.03)	(.031)
Girl × Vacc92	−59.79	−159.63**
	(59.67)	(70.08)
Girl × Vacc92 Sq.	15.67	41.00**
	(13.80)	(17.61)
Birth Yr. × Vacc92	−.0395*	−.0485**
	(.021)	(.022)
Birth Yr. × Vacc92 Sq.	.0064	.0095*
	(.005)	(.005)
Vacc92	78.39*	96.35**
	(41.24)	(43.23)
Vacc92 Sq.	−12.75	−18.95*
	(9.16)	(10.15)
Birth Yr.	.0334	.0468**
	(.022)	(.021)
Number of Observations	68,857	60,281

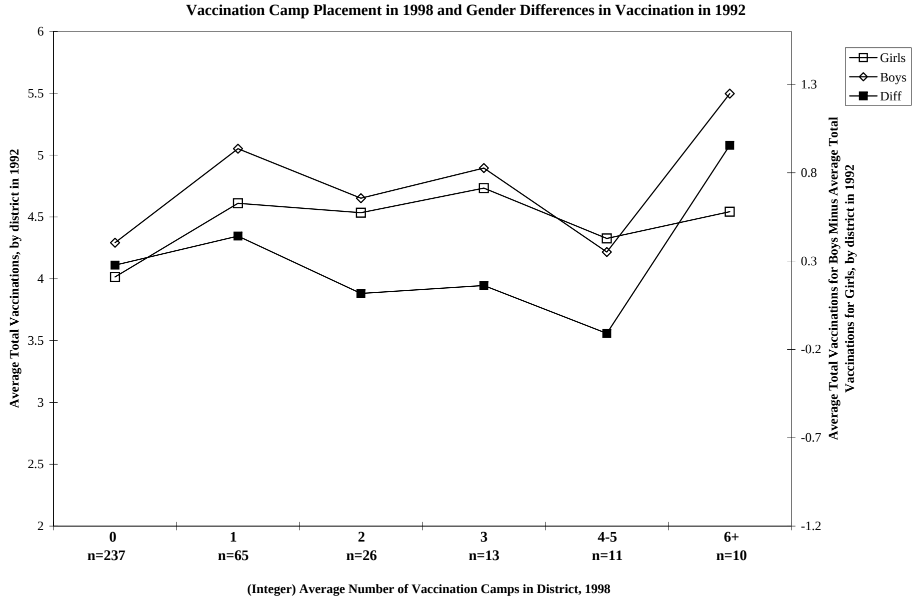
Notes: This table estimates a the evolution of gender inequality in mortality over the period from 1982 to 1993, using a created panel based on children of different ages. The coefficient are from a probit model. The dependent variable is an indicator for whether the child died between 18 months and five years, conditional on having reached 18 months. The regression is limited to children born five to ten years before the survey. The two columns divide the sample by ideal gender ratio reported, with Column 1 including only individuals that report their ideal gender ratio is neutral or female-biased and Column 2 including those who report their ideal gender ratio is male-biased. Other controls: maternal age, maternal education, family income, child age (quadratic), birth order, Hindu and number of older brothers and number of older sisters. Full regressions with all controls reported are in Appendix Table W.1.6 (on author's website).
standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Figure 1:
Theoretical Framework Vaccination Cutoffs



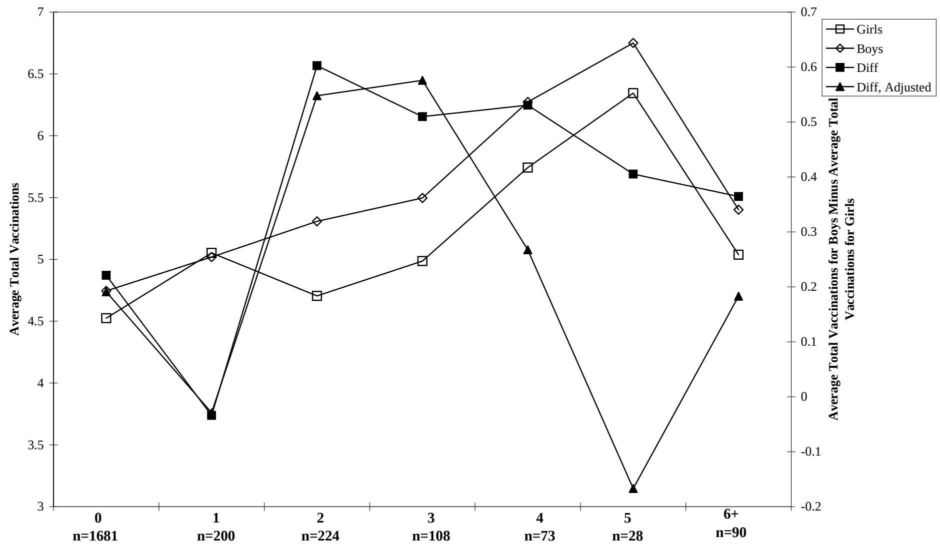
Notes: This figure shows the effect of decreasing the average vaccination cost (moving the distribution from the solid to the dotted line) on the difference across groups in investment for a high investment environment (D1,A1) and a low investment environment (D2,A2). Everyone with costs below the cutoff line gets the investment. In the high investment situation, moving the distribution increases vaccination for the disadvantaged group relative to the advantaged group; in the low vaccination environment, the converse is true.

Figure 2:
Vaccination Camp Placement in 1998 and Gender Differences in Vaccination in 1992



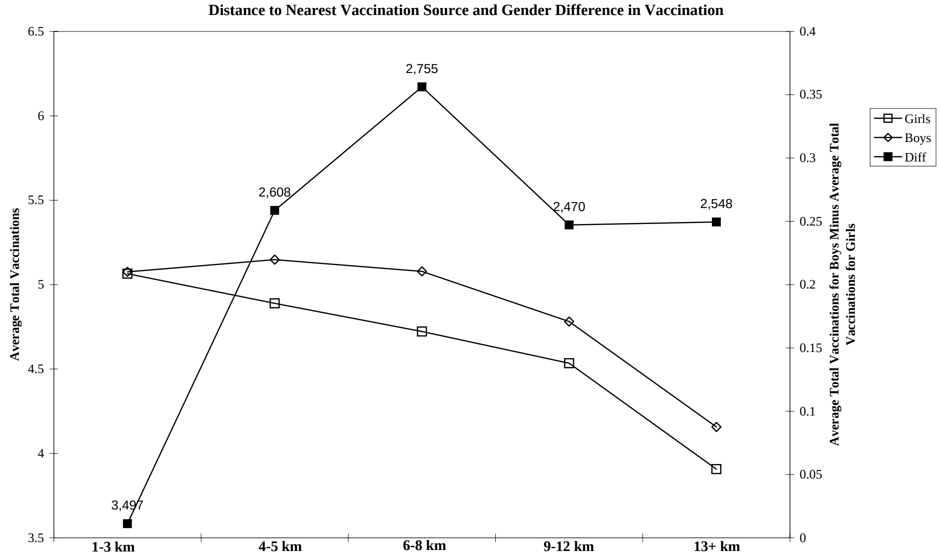
Notes: This figure shows the relationship between the (integer-rounded) average number of vaccination camps in village in the district in 1998 and the 1992 level of vaccinations and gender difference in vaccinations. All data is from the NFHS,. The sample sizes below represent number of districts in each cell.

Figure 3:
Vaccination Camps and Gender Difference in Vaccination



Notes: This figure reports differences in total number of vaccinations by gender and the average number of vaccinations graphed against the reported number of vaccination camps in the previous year. The data is from the National Family and Health Survey 1998-1999, for children aged 6 months to 2 years. Labels represent number of villages in each category.

Figure 4:
Distance to Nearest Vaccination Source and Gender Difference in Vaccination



Notes: This figure reports differences in total number of vaccinations by gender and the average number of vaccinations graphed against the distance to the nearest vaccination source (a primary health center, community health center or government hospital). The data is from the National Family and Health Survey 1998-1999. Labels represent number of children in each category. Data is limited to rural villages with no vaccination source in the village.