Insuring Girls' Lives Against Drought*

Preliminary Draft. Comments Welcome.

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July 31, 2018

Abstract

This paper revisits the relationship between agricultural productivity shocks and excess female mortality in India and focuses on investigating how this relationship changes when households have access to employment opportunities outside of agriculture. When household's preference for son coincides with adverse income shocks, in order to smooth consumption overtime, households tend to disproportionately reduce care (prenatal or postnatal) for their female children, which leads to excess female child mortality. Building on previous work (Rose, 1999), we show that agricultural productivity shocks in India, proxied by rainfall, continue to be an important predictor of the sex of an infant: the sex-ratio of infants is more balanced in good rainfall years and skewed towards boys during bad rainfall years. In addition, we show that the effect of rainfall during the year of birth on height-for-age is stronger for girls than for boys. We then show that a guaranteed rural workfare program in India, that provides labor opportunities outside of agriculture, attenuates the relationship between rainfall and both the sex-ratio of infants and height-for-age for girls. We also show that the negative relationship between agricultural productivity shocks (rainfall) and the number of dowry deaths (Sekhri and Storeygard, 2014) also dissipates after the introduction of the workfare program.

Keywords: sex ratio, health, human capital, consumption smoothing, India
JEL Codes: E20, H53, I15, O12

*We are grateful to Rachel M. Heath for her encouragement and guidance since ideation. We thank Chris Anderson, James D. Long, and Xu Tan for their comments and suggestions. We also thank the University of Washington's South Asia Library for access to the National Sample Surveys. An earlier version of this working paper was titled "Missing Girls, Income Shocks, and Consumption Smoothing."

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1 Introduction

An extensive literature shows that girls and boys are treated differently in countries where households exhibit a strong preference for sons. In extreme cases, this discrimination leads to sex-selection of children at early ages[1] through postnatal neglect or prenatal sex-selective abortions[2] (Chen et al., 2013; Bhalotra and Cochrane, 2010). In countries where families provide equal care for both daughters and sons, the sex-ratio is about 1050 females to 1000 males (Sen, 1992). One would expect the sex-ratio to improve with greater economic development over time. Figure 1A shows that, in India's case, the child sex-ratio has only worsened over the last half century during which India experienced rapid economic growth with an average annual GDP growth rate of about 5 percent[3]. Therefore, there is an urgent need to understand the determinants of sex-selection in-depth and device novel policies to tackle the issue.

Even for fetuses who are carried to term, there is a gender-gap in prenatal investments: For example, women who are pregnant with a boy are more likely to visit antenatal clinics (Bharadwaj and Lakdawala, 2013). Throughout their childhood, the unequal human capital investments continue by the means of breastfeeding (Jayachandran and Kuziemko, 2011), food allocation (Chen et al., 1981; Das Gupta, 1987), parental time allocation (Barcellos et al., 2014), vaccination (Borooah, 2004; Ganatra and Hirve, 2001), other health-care allocations (Ganatra and Hirve, 1994), and education (Song et al., 2006).

Income shocks in developing countries tend to exacerbate these gender-gaps. Notably, Rose (1999) finds that, in a primarily agrarian society like rural India, the probability that a child born during a given year is a girl increases with the rainfall in that year (proxy for a positive agricultural shock). When son-preference coincides with the lack of formal mechanisms to insure against

[1] This has been argued as one of the leading causes of unbalanced sex-ratios in South and Southeast Asian countries. In his seminal work, Sen (1990) estimated that more than 100 million women were "missing" worldwide. More recent estimates suggest that this number has been steadily increasing over time (reaching 126 million in 2010) and that India and China account for most of this deficit (Bongaarts and Guilmoto, 2015).

[2] Specifically, since the introduction of reliable ultrasound technology in the 1980s.

[3] Jayachandran (2017) finds that sex-selection of children in India is increasing with declining fertility as households still prefer to have at least one son.

bad agricultural shocks, these households reduce investments in their female children in order to smooth consumption. This leads to adverse outcomes for the female children and in extreme cases culminates into excess female child mortality. Moreover, increased female mortality in the face of negative income shocks is not restricted only to the young. Using witch killings in Tanzania (Miguel, 2005) and dowry deaths in India (Sekhri and Storeygard, 2014), recent research shows that adult women in developing countries are also less likely to survive during bad agricultural years. Figure 1B shows that, similar to the worsening sex-ratio, dowry deaths are also increasing over time and is of urgent concern to policymakers.

Throughout this literature that shows an increase in the mortality of women in response to an adverse income shock, the authors highlight that the developing world lacks the formal insurance mechanisms that could enable consumption-smoothing during these bad times and can potentially attenuate these gender-biased mortality effects. Therefore, the common conclusion in this body of literature is that an important policy measure to improve women's lives moving forward is the provision of these formal insurance mechanisms. However, despite the growing number of risk-coping programs implemented in developing countries today, there still remains a gap in the literature that empirically tests whether these policies help in consumption-smoothing and reduce female mortality during adverse income shocks. To our knowledge, this is the first paper that formally tests this policy implication. Specifically, in the context of infant mortality and dowry deaths in India, we provide the first evidence of how the relationship between agricultural productivity shocks and female mortality attenuates when a national workfare program enables consumption-smoothing during bad years.

We develop an inter-temporal consumption maximization problem in which a household decides how much to invest in their male and female children during the first period, and how much time to spend in dowry appropriation from their daughters-in-law in the second period. This model yields three main testable predictions: First, if having a girl entails a large future cost – which is likely in a society that typically practices dowry, such as India – then a positive agricultural shock leads to more investment in female children and, consequently, a higher likelihood of their survival; Second, a positive agricultural shock decreases the marginal product of labor hours spent in dowry appropriation relative to agricultural work. Therefore, less time is spent on appropriation behavior and, consequently, it is less likely that a daughter-in-law is killed due to dowry demands; Third, the introduction of a non-agricultural labor market with guaranteed minimum wages (to which labor can move freely during bad agricultural years) attenuates the relationship between agricultural productivity shocks and excess female mortality through consumption-smoothing.

To empirically test these predictions, we use: (a) deviation of district-level rainfall from its long-run average as a proxy for agricultural productivity shocks; and (b) the interaction of (a) with the spatial and temporal variation in the roll-out of the national workfare program. There is a growing body of literature on the effects of India's workfare program, the Mahatma Gandhi National Rural Employment Guarantee Scheme (NREGS)[4], on various development outcomes such as wages (Imbert and Papp, 2015; Merfeld, 2017), consumption (Jha et al., 2011; Ravi and Engler, 2015), risk (Foster and Gehrke, 2017; Gehrke, 2017; Fetzer, 2014), and time allocation decisions (Merfeld, 2018; Shah and Steinberg, 2015). The most relevant to this paper is the work by Santangelo (2016), where she shows that NREGS attenuates the pro-cyclical response of local wage, income, and consumption to agricultural productivity shocks in rural India[5]. Therefore, NREGS is an ideal income-risk-coping policy to study how a disruption in the positive relationship between agricultural productivity shocks and household consumption can affect excess female infant mortality and dowry deaths.

Consistent with previous literature and the model predictions, we find that rainfall continues to be a significant predictor of the gender of an infant and dowry deaths in India in more recent years and prior to the implementation of NREGS: An increase in annual rainfall by one standard deviation (from the 10 year long mean) increases the probability that an infant born during that years is a girl by 2 percentage points. However, in contrast to Rose (1999)'s findings in 1970's, we do not find that rainfall is a significant determinant of the gender of older children in 2000's.

[4]NREGS guarantees up to 100 days of wage employment at the state-level minimum wage in a financial year to every household in India whose adult members volunteer to do unskilled manual work.

[5]Santangelo (2016) shows these results using the National Sample Surveys. We replicate the effects on consumption using the last wave of the Rural Economic and Demographic Surveys for further support.

This is consistent with more recent findings that a large part of the sex-selection of children is at early stages since the advent of reliable ultrasound technology. We also find that and increase in annual rainfall by one standard deviation (from the 10 year long mean) decreases dowry deaths by 1.5 percent.

We then present evidence that these relationships are attenuated after the introduction of NREGS. One standard deviation increase in rainfall increases the probability that a child born in a non-NREGS district is 5.4 percentage points more likely to be a girl. Following the introduction of the program, this effect is 4.6 percentage points lower for NREGS districts. This suggests that there is almost no relationship between agricultural productivity shocks and the sex of an infant following the implementation of NREGS. Similarly, the negative relationship between dowry deaths and rainfall dissipates following the intervention of NREGS.

We also examine the effect agricultural productivity shocks at the time of birth on the long-run health of the surviving children. In particular, we explores the relationship between rainfall during the year of birth and child anthropometrics. We first confirm that rainfall during year of birth is a significant predictor of height-for-age for both boys and girls in India, similar to recent results from Indonesia (Maccini and Yang, 2009). As previous literature suggests that those girls who manage to survive sex-selection at birth still receive gender-biased early-life investments. This discrimination in care during the year of birth is likely to have long-run gender-gaps in the health of the surviving children. Consistent with this, we find that prior to the implementation of NREGS, an increase in annual rainfall by one standard deviation increases the height-for-age of female children by 0.6 standard deviations compared to the male children. Post NREGS, this relationship is significantly attenuated.

While is not possible to provide direct evidence of mechanisms, we present suggestive evidence that an improved ability to smooth consumption is responsible for these findings. To add support to Santangelo (2016)'s findings with National Sample Survey data, we use the most recent Rural Economic Demographic Survey to show that NREGS attenuates the positive relationship between rainfall and consumption. Additionally, we show that NREGS has no effect on household alcohol consumption, tobacco consumption, clothing expenditures for girls, or education expenditures for girls, which are typically dependent on gender-specific bargaining power within a household. Therefore, overall, the evidence suggests that consumption smoothing is indeed the main mechanism for the effects of NREGS on the infant sex ratio, anthropometrics, and dowry deaths.

This paper primarily contributes to three strands of existing literature: First, this work fits into the research on how sex-selection is affected by changing economic conditions (Rose, 1999; Bhalotra et al., 2016; Qian, 2008). Second, the study contributes to the literature on the effectiveness of different policies for the well-being of girls and women, such as greater political participation of women (Kalsi, 2017) and financial incentives offered for having daughters (Anukriti, forthcoming; Balakrishnan, 2017). Finally, these results add to our the growing literature on the risk-mitigation effects of rural workfare programs and the subsequent effects on development outcomes, including conflict (Fetzer, 2014) and child education (Foster and Gehrke, 2017).

The rest of this paper proceeds as follows: Section 2 provides a simple theoretical framework that provides testable predictions; Section 3 describes the data and variable construction; Section 4 provides the empirical strategy used to test them; Section 5 gives results; and Section 6 concludes.

2 Conceptual Framework

Building on the framework developed in Eswaran (2002), Rosenblum (2013) and Balakrishnan (2017), and the intuition described in Sekhri and Storeygard (2014), we present a simple theoretical model to demonstrate the following: In a primarily agrarian society, where the birth of a girl is associated with very high future costs[6], a favorable agricultural productivity shock can increase the survival of daughters and decrease dowry-motivated killing of daughters-in-law. Using this model, we then show that access to employment opportunities outside the agricultural sector can alleviate these effects.

[6]Miller (1981) argues that the practice of dowry, a financial transfer from the bride's household to the groom's household at the time of marriage, is one of the major determinants of the gender bias observed in India. Using the prices of gold, which is an important part of dowries in India, Bhalotra et al. (2016) empirically formalize this idea and show that higher gold prices leads to higher mortality of fetal and newborn girls.

2.1 Set Up

In this model, the household lives for two periods. The household's utility u and follows $u'(.) > 0$ and $u''(.) < 0$. In the first period, the household chooses consumption (c_1), the number of children they have (N), and the health investments in their male children (k_b) and female children (k_g). The probability of a child's survival into the second period is increasing in the investments made during the first period and is given by $p(k_j)$ (where $j = b, g$, $p'(.) > 0$, and $p''(.) < 0$). The probability that a child born is a boy is θ and the probability that a child born is a girl is $(1 - \theta)$. Therefore, in the second period, the surviving number of male children is $N\theta p(k_b)$ and female children is $N(1 - \theta)p(k_b)$.

In the second period, the household derives utility from consumption (c_2) and the total number of surviving children. During this period, the household derives a net benefit ($B \times A$) from its alive male children and incurs a net cost (G) from its female children. The net benefit from alive sons are the dowry receipts from their spouses and is therefore assumed to be linearly increasing in labor hours spent in dowry appropriation behavior (A)[7]. The household has no intrinsic preferences over its male and female children. Instead, preference for sons stems from the future benefits they bring and the future costs associated with daughters. The net cost of alive daughters may be thought of as dowry payments upon marriage.

In each period, the household has a unit of total labor hours. Therefore, the household's labor supply is inelastic and equal to one in the first period. In the second period, the household chooses how much to allocate to agricultural labor hours (L_2) and dowry appropriation hours (A). The household derives an income from its agricultural labor hours and the profits from its agricultural enterprise, $y_t = \pi_t^* + w_t L_t$. The agricultural production function is given by $\alpha_t F(L_t)$, where α_t is the agricultural productivity parameter, $F'(.) > 0$, and $F''(.) < 0$.

[7]The model can assume that the net benefit from the male children includes labor income from sons and their spouses but that will not affect the main predictions of the model.

Therefore, the household's optimization problem is given by:

$$
\begin{aligned}
\underset{c_1,c_2,N,k_b,k_g}{\text{maximize}} \quad & U = u_1(c_1) + \beta u_2(c_2) + \beta u_c(p(k_b)\theta N + p(k_g)(1-\theta)N) \\
\text{subject to} \quad & c_1 + k_b\theta N + k_g(1-\theta)N \leq \pi_1^* + w_1 L_1 \\
& c_2 \leq \pi_2^* + w_2 + \theta N p(k_b) BA - (1-\theta)Np(k_g)G \\
& \pi_t^* = \underset{L_t}{\text{maximize}} \alpha_t F(L_t) - w_t L_t \\
& L_1 = 1 \\
& L_2 + A = 1
\end{aligned}
\tag{1}
$$

Introducing NREGS

The Mahatma Gandhi Rural Employment Guarantee Act entitles every rural household in India to 100 days of employment in public works at the state-level minimum wage. Therefore, we assume that the introduction of NREGS imposes a wage floor in the labor market (Santangelo, 2016) such that $w_t \geq w^N$.

2.2 Testable Predictions

The above model gives the following predictions that guide our empirical work. The proofs of these propositions are reported in the Appendix.

Prediction 1 *A positive agricultural shock in a year leads to less time spent on dowry appropriation behavior in that year and consequently lower number of dowry-related deaths.*

The proof is in the Appendix. Intuitively, as the agricultural productivity parameter increases for a period, the marginal product of labor in agriculture increases in that period. Therefore, the optimal amount of labor hours spent in agricultural work increases and he optimal amount of labor hours spent in dowry appropriation decreases.

Prediction 2 *If the future net costs of a girl is large enough then a positive agricultural shock leads to more investment in female children and consequently a higher likelihood of their survival.*

The proof is in the Appendix. Intuitively, the optimal health investment in female children is chosen such that the marginal utility from consumption in the first period is equal to net discounted marginal utility derived from the surviving female children in the second period. This is described by the Euler equation in 11. An increase in the agricultural productivity parameter increases profits from the agricultural sector, and therefore, diminishes the positive marginal utility from consumption in the first period. Following this, the household can operate at the Euler equation by increasing in the health expenditure on the female children.

Prediction 3 *The elasticity of health investments in a girl and time spent in dowry appropriation with respect to agricultural productivity is lower in the presence of NREGS.*

Intuitively, negative agricultural productivity shock decrease the farm profits in the first period and the marginal product of labor in agriculture in the second period. As NREGS provides guaranteed non-farm employment at the state-level minimum wage, labor can move from the agricultural sector to the non-farm sector during the bad agricultural years. Therefore, households do not have to reduce care for their female children in the first period or increase dowry appropriation hours in the second period.

3 Data

First, we use the 0.5 degree by 0.5 degree grid monthly precipitation data from the University of East Anglia's Climate Research Unit (CRU) to construct agricultural productivity shocks. We aggregate the CRU data to annual precipitation and then match the district centroids to the closest grid in the CRU data to construct district-level annual rainfall. Our measure of rainfall shock is the deviation of annual district-level rainfall from its long-run mean (using previous 10 years) and scaled by the long-run standard deviation.

Second, the data on the gender of infants is from the National Sample Surveys (NSS). We use is the nationally representative labor survey, Employment and Unemployment rounds of the NSS, collected by the Government of India's Ministry of Statistics and Programme Implementation. We use the 2004-05, 2007-08, and 2011-12 thick waves of NSS. This data records the age of every resident member of the interviewed households at the time of the survey. We use this to create a panel of the sex and year of birth of all surviving children born between 2001 and 2011. We take the data on the children born between these waves from the immediately succeeding wave.

Third, the data on children's anthropometric measure is from the 2011-12 wave of the India Human Development Survey (IHDS II). The IHDS II collects height and age of all children between 0 and 9 years of age of interviewed households[8]. Using this we construct height-for-age measures using the Center for Disease Control's (CDC) growth charts.

Fourth, we use National Crime Records Bureau of India's data on reported annual dowry deaths at the district-level to test the hypotheses on dowry appropriation behavior.

Lastly, we use publicly available information on the roll-out of the NREGS at the district-level to create an indicator variable that is equal to one if a district received the program during a year and zero otherwise. The NREGS was implemented in 200 districts starting April 2006, 130 districts starting June 2007, and the remaining districts received the program starting July 2008[9].

4 Empirical Strategy

We use the following estimation model to find NREGS's effect on the relationship between

[8] Who were present at the time of survey.

[9] Primarily urban districts like Kolkata, Mumbai, Chennai, and Delhi never rceived NREGS and are not included in this study.

rainfall and the gender of a child born in a given year:

$$
\begin{aligned}
Girl_{idt} =& Rainzscore_{dt} + NREGS_{dt} \times Rainzscore_{dt} \\
& + NREGS_{dt} + District_d + Birthyear_t + + DistrictVar_{dt} + Phase_d \times (t - 2001) + \epsilon_{idt}
\end{aligned} \tag{2}
$$

In Equation 2, $Girl_{idt}$ is an indicator variable that is equal to one if a child i born in district d and year t is a girl and is equal to zero otherwise. $Rainzscore_{dt}$ is the deviation of district d's rainfall in t from the 10-year mean and scaled by the 10-year standard deviation. $NREGS_{dt}$ is an indicator that is equal to one from 2006, 2007, and 2008 for Phase 1, Phase 2, and Phase 3 districts, respectively and otherwise zero. $District_d$ and $Birthyear_t$ are district and year of birth fixed effects, respectively. $District_d$ is a vector of interactions of 2001 census values of log population, sex-ratio, literacy rate, percentage of scheduled caste and scheduled tribe, employment rate, and percentage of rural population with year of birth dummies. Lastly, $Phase_d \times (t - 2001)$ are phase specific linear time trends which partially address the differential trends in outcome by the treatment status of the districts.

To investigate the effect of NREGS on the relationship between early-life agricultural productivity shocks and children's health, we use the following specification:

$$
\begin{aligned}
HAZ_{idt} =& Rainzscore_{dt} + NREGS_{dt} \times Rainzscore_{dt} \times Girl_{idt} + NREGS_{dt} \times Rainzscore_{dt} \\
& + NREGS_{dt} \times Girl_{idt} + Rainzscore_{dt} \times Girl_{idt} + NREGS_{dt} + Girl_{idt} \\
& + District_d + Birthyear_t + + DistrictVar_{dt} + Phase_d \times (t - 2001) + \mu_{idt}
\end{aligned} \tag{3}
$$

In Equation 3, HAZ_{idt} is height for age of child i born in district d and year t and $Girl_{idt}$ is an indicator for whether this child is a girl.

Lastly, we look at the effect of NREGS on the number of dowry deaths using the following specification:

$$\begin{aligned} DowryDeaths_{dt} =& Rainzscore_{dt} + NREGS_{dt} \times Rainzscore_{dt} + NREGS_{dt} \\ & + District_d + Year_t + DistrictVar_{dt} + Phase_d \times (t - 2001) + \mu_{idt} \end{aligned} \tag{4}$$

where, $DowryDeaths_{dt}$ is the number of dowry deaths in district d and year t and $Year_t$ is a vector of fixed effects for the year of the dowry death police report.

5 Results

We begin with a simple graphical representation of our key motivation in Figure 2. It shows kernel-weighted polynomial regressions of infant-gender (Panel A), child's height-for-age by gender (Panel B), and dowry deaths (Panel B) on the rainfall during the year of birth (for Panels A and B) or the year of police report (for Panel C). These figures clearly show that agricultural productivity shocks are positively related to the survival and health of women. In other words, during bad agricultural years female mortality is high. Taken together, these results suggest that there is a still a lack of formal consumption-smoothing mechanisms in India and supports that loss of female life may still be a common consumption-smoothing strategy.

We move to a more robust empirical examination of this relationship in Table 2. In all columns, the dependent variable is a dummy variable indicating whether a child is female. In the first five columns, we restrict estimation to children under the age of one. In columns one through three, we examine the relationship between between rainfall and child gender prior to implementation of NREGS. Column one presents the most basic specification. The coefficient on rainfall indicates that a one-standard-deviation increase in rainfall increases the probability that a randomly chosen child is female by 1.4 percentage points. Adding more control variables for district characteristics and household characteristics in columns two and three increases the estimated effect size slightly; the coefficient in both columns is around 1.9 percentage points. In all three cases, the coefficient is significantly different from zero ($p<0.01$).

Column four removes the sample restriction to pre-NREGS years and estimates the relationship for the years 2001-2011.[10] Comparing the same specifications in columns three and four, removing the year restriction decreases the coefficient by more than 40 percent, from 0.019 to 0.011. This is suggestive evidence that something happened between 2006 and 2011 to attenuate this relationship; below, we present additional evidence that NREGS may be responsible.

In the fifth column, we add the previous year's rainfall and the following year's rainfall to the regression. Both coefficients are small and statistically insignificant. This evidence is consistent with rainfall right around birth being the most important component of child survival. We explore this possibility further in columns six and seven. Rose (1999) found that rainfall during the ages of one and two also had a significant impact on the sex ratio. While the results in column five suggest this is unlikely to be the case, we now test this explicitly. In neither columns six nor seven is the coefficient on rainfall significant. In fact, the coefficient in column six is just 0.003 and the coefficient in column seven is actually negative. These results again suggest that only rainfall right around birth is an important predictor of child gender in modern India. This also supports the argument in Bharadwaj and Lakdawala (2013) that families are more now more likely to sex-select during pregnancy, relative to previous decades.

Table A1 presents several robustness checks, mostly related to specification choices. We first show that the inclusion of state by wave fixed effects does not affect the conclusions and, in fact, increases the coefficient to 0.026. We also explore different definitions of our rainfall variables, including bins, a simply dummy, and an ordinal variable as in Jayachandran (2006). In all cases, substantive conclusions are unchanged by these specification changes.

We next move to an analysis of the effects of NREGS on the relationship between rainfall and newborn gender in Table 3. In columns one through four, we include the continuous rainfall variable and the years 2001-2011. The coefficient on "Current rainfall (Z)" is positive in all four columns, suggesting the effect of rainfall on the probability of being female is positive prior to

[10]Recall that NREGS was implemented in 2006 for phase one districts, 2007 for phase two districts, and 2008 for phase three districts.

NREGS's implementation. However, the interaction term is negative, suggesting this relationship decreases markedly following implementation. In all four columns, the interaction term is more than 80 percent as large as the coefficient on rainfall and the linear combination is never significant (results not shown), suggesting NREGS almost completely reverses the relationship between rainfall and the sex ratio. Additionally, the coefficients are very stable across specifications. Column two adds year of birth fixed effects, column three adds household variables, and column four adds phase linear trends.

Columns one through four utilize the entire panel we have constructed, from 2001-2011. While we include district and year of birth fixed effects, there may still remain concerns that we are isolating variation in years far removed from NREGS implementation. To test this possibility, in column five we restrict estimation only to the years 2005-2009, one year prior to NREGS to one year following the final phase of NREGS. Though the results are slightly more imprecise, conclusions are unchanged. In fact, the interaction term is now slightly larger than the rainfall coefficient.

The previous results focused on the sex ratio. However, does the effect of rainfall at the time of birth also extend to long-run indicators of female human capital investments, like anthropometrics? Figure 2 has already presented suggestive evidence that this is indeed the case. Table 4 presents a number of different specifications exploring this. The dependent variable in all columns is height-for-age, defined using CDC growth charts. Column one estimates the effect of year-of-birth rainfall on height-for-age in 2012. The coefficient on rainfall is positive but small and insignificant. The coefficient on the female dummy is negative and significant suggesting that there is differential investment in boys and girls in India. We can see this in Figure 2 as well, the curve for girls always lies below that of boys.

The coefficient on female in conjunction with our previous results raises the possibility that rainfall may differentially affect height-for-age for boys and girls. To explore this possibility, the specification in column two adds an interaction between female and rainfall. The coefficient on rainfall decreases modestly to approximately zero. Moreover, the coefficient on the interaction term between rainfall and female is positive and significant, and the linear combination of this coefficient with the coefficient on rainfall is also significant (results not shown; p=0.049). It is also worth noting that this relationship is only identified off of surviving children. It seems plausible that poorer households may be more affected by rainfall shocks, such that children who do not survive would come from the lower end of height-for-age distribution. If so, then the true results are actually much stronger than the results in Table 4 would indicate (Barcellos et al., 2014).

Column three again removes the pre-NREGS restriction and estimates the relationship over the years 1998-2012. Similar to Table 2, the result is no longer significant and, in fact, actually reverses, though the coefficients are small in magnitude. This also supports the contention that something changed between 2006 and 2012.

Column four explores the effects of NREGS on the relationship between rainfall and height-for-age, restricting the effect to be the same for both boys and girls. Consistent with the results in column one, it does not appear that NREGS affects the average relationship between rainfall and height-for-age. Nonetheless, the coefficients are in the expected direction and the coefficient on rainfall – which now represents the effect of rainfall on height-for-age prior to NREGS implementation – is actually marginally significant.

Column five allows the effects of NREGS to vary by gender, consistent with previous results. We find further evidence that NREGS impacts human capital investments differently for girls and boys. In particular, the triple interaction of *NREGS* $\times$ *Female* $\times$ *Rainfall* is negative and marginally significant, suggesting NREGS attenuated the relationship between rainfall and height-for-age more for girls than for boys. Since these results use the IHDS, we are also able to control for village fixed effects, which we do in column five. Many health outcomes are determined at levels below the district – due to differences in medical care, nutrient availability, etc. – so the inclusion of village fixed effects might be expected to affect the results. However, it appears that the inclusion of village fixed effects has no effect on our substantive conclusions and increases precision, providing further evidence that NREGS may help households smooth consumption in the face of negative income shocks.

Table 5 shows the effect of rainfall on the number of dowry deaths and how it changes after the implementation of NREGS. Column one shows that, prior to NREGS, one standard deviation increase in rainfall leads to a decrease in the number of dowry deaths by 0.17. Column two adds the number of all other reported crimes to the specification. This increases the coefficient on rainfall to 0.19. Evaluated at the average number of dowry deaths before NREGS (11.28), this shows a 1.7% decline in the incidence of dowry deaths. Column three removes the pre-NREGS restriction on the sample and re-estimates the effect of rainfall on dowry deaths for all years between 2001 and 2012.

Columns four and five investigates the effect of rainfall on dowry deaths by the availability of the NREGS program in a district during a year. We find that the coefficient on rainfall before the implementation of NREGS is negative, however, smaller and imprecise. The coefficient on the interaction between rainfall and NREGS is positive and statistically significant. This implies the after the implementation of NREGS the negative relation between rainfall and dowry deaths is attenuated. The results are robust to the inclusion of NREGS phase specific linear trends.

6 Conclusion

In this paper, we explore the effects of risk-mitigation through workfare programs in rural India on the relationship between agricultural productivity shocks and sex-selection of infants. First, using more recent data, we re-establish that a positive agricultural shock reduces female child mortality. Second, we show that the introduction of NREGS reduces consumption volatility. Third, as a consequence, the introduction of NREGS mitigates the effect of income shocks on the sex-selection of infants. Fourth, we find that prior to the advent of NREGS, a positive agricultural shock also more positively related to the health of surviving female children compared to male children. Lastly, this relationship between income shocks and health of girls is mitigated after the introduction of NREGS.

This paper establishes that policies that are successful in providing tools for consumption-smoothing to rural households in India can also successfully reduce sex-selection of infants and decrease differential child health investments by gender. Though the paper uses one such policy, a rural workfare program, to show that a program which provides households with insurance during lean agricultural years reduces sex-selection among children, the channels explored in this paper more broadly establish that policies that help risk-mitigation can decrease sex-selection when son-preference prevails. This is especially important since the most common policy directed at reducing female child mortality is providing households with financial incentives for having daughters. However, recent literature shows that the success of such policies are very sensitive to the design of these policies Anukriti; Balakrishnan (2017). Therefore, risk-mitigation programs may be an attractive development intervention, with favorable consequences for the sex-ratio and female health investments, as well.

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Figures & Tables

Figure 1: Rainfall in Year of Birth and Child Outcomes

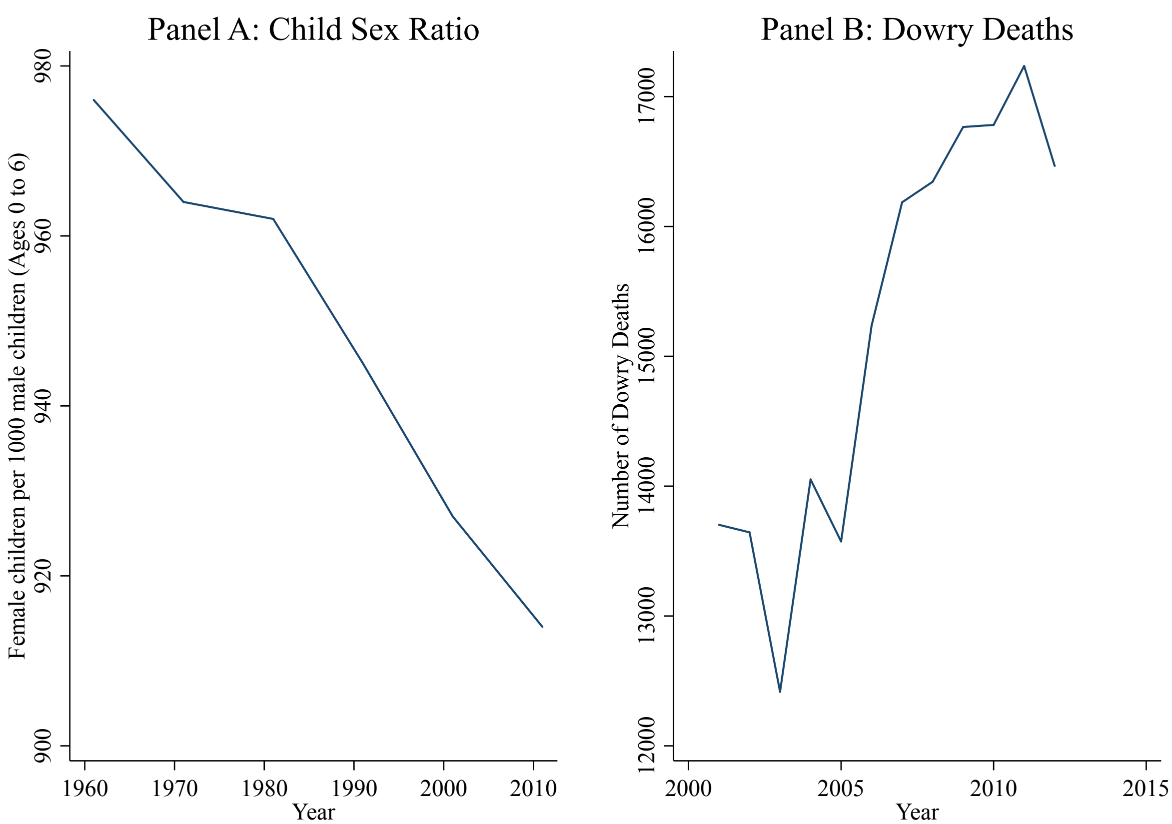
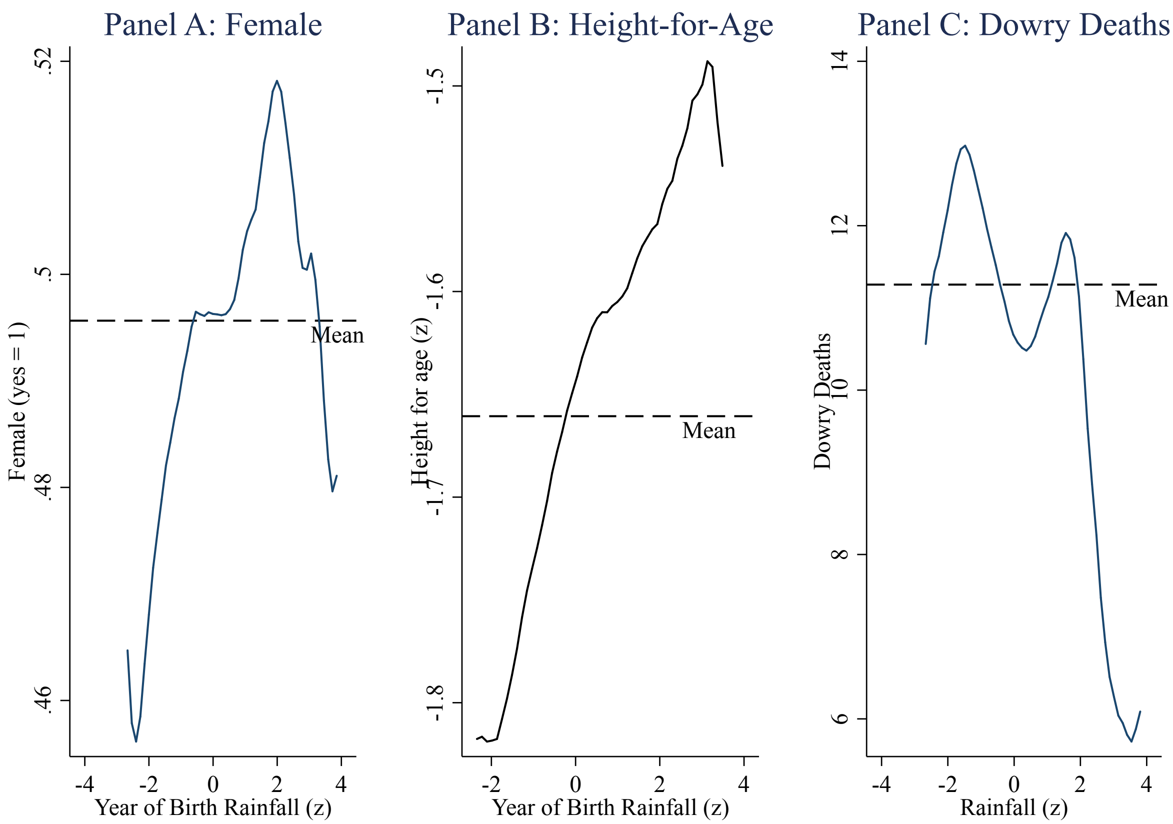


Table 1: Summary Statistics

	Phase 1	Phase 2	Phase 3
Panel A: NSS Individuals			
Girl (if < 1 year old)	0.49	0.48	0.48
	(0.50)	(0.50)	(0.50)
Girl (if one year old)	0.49	0.48	0.49
	(0.50)	(0.50)	(0.50)
Girl (if two years old)	0.48	0.47	0.48
	(0.50)	(0.50)	(0.50)
Household size	6.55	6.51	6.59
	(2.92)	(2.93)	(2.95)
Head is male	0.93	0.93	0.93
	(0.25)	(0.26)	(0.26)
Head age	41.62	42.00	42.63
	(13.64)	(13.80)	(14.37)
Head education	1.90	2.00	2.26
	(1.36)	(1.43)	(1.51)
Panel B: IHDS Individuals			
Girls' height for age (Z)	-1.65	-1.73	-1.57
	(1.56)	(1.52)	(1.53)
Boys' height for age (Z)	-1.53	-1.80	-1.33
	(1.45)	(1.45)	(1.46)
Panel C: NCIB Districts			
Dowry deaths	12.75	10.97	10.14
	(16.05)	(11.85)	(12.29)
Other crimes against girls	220.80	228.83	255.94
	(207.16)	(221.38)	(256.25)
All other crimes	2028.20	2243.32	3205.94
	(1721.05)	(1829.61)	(3668.59)
Panel D: Census Districts			
Percent SC/ST	0.38	0.31	0.27
	(0.20)	(0.21)	(0.22)
Percent literatre	0.47	0.53	0.58
	(0.11)	(0.13)	(0.10)
Labor force participation	0.42	0.40	0.40
	(0.07)	(0.07)	(0.07)
Population (log)	14.06	14.11	13.98
	(0.87)	(0.89)	(1.09)
Percent rural	0.86	0.82	0.72
	(0.09)	(0.13)	(0.17)
Sex ratio	945.83	940.27	926.76
	(45.99)	(46.97)	(64.60)

Statistics are means. All individual statistics are nationally representative and are estimated using survey weights. The individual statistics for the NSS are for children less than two years old, for the years 2001-2005. The NSS Districts data are from the 2000 census. The IHDS anthropometrics are constructed using CDC charts and the *zanthro* command in Stata (Vidmar et al., 2004).

Figure 2: Rainfall in Year of Birth and Child Outcomes



Graphs are kernel-weighted local polynomial regressions. All observations are before the implementation of NREGS in a district. The top and bottom one percent of rainfall values are trimmed for ease of presentation.

Table 2: Rainfall and Child Gender

	Newborns					One-Year Olds	Two-Year Olds
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Current rainfall (Z)	0.014***	0.019***	0.019***	0.011*	0.019***	0.003	−0.006
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)
Previous rainfall (Z)					0.001		
					(0.006)		
Next rainfall (Z)					0.006		
					(0.006)		
Pre NREGS	Yes	Yes	Yes	No	No	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Vars	No	Yes	Yes	Yes	Yes	Yes	Yes
Household Vars	No	No	Yes	Yes	Yes	Yes	Yes
Observations	66312	65810	65791	88547	65791	72315	78593

Standard errors are in parentheses and are clustered at the district level. Columns one through three and five through seven use the years 2001-2007; column four uses the years 2001-2011. All data are from NSS waves 61, 64, and 68. Newborns are defined as chilren less than one year of age. Current rainfall is standardized using the mean and standard deviation of the previous 10 years. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 3: NREGS, Rainfall, and Child Gender

	Years 2001-2011				Years 2005-2009
	Model 1	Model 2	Model 3	Model 4	Model 5
Rainfall (z) times NREGS	−0.044**	−0.044**	−0.045**	−0.046**	−0.054**
	(0.020)	(0.020)	(0.020)	(0.020)	(0.025)
Year of birth rainfall (Z)	0.051***	0.053***	0.053***	0.054***	0.052*
	(0.019)	(0.020)	(0.020)	(0.020)	(0.027)
NREGS	−0.029	−0.025	−0.024	0.017	0.006
	(0.036)	(0.037)	(0.037)	(0.042)	(0.043)
District FE	Yes	Yes	Yes	Yes	Yes
District Vars	Yes	Yes	Yes	Yes	Yes
Year of Birth FE	No	Yes	Yes	Yes	Yes
Household Vars	No	No	Yes	Yes	Yes
Phase Linear Trend	No	No	No	Yes	No
Observations	88570	88570	88547	88547	38451

Standard errors are in parentheses and are clustered at the district level. The dependent variable in all columns is whether a newborn (defined as less than one year of age) is a girl. Columns one through four use the years 2001-2011, while column five restricts estimation to just one year prior to NREGS to one year following implementation of the final phase. Current rainfall is standardized using the mean and standard deviation of the previous 10 years. * p<0.1 ** p<0.05 *** p<0.01

Table 4: NREGS, Rainfall, and Child Height-for-Age

	District FE					Village FE
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Year of birth rainfall (Z)	0.026	−0.001	0.023	0.033*	0.010	0.044***
	(0.021)	(0.025)	(0.018)	(0.018)	(0.023)	(0.015)
Female	−0.104***	−0.108***	−0.050*	−0.051*	−0.099***	−0.102**
	(0.039)	(0.038)	(0.030)	(0.030)	(0.038)	(0.042)
Female times Rainfall		0.057*	−0.005		0.047	0.032
		(0.033)	(0.023)		(0.032)	(0.021)
NREGS				0.006	−0.052	−0.128*
				(0.101)	(0.101)	(0.071)
Rainfall (z) times NREGS				−0.028	0.028	0.029
				(0.033)	(0.042)	(0.032)
Female times NREGS					0.129**	0.129***
					(0.061)	(0.032)
NREGS times Female times Rainfall					−0.118*	−0.107**
					(0.062)	(0.048)
Years	Pre NREGS	Pre NREGS	1998-2012	1998-2012	1998-2012	1998-2012
Year of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
District Vars	Yes	Yes	Yes	Yes	Yes	Yes
Household Vars	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12354	12354	19440	19440	19440	19440

Standard errors are in parentheses and are clustered at the district level (columns one through five) or village level (column six). Columns one and two include children born between the years 1998 and 2005, though only 3.38 percent of observations come from prior to 2002. Columns three through six includes children born during the years 1998-2011 (only 1.20 percent of observations are from prior to 2002). The dependent variable in all columns is height-for-age, standardized using the CDC charts and the *zanthro* command in Stata (Vidmar et al., 2004). Rainfall is always defined as rainfall during year of birth. * p<0.1 ** p<0.05 *** p<0.01

Table 5: Rainfall, NREGS, and Dowry Deaths

	(1)	(2)	(3)	(4)	(5)
Rainfall (z)	-0.17*	-0.19*	0.02	-0.12	-0.11
	(0.10)	(0.10)	(0.07)	(0.11)	(0.11)
NREGS				-0.05	-0.11
				(0.53)	(0.53)
Rainfall (z) × NREGS				0.26*	0.25*
				(0.14)	(0.14)
Years	Pre-NREGS	Pre-NREGS	2001-2012	2001-2012	2001-12
Year Effects	Yes	Yes	Yes	Yes	Yes
District Vars	Yes	Yes	Yes	Yes	Yes
Other Crime Variables	No	Yes	Yes	Yes	Yes
Phase Trends	No	No	No	No	Yes
Observations	3316	3316	6499	6499	6499

All specifications include district fixed effects. Standard errors are in parentheses and are clustered at the district level. * p<0.1 ** p<0.05 *** p<0.01

Table 6: Testing the Parallel Trends Assumption

	Female	HAZ		Dowry Deaths
	Full Sample	Female	Male	Full Sample
Phase=2 times Rainfall times Year	-0.003	0.081	-0.016	-0.242
	(0.006)	(0.092)	(0.082)	(0.245)
Phase=3 times Rainfall times Year	0.001	0.099	0.050	-0.204
	(0.005)	(0.077)	(0.063)	(0.216)
Phase=2 times Year	0.013**	0.036	0.000	0.288
	(0.007)	(0.094)	(0.095)	(0.254)
Phase=3 times Year	0.008	0.084	-0.003	-0.332
	(0.008)	(0.098)	(0.082)	(0.208)
Phase=2 times Rainfall	5.215	-161.578	32.088	485.669
	(12.218)	(184.849)	(164.206)	(491.819)
Phase=3 times Rainfall	-1.158	-197.626	-99.519	409.309
	(10.612)	(154.145)	(125.401)	(433.764)
Rainfall times Year	0.003	-0.059	-0.070	0.416**
	(0.005)	(0.074)	(0.049)	(0.201)
Rainfall	-6.105	119.082	139.141	-834.539**
	(9.114)	(147.868)	(98.371)	(403.236)
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District Vars	Yes	Yes	Yes	Yes
Household Vars	Yes	Yes	Yes	Yes
Observations	49858	4501	4723	2706

Standard errors are in parentheses and are clustered at the district level. All four columns use observations up to the year 2005. Column one uses the NSS, columns two and three use the IHDS 2004-05, column four uses NCRB. The *Years to NREGS* variable is constructed by subtracting the year of observation from 2005. * p<0.1 ** p<0.05 *** p<0.01

Appendix: Conceptual Framework

After substituting the budget constraints in the utility maximization problem, equation (2) becomes:

$$\begin{aligned}\underset{N,k_b,k_g,A}{\text{maximize}}\, U =&u_1[\alpha_1 F(1) - k_b\theta N - k_g(1-\theta)N] \\ &+ \beta u_2[\alpha_2 F(1-A) + \theta N p(k_b)BA - (1-\theta)Np(k_g)G] \\ &+ \beta u_c[p(k_b)\theta N + p(k_g)(1-\theta)N]\end{aligned} \tag{5}$$

For a given number of children and optimal health made investments in male and female children during the first period, the optimal labor hours in dowry appropriation in the second period is given by:

$$\begin{aligned}&\frac{\partial U(N,k_b,k_g,A)}{\partial A} \\ &\qquad = \beta u_2'[-\alpha_2 F'(1-A) + \theta N p(k_b)B] = 0. \\ &\qquad \implies \alpha_2 F'(1-A) = \theta N p(k_b)B\end{aligned} \tag{6}$$

Solving equation 6 yields:

$$A^* = 1 - F'^{-1}\left[\frac{\theta N p(k_b)B}{\alpha_2}\right]. \tag{7}$$

From equation 7, we get the proof of Prediction 1, that is,

$$\frac{\partial A^*}{\partial \alpha_2} < 0. \tag{8}$$

We denote the optimal dowry appropriation hours $A^* = A^*(N, K_b)$ and re-wirte the household's problem as:

$$\begin{aligned}\underset{N,k_b,k_g}{\text{maximize}}\, U =&u_1[\alpha_1 F(1) - k_b\theta N - k_g(1-\theta)N] \\ &+ \beta u_2[\alpha_2 F(1-A^*(N,K_b)) + \theta N p(k_b)BA^*(N,k_b) - (1-\theta)Np(k_g)G] \\ &+ \beta u_c[p(k_b)\theta N + p(k_g)(1-\theta)N]\end{aligned} \tag{9}$$

For a chosen number of children, the household's optimal health investment in its male children is given by:

$$\begin{aligned}\frac{\partial U(N,k_b,k_g)}{\partial k_b} &= -u_1'\theta N + \beta u_2' p'(k_b) B A^*(N,k_b)\theta N + \beta u_c' p'(k_b)\theta N = 0 \\ &\implies u_2' B A^*(N,k_b) + u_c' = \frac{u_1'}{\beta p'(k_b)} > 0\end{aligned} \tag{10}$$

and female children is given by:

$$\begin{aligned}\frac{\partial U(N,k_b,k_g)}{\partial k_g} &= -u_1'(1-\theta)N - \beta u_2' p'(k_g) G(1-\theta)N + \beta u_c' p'(k_g)(1-\theta)N = 0 \\ &\implies u_c' - u_2' G = \frac{u_1'}{\beta p'(k_g)} > 0\end{aligned} \tag{11}$$

After the total differentiation of equations 11 and 12 with respect to α_1, we get:

$$\begin{aligned}\frac{\partial^2 U(N,k_b,k_g)}{\partial k_b^2}\frac{\partial k_b^*}{\partial \alpha_1} + \frac{\partial^2 U(N,k_b,k_g)}{\partial k_b \partial k_g}\frac{\partial k_g^*}{\partial \alpha_1} + \frac{\partial^2 U(N,k_b,k_g)}{\partial k_b \partial \alpha_1} = 0 \\ \frac{\partial^2 U(N,k_b,k_g)}{\partial k_g \partial k_b}\frac{\partial k_b^*}{\partial \alpha_1} + \frac{\partial^2 U(N,k_b,k_g)}{\partial k_g^2}\frac{\partial k_g^*}{\partial \alpha_1} + \frac{\partial^2 U(N,k_b,k_g)}{\partial k_g \partial \alpha_1} = 0\end{aligned} \tag{12}$$

The second partial derivatives are as follows:

$$\begin{aligned}\frac{\partial^2 U(N,k_b,k_g)}{\partial k_b^2} =& u_1''\theta^2 N^2 + \beta u_2''\theta^2 N^2 p'(k_b)^2 B^2 A^*(N,k_b)^2 + \beta u_2'\theta N B[p''(k_b)A^*(N,k_b) \\ &+ p'(k_b)A^{*\prime}(N,k_b)] + \beta u_c'' p'(k_b)^2\theta^2 N^2 + \beta u_c' p''(k_b)\theta N < 0,\end{aligned} \tag{13}$$

as A^* decreases in k_b.

$$\begin{aligned}\frac{\partial^2 U(N,k_b,k_g)}{\partial k_b \partial k_g} =& u_1''\theta(1-\theta)N^2 - \beta u_2''\theta(1-\theta)N^2 p'(k_b)p'(k_g) G B A^*(N,k_b) \\ &+ \beta u_c'' p'(k_b)p'(k_g)\theta(1-\theta)N^2 > 0,\end{aligned} \tag{14}$$

if G is large enough.

$$
\begin{aligned}
\frac{\partial^2 U(N,k_b,k_g)}{\partial k_g^2} =& u_1''(1-\theta)^2N^2 + \beta u_2''(1-\theta)^2N^2p'(k_g)^2G^2 - \beta u_2'(1-\theta)Np''(k_g)G \\
&+ \beta u_c''p'(k_g)^2(1-\theta)^2N^2 + \beta u_c'p''(k_g)(1-\theta)N \\
=& u_1''(1-\theta)^2N^2 + \beta u_2''(1-\theta)^2N^2p'(k_g)^2G^2 + \beta u_c''p'(k_g)^2(1-\theta)^2N^2 \\
&+ \beta(1-\theta)Np''(k_g)[u_c' - u_2'G] < 0,
\end{aligned} \tag{15}
$$

using equation 12.

$$
\frac{\partial^2 U(N,k_b,k_g)}{\partial k_b \partial \alpha_1} = -u_1''F(1)\theta N > 0 \tag{16}
$$

$$
\frac{\partial^2 U(N,k_b,k_g)}{\partial k_g \partial \alpha_1} = -u_1''F(1)(1-\theta)N > 0 \tag{17}
$$

Using Cramer's rule, we solve the system of equations in (5) to find:

$$
\frac{\partial k_b^*}{\partial \alpha_1} = \frac{\begin{vmatrix} -\frac{\partial^2 U(N,k_b,k_g)}{\partial k_b \partial \alpha_1} & \frac{\partial^2 U(N,k_b,k_g)}{\partial k_b \partial k_g} \\ -\frac{\partial^2 U(N,k_b,k_g)}{\partial k_g \partial \alpha_1} & \frac{\partial^2 U(N,k_b,k_g)}{\partial k_g^2} \end{vmatrix}}{\begin{vmatrix} \frac{\partial^2 U(N,k_b,k_g)}{\partial k_b^2} & \frac{\partial^2 U(N,k_b,k_g)}{\partial k_b \partial k_g} \\ \frac{\partial^2 U(N,k_b,k_g)}{\partial k_g \partial k_b} & \frac{\partial^2 U(N,k_b,k_g)}{\partial k_g^2} \end{vmatrix}} = \frac{\begin{vmatrix} - & + \\ - & - \end{vmatrix}}{\begin{vmatrix} - & + \\ + & - \end{vmatrix}} \tag{18}
$$

$$
\frac{\partial k_g^*}{\partial \alpha_1} = \frac{\begin{vmatrix} \frac{\partial^2 U(N,k_b,k_g)}{\partial k_b^2} & -\frac{\partial^2 U(N,k_b,k_g)}{\partial k_b \partial \alpha_1} \\ \frac{\partial^2 U(N,k_b,k_g)}{\partial k_g \partial k_b} & -\frac{\partial^2 U(N,k_b,k_g)}{\partial k_g \partial \alpha_1} \end{vmatrix}}{\begin{vmatrix} \frac{\partial^2 U(N,k_b,k_g)}{\partial k_b^2} & \frac{\partial^2 U(N,k_b,k_g)}{\partial k_b \partial k_g} \\ \frac{\partial^2 U(N,k_b,k_g)}{\partial k_g \partial k_b} & \frac{\partial^2 U(N,k_b,k_g)}{\partial k_g^2} \end{vmatrix}} = \frac{\begin{vmatrix} - & - \\ + & - \end{vmatrix}}{\begin{vmatrix} - & + \\ + & - \end{vmatrix}} \tag{19}
$$

If G is large enough, then the numerators in equation 19 and 20 are postive. Additionally, if

$u_c'' > u_2''GBA^*(N, k_b)$, then the denominators are also positive. Therefore,

$$\frac{\partial k_b^*}{\partial \alpha_1} > 0 \text{ and } \frac{\partial k_g^*}{\partial \alpha_1} > 0 \tag{20}$$

The second inequality proves Prediction 2.

Appendix: Results

Table A1: Rainfall Robustness

	Model 1	Model 2	Model 3	Model 4
Year of Birth Rainfall (Z)	0.026***			
	(0.007)			
Rain <-2		-0.085***		
		(0.029)		
Rain between -1 and -2		-0.050**		
		(0.024)		
Rain between 0 and -1		-0.045**		
		(0.019)		
Rain between 0 and 1		-0.024		
		(0.019)		
Rain between 1 and 2		-0.010		
		(0.020)		
Good year (Z>1)			0.027*	
			(0.015)	
Ordinal Rainfall (cuts -1 and 1)				0.021**
				(0.010)
District FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Household Vars	Yes	Yes	Yes	Yes
State/Year of Birth FE	Yes	No	No	No
Observations	65791	65791	65791	65791

Standard errors are in parentheses and are clustered at the district level. The first column repeats results from Table 2 but adds state by wave fixed effects. Column two creates "bins" of rainfall. Column three uses a simple dummy variable equal to one if rainfall is greater than $Z = 1$. Column four defines an ordinal variable, similar to Jayachandran (2006).
* p<0.1 ** p<0.05 *** p<0.01

Table A2: NREGS and Bargaining Power I

	Alcohol		Cigarettes	
	Any	Log (R's + 1)	Any	Log (R's + 1)
NREGS times Post	−0.048	−0.144	−0.010	0.099
	(0.065)	(0.622)	(0.066)	(0.480)
District FE	Yes	Yes	Yes	Yes
District Vars	Yes	Yes	Yes	Yes
Household Vars	Yes	Yes	Yes	Yes
Observations	8296	8296	8296	8296

Standard errors are in parentheses and are clustered at the district level. All regressions use the ARIS/REDS, collected in 1999 and 2008. The dependent variable (DV) in column one is a dummy variable for whether a household purchased any alcohol. In column two, the DV is amount spent on alcohol (log of rupees plus one). In column three, the DV is a dummy variable for cigarette purchases, while the DV in column four is total spent on cigarettes (log of rupees plus one).
* p<0.1 ** p<0.05 *** p<0.01

Table A3: NREGS and Bargaining Power II

	Girl Clothing Exp. Percent (log R's + 1)		Girl Education Exp. Percent	
	All	Both	Both	All
NREGS times Post	0.080**	−0.011	0.015	−0.035
	(0.039)	(0.025)	(0.046)	(0.037)
District FE	Yes	Yes	Yes	Yes
District Vars	Yes	Yes	Yes	Yes
Household Vars	Yes	Yes	Yes	Yes
Observations	5634	2928	4734	2027

Standard errors are in parentheses and are clustered at the district level. All regressions use the ARIS/REDS, collected in 1999 and 2008. The dependent variable (DV) in column one is total spent on girls' clothing as a percentage of total children's clothing purchases. In column two, the DV restricts the sample to only households that purchased both girls' and boys' clothing. In columns three and four, the DV is similary defined but for education expenditures instead of clothing.
* p<0.1 ** p<0.05 *** p<0.01