Eradicating the Disease of the Empty Granary: Health, Structural Transformation, and Intergenerational Mobility in Ghana*

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Abstract

Guinea worm disease (GWD) was known as "the disease of the empty granary" because it often incapacitated adult farmers for weeks during peak agricultural seasons. Using a difference-in-differences design, we show that its post-1989 eradication from Ghana increased agricultural productivity and women's paid employment and decreased child marriage rates. In the long run, adults who were children around 1990 are more likely to hold formal employment outside of agriculture, be literate, and live in urban areas. We also find spillover effects onto other generations: their sons' literacy rates increased and their mothers are more likely to still be alive. These results show that adult health improvements—especially those resulting from neglected tropical disease control—can be an important input into structural transformation, the loosening of intergenerational poverty traps, and healthy aging in the developing world.

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1. Introduction

Structural transformation—the reallocation of labor from agriculture into higher-productivity sectors—is a central feature of economic development. However, the microfoundations of this process remain poorly understood (Foster and Rosenzweig, 2008). An emerging literature has emphasized the role of technological change and infrastructure investments in catalyzing industrialization through improved agricultural productivity (e.g., Bustos, Garber and Ponticelli, 2020; Asher et al., 2024). While such shocks were clearly important, it is not clear that low-income countries can catalyze them on their own, as their firms may not have sufficient research and development budgets and their governments can find it difficult to raise sufficient tax revenue or borrow on international capital markets. Thus, are there relatively low-cost and scalable interventions that developing countries can implement to increase agricultural productivity?

In this paper, we study whether the post-1989 control of the neglected tropical disease (NTD) dracunculiasis (Guinea worm disease, or GWD) contributed to structural transformation in Ghana. Caused by the roundworm *Dracunculus medinensis*, GWD was known among the Dogon people of Mali as "the disease of the empty granary" because it largely occurred among adult farmers and caused them weeks of disability during peak agricultural periods (Cairncross, Muller and Zagaria, 2002).[1] Farmers were particularly at risk because they often drank from stagnant water sources contaminated with *D. medinensis* larvae while working in the dry season. As such, the eradication of GWD greatly improved farmers' health, potentially spurring structural change by increasing agricultural labor productivity (Bustos, Caprettini and Ponticelli, 2016).

To test this hypothesis, we use a difference-in-differences approach that compares high- and low-GWD districts before and after Ghana's eradication program began. We examine outcomes across three domains: agricultural productivity, structural transformation, and intergenerational spillovers. First, we find that districts with higher initial GWD burdens experienced greater growth in agricultural productivity in the years following eradication, implying that health improvements can play a role in driving rural transformation. Next, we show that young women in

[1] While this disease is caused by a parasitic worm (helminth), there is no overlap between the pathology of GWD and other helminthiases, in which morbidity arises from intestinal blood loss (e.g., hookworm infection) or inflammation caused by eggs becoming lodged in the host's tissues (schistosomiasis).

these areas shifted from self-employment into paid employment on farms, likely because higher agricultural incomes allowed these households to hire additional workers. In line with previous research showing that positive weather shocks decrease child marriage rates in agricultural areas where bride price is practiced (Corno, Hildebrandt and Voena, 2020), we also find that improving adult farmers' health reduced the likelihood that girls were married off.

We then turn to studying the long-run effects in these domains by comparing adults who were children before versus after 1990 across high- versus low-GWD birth districts. Given that the disease primarily affected adults, these impacts should be interpreted as the effects of children *having parents* no longer exposed to it. Here we find evidence of structural transformation—individuals were more likely to hold formal non-agricultural employment and live in urban municipalities—along with increased literacy. Our results also reflect reductions in child marriage, as women in these cohorts reported being older at the time of their first birth. Lastly, we document spillover effects onto other generations: the sons of men in these cohorts are more likely to be literate and their mothers are more likely to still be alive.

Our results contribute to several literatures. First, building upon seminal works in development economics (e.g., Lewis, 1954), we add to the emerging evidence linking agricultural productivity and structural transformation (Bustos, Caprettini and Ponticelli, 2016; Bustos, Garber and Ponticelli, 2020; Asher et al., 2024) by showing that a simple health intervention can spark these phenomena. Our findings also highlight the positive economic effects of disease control (e.g., Bleakley, 2010; Bütikofer and Salvanes, 2020), building on recent work showing that reducing morbidity can impact macroeconomic development (Weil, 2014; Tompsett, 2020; Denton-Schneider and Montero, 2025). We depart from many such studies by focusing on a disease affecting adults' health (e.g., Thomas et al., 2006; Stephens and Toohey, 2022) and extending the analysis into long-run effects on those individuals—as healthy aging is highly understudied in Sub-Saharan Africa (Duhon et al., Forthcoming)—and the spillover effects onto subsequent generations. In this vein, we also speak to the impacts on non-Western marriage markets of childhood circumstances (Ashraf et al., 2020; Corno, Hildebrandt and Voena, 2020), and specifically of controlling NTDs (Denton-Schneider, 2024). Taken together, our results underscore the urgency of eradicating these scourges on the lives of the world's poorest people (Hotez, 2022).

2. Background

Ghana in the late 1980s was a predominantly agrarian society, with approximately 60% of its population engaged in subsistence agriculture, especially in the northern half of the country. The Northern, Upper East, and Upper West regions, characterized by savanna landscapes and a single rainy season (May through October), relied on rain-fed crops such as millet, sorghum, and maize. Chronic shortages during the dry season forced communities to rely on surface water sources (e.g., ponds and streams) because few had access to boreholes or piped water. Thus, northern Ghana was particularly susceptible to GWD's devastating effects, which disrupted agricultural productivity and perpetuated poverty, as we describe below.

2.1. GWD Pathology

Appendix A1 shows the life cycle of the tissue parasite *D. medinensis*. It primarily infects humans consuming unfiltered stagnant water, a common practice among farmers working in fields during the dry season. If *D. medinensis* larvae are ingested, they mature and mate in the intestines. Around a year later, a fertilized female—ranging from 60 to 100 cm (2 to 3 feet) in length—migrates to the connective tissue of a host's leg and triggers a painful blister through which it slowly emerges over the course of several weeks. To relieve the debilitating pain from these lesions, hosts often place their legs in a nearby body of water, at which point the worm releases the roughly 3 million larvae it carries. Throughout the month or more in which it exits the host's leg, walking is nearly impossible and they are largely confined to bed.

2.2. Contributions to Low Agricultural Productivity

For farmers, GWD could decimate their yields for the year if it occurred during the planting or harvest seasons (hence the "empty granary" moniker). To illustrate the degree of overlap in northern Ghana, Appendix A2 shows the seasonal patterns in GWD and rainfall in the Northern Region's capital in 1991 and Appendix A3 does the same for a district in the Upper West Region in 1970-71. Peak GWD prevalence occurred at different times in these two years—January through March in the former and May through July in the latter—likely as a result of rainfall patterns in the previous year, a lag that would be expected from the worm's life cycle. The FAO Crop Calendar for northern Ghana in Appendix A4 shows that these peaks (or ones at any point between them) would have overlapped with the planting seasons for up to eight of out of ten staple crops in the region and the harvesting seasons for up to two of them.

The links to agriculture were not simply hypothetical: Belcher et al. (1975) documented that in six southern Ghanaian villages in 1973, around three-quarters of male farmers aged 25 to 44 had GWD during the year, as did about two-fifths of their female peers. In contrast, there were no cases among children aged 0 to 4. The authors summarized their findings by noting that

> [GWD] coincided with the two peak agricultural periods. Untreated farmers were completely disabled for over 5 weeks, and few households succeeded in finding alternative labor sources so that a major crop was lost. The cost of [GWD] in a self-employed farmer is not easy to measure, but it is clearly more than a month of [a] laborer's [wages]. . . . Adult patients lying around with [G]uinea worm ulcers and swollen legs are incapable of increased agricultural production or of innovating with improved farming technology. [GWD] is the major preventable cause of agricultural work loss in the [study] areas. Few other diseases coincide with major agricultural activities, and even year-round malaria causes little prolonged disability in relatively immune adults. (Belcher et al., 1975, p. 248)

Consequently, farming households in which adults suffered from GWD faced the prospect of drastically reduced harvests. In a study that in part inspired this one, Ahearn and De Rooy (1996) compared a Nigerian district where a GWD intervention took place in mid-1984 to two adjacent ones and showed that on a day in late January 1991, a satellite measure of vegetation had increased more in the treated area relative to its value on a day in early January 1985.

2.3. *Contributions to Underdevelopment*

One way to prevent the worst agricultural outcomes was to take a child out of school to work in the fields in place of an incapacitated parent, but they would still be less productive than a healthy adult. Therefore, in either case the child's human capital would suffer due to limited nutrition, limited education, or a combination of the two (Hotez, 2022). Moreover, in areas where GWD rates were very high, so many students could be substituting for their parents at the same time that schools would close for a month, meaning the impacts thus spilled over onto the education of children in non-afflicted households (Cairncross, Muller and Zagaria, 2002). Alternatively, families could call on neighbors or relatives, mitigating the impacts on their households but partially displacing the agricultural productivity shock onto the assisting individuals by reducing the time available to work on their own farms. In these ways, "the disease ultimately impoverishes the whole community" (Smith et al., 1989, p. 1048).

As with other NTDs, GWD was an important cause of poverty, but exposure was also a consequence of this deprivation.[2] While Belcher et al. (1975) found that wound hygiene and antibiotics to combat secondary infections were associated with shorter GWD disability durations, many poor households in rural Ghana did not know about or could not afford such care, or the clinics that offered it were too far away. In addition, many of their communities did not have the resources to drill boreholes or otherwise access uncontaminated drinking water, further perpetuating the poverty trap of GWD in the long run and into subsequent generations.

2.4. *Eradication Efforts in Ghana*

In the 1980s, the annual incidence of GWD among Africans living between the Sahara Desert and the equator was estimated to be over 3.3 million, and the population at risk in this region was believed to be 120 million (Watts, 1987*a*). The majority of these infections occurred in ten West African countries including Ghana, the nation that reported some of the highest case rates (Ruiz-Tiben and Hopkins, 2006).[3] Hunter (1997) showed that prevalence was highly concentrated in the country's north, and in the most affected district it was almost 20%.

In response, the Carter Center collaborated with Ghana's Ministry of Health to launch a national GWD eradication campaign in 1990. The program employed three key strategies: systematic case surveillance through village-based reporting, distribution of fine-mesh cloth filters to remove *D. medinensis* larvae from drinking water, and community education to promote safe water practices and case containment. Local volunteers were trained to monitor cases and distribute filters, fostering community ownership of the eradication process. By the mid-1990s, incidence had fallen dramatically, and Ghana was ultimately certified as GWD-free in 2015.[4]

[2] See, e.g., Denton-Schneider and Montero (2025) for a similar feedback loop due to Chagas disease.

[3] The other West African countries were Benin, Burkina Faso, Côte d'Ivoire, Mali, Mauritania, Niger, Nigeria, Senegal, and Togo. Additional cases occurred in East Africa, India, and Pakistan.

[4] For the WHO press release, which also describes GWD eradication progress in Africa as of January 2015, see: https://www.who.int/news/item/16-01-2015-who-certifies-ghana-free-of-dracunculiasis.

3. Difference-in-Differences Framework

To study the effects of Ghana's eradication program, we use a difference-in-differences strategy comparing high- and low-GWD districts (of birth) in pre- and post-treatment years (or cohorts).

3.1. *Treatment and Control Districts*

To quantify each district's exposure to GWD prior to eradication, we digitized and georeferenced archival data from Hunter (n.d.) on cases per 1,000 people in each district in 1989. Figure 1a shows the distribution of rates across Ghana. Districts in the second-highest (0.4-2.0% prevalence) and top (2.0-19.3%) quartiles lay almost exclusively within a band between the southwestern coastal region and the far north, which contained the bottom (0-0.04%) and second-lowest (0.04-0.2%) quartiles.[5] As is clear in Appendix B1, above-median GWD rates corresponded very closely to the overlap of low annual rainfall (less than 1,523 mm, or 60 in) and the basin of Voltaian sandstone in the northeastern part of the country. The hypothesis from Hunter (1997) was that surface water sources in this region would have been more stagnant (due to low precipitation) and had lower volumes (due to sandstone's permeability), increasing the chances of swallowing *D. medinensis* larvae when drinking from them.

Using these data, we define our treatment group as districts with above-median GWD rates in 1989. Our assumption is that prior to eradication, the geographic distribution of relative disease intensity was stable across time. Nonetheless, the extent that it was violated—i.e., there were treatment districts with little historical GWD exposure while some control districts had a lot—comparing these groups would understate the true impacts of eradicating the disease. Because the median was very close to 0% but very few districts had exactly zero cases, this approach balances the simple suggestion by Callaway, Goodman-Bacon and Sant'Anna (2024) of using a binary indicator for a positive "dosage" when estimating average level treatment effects with the desire to maximize power by having treatment and control groups of equal size.[6] We

[5] It is also important to note that case rates were reported relative to the entire population but much of the GWD burden was borne by adult farmers, so prevalence among them would have been even higher.

[6] Given the year-long lag between ingestion of *D. medinensis* larvae and symptomatic GWD, many of these very low but strictly positive case rates were likely due to circular migration from endemic to non-endemic districts (Watts, 1987*b*). Thus, it is plausible that our treatment-control distinction captures the

quantify below the average pre-treatment differences across these groups in their GWD rates, the elimination of which should be interpreted as generating our estimated effects.

3.2. *Pre- and Post-Treatment Years and Cohorts*

Figure 1b shows that the reduction in Ghana's GWD cases occurred rapidly after the eradication program began. Specifically, within one year they had fallen by nearly one-third, by 1991 they were down by almost two-thirds, and within five years they had declined by over 95%. The number of villages with endemic transmission followed a similar pattern. Because we could not find post-1989 district-level data on GWD cases, we assume that these declines occurred uniformly across our treatment group.

Therefore, when studying impacts on districts or their residents, we define our final pre-treatment year as 1989. In contrast, when we examine the effects of childhoods free of GWD exposure, we set the final pre-treatment birth year to be 1972, as members of this cohort were 18 years old when the eradication campaign began. The assumption in this case is that the 1973 cohort (aged 17 in 1990) was the first to experience benefits from GWD eradication *during childhood*, which is distinct from assuming that it was the first to experience any benefits at all. As such, this approach only allows us to estimate long-run and intergenerational effects arising from changes in the childhood environment, which would be biased toward null results if the youngest adults also benefited from GWD eradication.

3.3. *Pre-Treatment Differences*

In Figures 1c and 1d, we compare our treatment and control groups prior to 1990 using the IPUMS 10% sample of the 1984 census (Ruggles et al., 2024) and the Ghana Living Standards Survey (GLSS) rounds 1 (1988) and 2 (1989) from the Ghana Statistical Service (GSS).[7] We regress our outcomes of interest on an indicator for being in control group ("low-GWD") districts and normalize estimates and standard errors by the mean in treatment group ("high-GWD") districts. At the top of both figures is the average estimated difference in 1989 GWD cases per 1,000 people,

effect of eliminating any exposure to endemic GWD transmission.

[7] The GLSS is part of the World Bank's Living Standards Measurement Survey (LSMS), which asks a wide range of highly detailed and consistent questions regarding topics like occupation and health.

which was almost 30 in the census sample and just above 26 in the GLSS data. As rates in the control group were effectively 100% lower, our estimates capture the difference in outcomes where GWD prevalence averaged 2.6-3.0% versus where it was 0%.

At first glance, these rates might seem too low for GWD to have been a serious health issue in these areas, let alone one that could have affected their agricultural productivity. However, in the GLSS data, nearly 15% of prominent local individuals in treatment districts listed it as their community's most important health concern, meaning it beat out other scourges like malaria and diarrhea.[8] Notably, this rating was only 50% (7.4 p.p.) less common in low-GWD districts, implying substantive fears of its consequences even where prevalence was below 0.2%.

Figure 1c also shows that basic characteristics such as age, sex, and labor force participation were the same across treatment and control groups in the census data. But in low-GWD districts, the shares of adults working for wages and of children attending school were both 25% (respectively 3.5 and 12.1 p.p.) higher while the share of adults working on farms was 8% (5.6 p.p.) lower, though the last of these differences is imprecisely estimated. Other labor market contrasts in the GLSS data are apparent in Figure 1d: adults in control districts were over 20% (16.4 p.p.) less likely to be self-employed in agriculture and farming households were just under 20% (5.2 p.p.) less likely to pay female workers, but there were no differences in the near-universal share of farming households that paid male labor. Surprisingly given the discussion in the previous section, the average number of days inactive due to illness or injury in the past month were equal across low- and high-GWD districts. However, in line with the link between agricultural precarity and child marriage in bride price socities (Corno, Hildebrandt and Voena, 2020), these rates were one-third (4.0 p.p.) lower in the control group.

4. Effects on Districts

We begin our analysis by studying the district-level impacts of GWD eradication. We test for increases in agricultural productivity and examine its implications for labor markets and children.

[8] The community questionnaire was "to be asked of a group of people who are well informed about the activities, events and infrastructure of the community. The group can consist, for instance, of the chief, leading citizens, [Committee for the Defense of the Revolution] officers, traders, teachers, or others who have lived in the community for several years" (Ghana Statistical Service, 1987, p. 46).

4.1. Data

Our first outcome of interest is a proxy for agricultural productivity based on remotely sensed NDVI data obtained through GeoQuery (Goodman et al., 2019). NDVI measures vegetation greenness on a scale from -1 to 1, with higher values indicating denser vegetation. However, NDVI alone cannot distinguish between agricultural activity and other forms of vegetation growth. To better isolate agricultural cycles, we calculate the difference between the maximum and minimum monthly NDVI for each district in a given year (as in Asher et al., 2024). This within-year NDVI range is designed to capture the seasonal greening and harvesting patterns that typify agricultural production. Increases in this range can indicate more intensive or productive cultivation over the year and should reflect greater agricultural production during the growing season rather than higher values at other times of the year.

To understand the impacts of changes in agricultural productivity, we use repeated cross-sectional data from GLSS rounds 1, 2, and 4 (1998), which allow us to match respondents to consistent districts.[9] Our outcomes of interest are whether an adult is employed for wages (as opposed to self-employed) and is working in agriculture, which capture changes in labor markets and farm production. As a mechanism, we also examine the number of days that an adult reports they were inactive due to illness or injury in the past month. Additionally, we use these three GLSS rounds as well as the IPUMS 10% samples of the 1984 and 2000 censuses to study impacts on children.[10] Our outcomes of interest are whether a girl ages 12 to 18 has ever been married (GLSS) and whether a child ages 6 to 18 is attending school (census).

4.2. Empirical Specification

To test for effects of GWD eradication on agricultural productivity, we use the dynamic two-way fixed effects (TWFE) specification

$$y_{d,t} = \alpha_d + \gamma_t + \sum_{k \neq 1989} \left(\tau_k \cdot \mathbb{1}[t = k] \cdot \mathbb{1}[\text{GWD}_{d,1989} > \text{GWD}_{\text{median},1989}] \right) + \gamma_t \times \delta_{r(d)} + \mathbf{X}_{d,t}\beta + \epsilon_{d,t}, \quad (1)$$

[9] We could not find a map of survey clusters for round 3 (1992) and district codes were reported for the first time in the round 4 dataset.

[10] With only one pre-treatment census, those district-level results can only provide suggestive evidence.

where $y_{d,t}$ is the outcome for district d in year t, α_d and γ_t are district and year fixed effects, $\mathbb{1}[t = k]$ indicates whether an observation is from the given year k, $\mathbb{1}[\text{GWD}_{d,1989} > \text{GWD}_{\text{median},1989}]$ indicates whether a district had an above-median GWD rate in 1989, $\gamma_t \times \delta_{r(d)}$ is the interaction of fixed effects for the year and a district's region, $\mathbf{X}_{d,t}$ is a vector of time-varying controls (annual precepitation and average temperature), and $\epsilon_{d,t}$ is the idiosyncratic error term. For the GLSS and census data, we make slight modifications to equation (1): the outcome $y_{i,d,t}$ and error term $\epsilon_{i,d,t}$ are for individual i and the vector of controls X_i contains only fixed effects for age and sex.

The coefficients of interest are the τ_k, which capture the average difference in the outcome between high- and low-GWD districts within a region in a given year relative to the size of that difference in 1989. Under the identifying assumption of parallel trends, we interpret economically and statistically significant estimates of the post-1989 τ_k as evidence of the impacts of GWD eradication. For agricultural productivity, we use Poisson regression, which recovers the treatment effect as a percentage of the mean in the control group while avoiding the problems associated with log-linearization (Santos Silva and Tenreyro, 2006). In the difference-in-differences context, it is identical to the Borusyak, Jaravel and Spiess (2024) imputation estimator, and it requires that the parallel trends assumption holds for the ratio of the means (Wooldridge, 2023). For individual-level outcomes, we use OLS. In all cases, we cluster standard errors by the 128 districts that existed in Ghana when eradication began.

4.3. *Agricultural Productivity*

We first examine the maximum-minimum gap in NDVI values. For parsimony and because it took five years for cases to fall by 95% (see Figure 1b), Table 1 Panel A reports the average effects in 5-year bins (1990-94 and 1995-99). Column (3) shows that in our full specification, this measure of agricultural productivity increased 1.8% more in treatment districts while cases were still falling, though it is imprecisely estimated. However, after GWD cases had been reduced by over 95%, the agricultural productivity measure had increased by a precisely estimated 6.6%, or an average of 0.8% per year over the 1990-99 period.

Figure 2a shows that the ratio of the outcomes evolved in parallel prior to 1990 and that the post-treatment divergence grew in magnitude over time. Additionally, in Appendix C1 we verify that the results are similar when using OLS and the log of the outcome as well as an alternative measure—the average annual NDVI value—in Poisson regression and OLS after a log transformation.[11] We also present evidence in Appendices C2 and C3 that the (log-transformed) results are largely unchanged when using new difference-in-difference estimators (Arkhangelsky et al., 2021; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfœuille, 2020; Sun and Abraham, 2021), albeit with wider confidence intervals given their greater data requirements, and they are mostly robust to linear violations of the parallel trends assumption along with deviations from linearity (Rambachan and Roth, 2023), which we measure in standard errors of the average estimated effect in pre-treatment years.

4.3.1. Mechanisms

To examine the underlying channels, we turn to the GLSS data and estimate the individual-level version of equation (1) using OLS and the indicator for whether an adult aged 15 to 55 reported being active in all days in the previous month. Table 1 Panel B Column (3) shows that this measure had increased by 8.1 p.p. (11% of the pre-1990 high-GWD mean) more in treatment districts by 1998, and Figure 2b suggests that trends were parallel in the immediate pre-treatment period. In Appendices C4 and C5, we show that these results are similar across sex and age groups and robust to using the new difference-in-differences techniques. We also find evidence consistent with the GWD eradication program generating these effects: Appendix C6 shows that treatment districts experienced larger (but imprecise) increases in the shares of communities reporting that GWD was not their biggest health concern and households reporting that their drinking water did not come from surface sources.

4.4. Agricultural Labor Markets

Next, we study how the increase in agricultural productivity affected labor markets. The estimate in Table 1 Panel C Column (3) shows that by 1998, young women (ages 15-35) in formerly high-GWD districts were 5.3 p.p. more likely to be working for wages, which was 65% of their pre-

[11] In all district-years, average NDVI values were strictly positive. The results with this agricultural productivity measure verify that the effects on our preferred one arise from increasing the maximum.

treatment mean. But the null estimate in Panel D suggests that this change was not accompanied by a movement of young women out of agriculture. Instead, they imply that young women began to earn wages while working on farms, which we interpret as increased agricultural productivity allowing for them to be hired for pay. Figures 2c and 2d show that these post-treatment patterns do not seem to stem from a violation of parallel trends before 1990, and the result for wage labor is mostly robust to using the new difference-in-differences techniques in Appendix C7.

In Appendices C8 and C9, we find that there were no increases for women aged 35 to 55 in the share earning wages or working in non-agricultural sectors, implying that the suggestive evidence of an increase in farm households paying female labor was due entirely to the younger age group. However, while the evidence for men is more difficult to interpret given large violations of parallel trends, they are consistent with increases in these measures in both age groups.

4.5. *Child Marriage and Schooling*

Lastly, we examine the impacts on children over this period. Because positive weather shocks have been shown to reduce child marriage in agricultural communities that practice bride price (Corno, Hildebrandt and Voena, 2020), we test whether this health shock and the resulting increase in agricultural productivity had similar effects. In Table 1 Panel E Column (3), we find that girls aged 12 to 18 in treatment districts in 1998 were 10.1 p.p. (11%) more likely to have never been married, and this estimate is precise and does not appear to arise from a violation of parallel trends (see Figure 2e). In Appendix C10, we also show that it is strongly robust to the new difference-in-differences techniques.

Table 1 Panel F provides suggestive evidence that children's schooling also increased more in formerly high-GWD districts. Using the 1984 and 2000 censuses, we estimate in Column (3) that children aged 6 to 18 in the treatment group were 3.3 p.p. (6%) more likely to be in school by 1998. While this effect is precisely estimated, Figure 2f emphasizes that there was only one pre-1990 census, so it is not possible to explore whether outcomes evolved in parallel prior to 1990. Nonetheless, in Appendix C11, we find slightly larger effects for females as well as suggestive evidence of similar effects (i.e., after adjusting for non-parallel trends) in the GLSS data. Taken together, these results are consistent with increased investments in children's education.

5. Effects on Individuals

The second part of our analysis focuses on the long-run and intergenerational effects of growing up after Ghana's eradication program began. Given that adult farmers—not children—had the highest rates of GWD (see Section 2), we interpret our estimates as the impact of a child *having parents* no longer exposed to the disease.

5.1. Data

We use the 10% sample of the 2021 census from the GSS. Our first outcomes of interest relate to structural transformation and human capital: whether an individual is formally employed outside of the agricultural sector, whether they can read or write in any language, and whether they live in an urban municipality (defined as having a population of at least 5,000 people). We then turn to demography and intergenerational effects by examining a woman's age at first birth, whether a man reports that his mother is still alive, and whether a man's son can read and write.

5.2. Empirical Specification

These data also contain individuals' districts of birth, which we assume to be where they spent their childhoods. Because the number of districts had increased to 261 by 2021, we overlaid these boundaries onto our 1989 map of GWD prevalence and assigned each current district the case rate in the former district it overlapped with most. We therefore estimate a dynamic TWFE specification similar to the previous specification:

$$y_{i,b,c} = \alpha_b + \gamma_c + \sum_{k \neq 1972} \left(\tau_k \cdot \mathbb{1}[c = k] \cdot \mathbb{1}[\text{GWD}_{b,1989} > \text{GWD}_{\text{median},1989}]\right) + \gamma_c \times \delta_{r(b)} + \mathbf{X}_i \beta + \epsilon_{i,b,c}, \tag{2}$$

where the new elements are the subscripts (for individual i from birth district b and cohort c), $\mathbf{X}_i$ contains fixed effects for i's sex and ethnic group, and all else is analogous to equation (1).

The coefficients of interest are again the τ_k, which now capture the average difference in the outcome between individuals from high- and low-GWD districts of birth in the same ethnic group and region of birth for a given cohort relative to the size of that difference for those born in

1972. Because all of our outcomes are indicator variables, we use OLS for estimation and cluster standard errors by the 241 districts of birth in our sample. We also extend the analysis to examine effects on the next generation. Specifically, we attach the information regarding a father's birth district and cohort to the children in his household and estimate a version of equation (2) that includes fixed effects for the child's age, sex, and ethnic group. Correspondingly, we cluster standard errors in this specification by fathers' districts of birth.

For several reasons, we focus on the average effects for (children of) the 1974-78 and 1984-88 cohorts. First, Ghana experienced a famine in 1983, so the cohorts from treatment districts that were aged 0 to 4 at that time (i.e., were born in 1979-83) may have had negative early childhood shocks that counteracted the effects of GWD eradication. Additionally, given age heaping in the data shown in Appendix D1, computing average effects for five-year bins centered around ages ending in 0 or 5 in 2021 (i.e., cohorts born in years ending in 1 or 6) helps to smooth out any distortions. However, we still show event study plots with estimates for each cohort.

5.3. *Structural Transformation and Human Capital*

Given the agricultural productivity results in Section 4.3, we begin by examining outcomes related to structural transformation. Table 2 Panel A Column (3) shows that adults in the treatment group are 1.2-1.4 p.p. more likely to hold formal employment outside of agriculture, which is about 11% of the mean for pre-1973 cohorts from high-GWD districts. Similarly, the estimates in Panel B are of a 1.6-1.9 p.p. (around 4%) greater increase in literacy for individuals born in high-GWD districts, and the estimates in Panel C show a 3.2-3.5 p.p. (about 6%) greater increase in the likelihood of living in an urban municipality. Overall, the findings indicate GWD eradication significantly influenced structural transformation. Figures 3a to 3c confirm these effects are not driven by pre-existing trends and are weaker among cohorts who were young during the 1983 famine.

In Appendices D2 through D7, we split the results out by subgroup and test the pooled results' robustness to new difference-in-differences techniques. While effects are generally slightly larger for men than women, the patterns are the same across these groups. Additionally, the effects are broadly robust to using new estimators (again with wider confidence intervals due to greater data requirements), though they are sensitive to deviations from linear violations of parallel trends. We also examine in Appendix D7 whether there was greater migration away from birth districts in the treatment group, but we find null effects, suggesting that the urban residence result is due to larger increases in population density in treatment districts since 1990.

5.4. Demography and Spillovers onto Other Generations

Finally, we study impacts on demographic outcomes and test for spillovers onto other generations. Consistent with the reduction in child marriage in Section 4.5, we find in Table 2 Panel D Column (3) that the share of women who did not give birth before age 22 rose 2.7-3.4 p.p. (around 5%) more among treated cohorts. Moreover, Figure 3d shows that it does not arise from non-parallel trends among pre-treatment cohorts. In Appendix D8, we find no evidence of differences in marriage rates or the likelihood of ever having children. Nevertheless, treated women exhibited greater reductions in the number of live births and larger increases in their ages at first live birth. In contrast, Appendix D9 shows that the main result is sensitive to using some of the new estimators as well as small non-linear violations of the parallel trends assumption.

Nonetheless, in line with reductions in child marriage and early fertility improving outcomes for the next generation, Table 2 Panel E Column (3) shows that sons aged 9 to 16 are 2.6-3.6 p.p. (about 5%) more likely to be literate if their fathers were born in formerly high-GWD districts.[12] Notably, this effect is not apparent for boys whose fathers were in early childhood during the 1983 famine (Figure 3e) or for daughters in the same age range (Appendix D10). But we do find in Appendix D11 that the results for sons are robust to using new difference-in-differences estimators and small deviations from a linear violation of parallel trends.

We also study the longevity of the previous generation, as adult sons in West Africa are often expected to financially support elderly parents—and because healthy aging is highly understudied in Sub-Saharan Africa (Duhon et al., Forthcoming). Table 2 Panel G Column (3) and Figure 3f show that likelihood of a man's mother being alive is 1.7-2.2 p.p. (around 3%) higher in the treated group. In Appendix D12, we show that this result is robust to using new estimators but not to non-linear violation of parallel pre-treatment trends. However, because we find that no

[12] We focus on these ages because their literacy rates ranged from 50 to 90% in the 2021 census.

evidence of similar effects on a woman's mother or anyone's father (Appendix D13), it suggests this result is due to men from post-treatment cohorts being more able to support their mothers. Thus, to our knowledge, we are the first to show that disease control during childhood can lead to greater longevity for parents.

6. Conclusion

In this paper, we investigate the agricultural, economic, and demographic impacts of GWD eradication in Ghana by leveraging its post-1989 eradication program in a difference-in-differences setup. Comparing across high- versus low-GWD districts before and after it began, we show that satellite measures of agricultural productivity increased, which led to more women earning wages for their farm labor and less child marriage. We also use present-day census data to compare outcomes across adults who were born in high- versus low-GWD districts and were children around 1990. We find higher rates of formal non-agricultural employment and urban residence as well as greater literacy, women delaying giving birth, and increases in the next generation's literacy and the previous generation's longevity. Therefore, our evidence suggests that improving the health of adults in low- and middle-income countries can be not only an important input into their macroeconomic development, but also a catalyst for weakening intergenerational poverty traps and promoting healthy aging.

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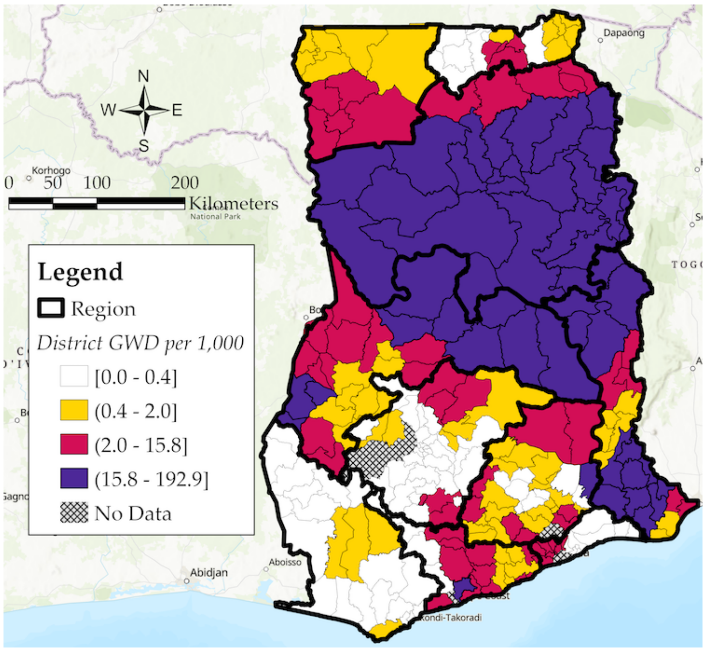
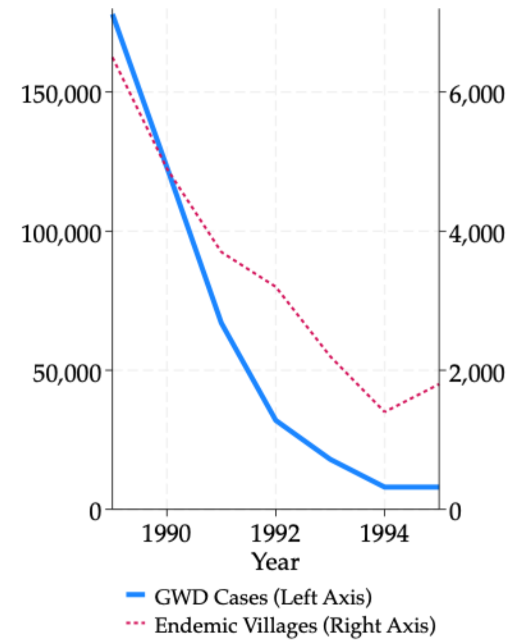
Figures and Tables

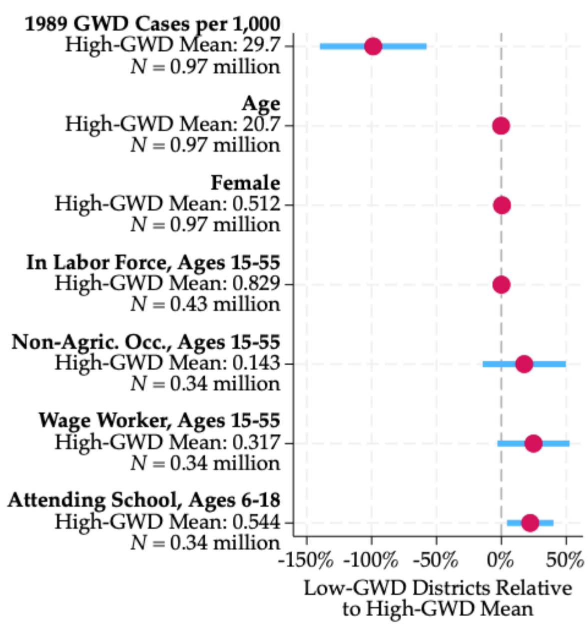
Figure 1: GWD in Ghana and Pre-Treatment Differences Across Districts [6, 7, 7, 10]



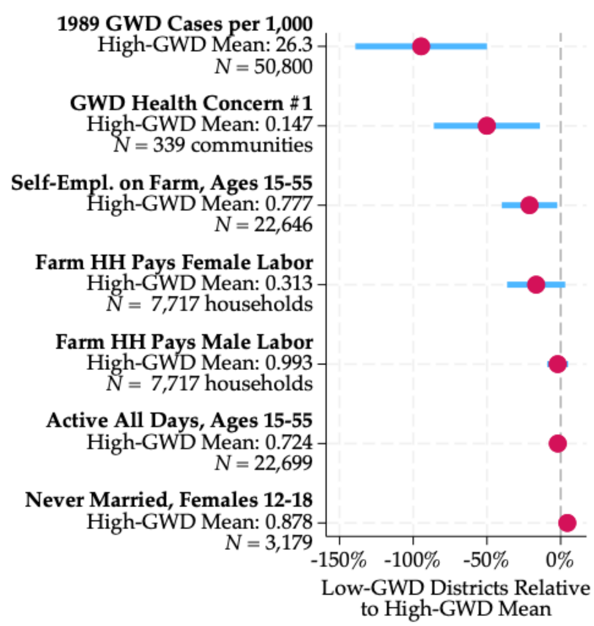
(a) GWD Cases per Thousand People, 1989



(b) GWD Eradication Progress, 1989-95



(c) Differences in 1984 Census



(d) Differences in 1988 and 1989 GLSS

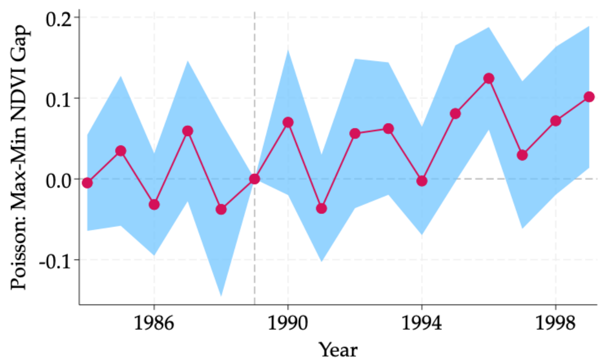
Notes: Top left panel shows quartiles of district-level 1989 GWD case rates. Top right panel shows the number of GWD cases and endemic villages in each year. Bottom panels show estimates and 95% confidence intervals from regressions of the outcome on an indicator for a district having a below-median (low) 1989 GWD rate, which are then scaled by the mean in above-median (high) GWD districts. Standard errors are clustered by district. Census data are the IPUMS 10% sample and GLSS data are from the GSS.

Table 1: District-Level Effects of GWD Eradication [10, 11, 12]

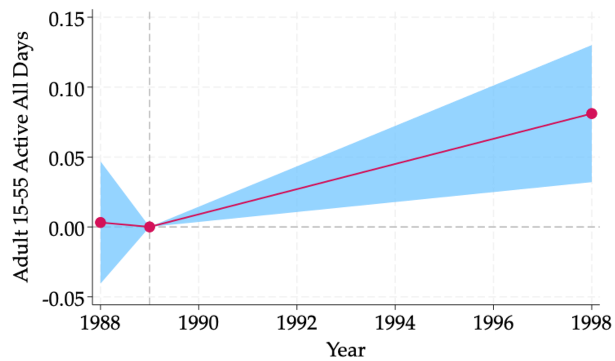
	(1)	(2)	(3)
Panel A. Poisson Regression: Maximum-Minimum Gap in NDVI Values			
Treat × 1990-94	-0.005	0.030	0.018
	(0.031)	(0.031)	(0.036)
Treat × 1995-99	0.041	0.082	0.066
	(0.033)	(0.035)	(0.037)
Average Annual Change 1990-99	0.5%/year	1.0%/year	0.8%/year
Panel B. GLSS: Active All Days in Past Month, Adults 15-55			
Treat × 1998	0.087	0.080	0.081
	(0.031)	(0.026)	(0.025)
Effect Relative to Pre-1990 High-GWD Mean	12%	11%	11%
Panel C. GLSS: Working for Wages, Females 15-35			
Treat × 1998	0.029	0.053	0.053
	(0.029)	(0.024)	(0.024)
Effect Relative to Pre-1990 High-GWD Mean	35%	64%	65%
Panel D. GLSS: Non-Agricultural Occupation, Females 15-35			
Treat × 1998	-0.034	0.023	0.024
	(0.061)	(0.078)	(0.079)
Effect Relative to Pre-1990 High-GWD Mean	-10%	7%	7%
Panel E. GLSS: Never Married, Females 12-18			
Treat × 1998	0.044	0.077	0.101
	(0.030)	(0.034)	(0.033)
Effect Relative to Pre-1990 High-GWD Mean	5%	9%	11%
Panel F. Census: Attending School, Children 6-18			
Treat × 2000	0.073	0.032	0.033
	(0.022)	(0.015)	(0.015)
Effect Relative to Pre-1990 High-GWD Mean	13%	6%	6%
District FE and Year FE	x	x	x
Region FE × Year FE		x	x
Additional Controls (Panel A) or FE (Panels B-F)			x
Observations in Panel A	3,888	3,888	3,888
Districts in Panel A	128	128	128
Observations in Panel B	22,699	22,699	22,699
Observations in Panel C	8,151	8,151	8,151
Observations in Panel D	5,454	5,454	5,454
Observations in Panel E	3,178	3,178	3,178
Districts in Panels B-E	105	105	105
Observations in Panel F	880,325	880,325	880,325
Districts in Panel F	106	106	106

Notes: Observations in Panel A are district-years and in Panels B-F are individuals. NDVI data are from GeoQuery, GLSS data (rounds 1, 2, and 4) are from the GSS, and census data (1984 and 2000) are from IPUMS. Panel A uses Poisson regression with districts weighted by land area, and Panels B-F use OLS. Additional controls in Panel A are for precipitation and temperature, and additional fixed effects in Panels B-F are for age and sex. Standard errors in parentheses are clustered by district.

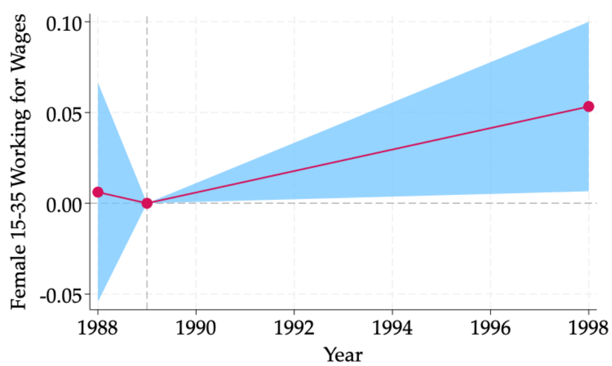
Figure 2: Plots for District-Level Effects [10, 11, 12]



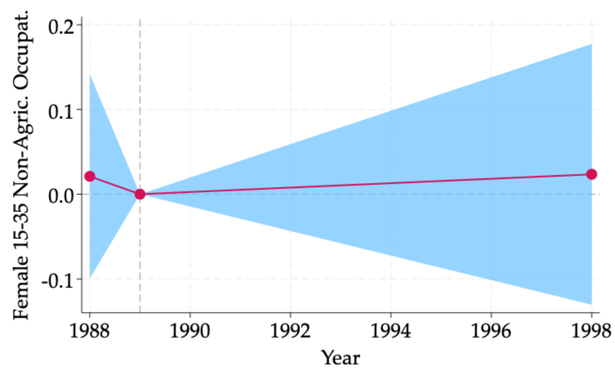
(a) Poisson: Max-Min Gap in NDVI Values



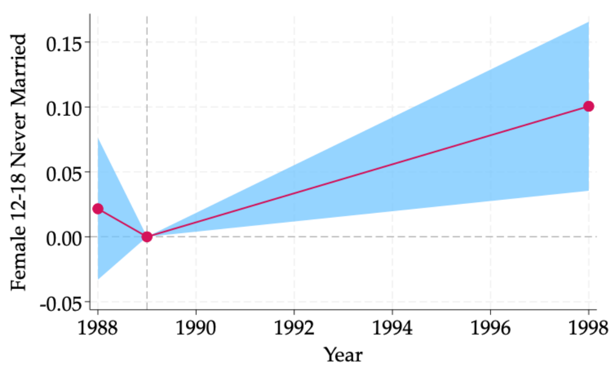
(b) GLSS: Active All Days in Past Month, Ages 15-55



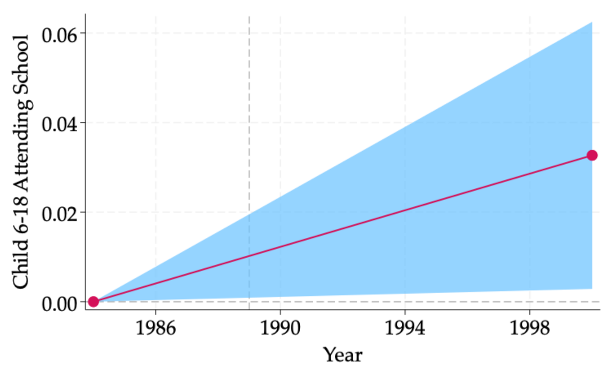
(c) GLSS: Working for Wages, Females 15-35



(d) GLSS: Non-Agricultural Occupation, Females 15-35



(e) GLSS: Never Married, Females 12-18



(f) Census: Attending School, Ages 6-18

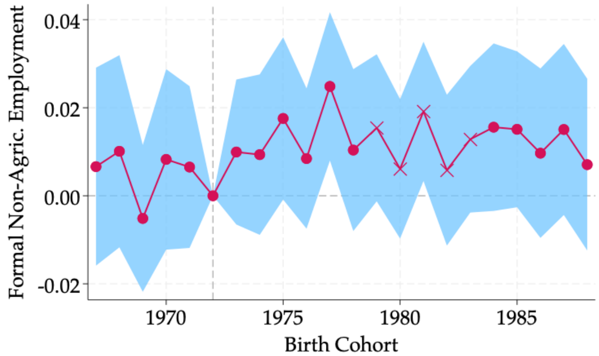
Notes: Graphs show estimates with 95% confidence intervals. NDVI data are from GeoQuery, GLSS data (rounds 1, 2, and 4) are from the GSS, and census data (1984 and 2000) are the IPUMS 10% samples. Top left panel uses Poisson regression with district, year, and region-by-year fixed effects and districts weighted by land area, as in Table 1 Column (2). All other panels use OLS with district, year, region-by-year, age, and sex fixed effects, as in Table 1 Column (3). Standard errors are clustered by district.

Table 2: Individual-Level Effects of GWD Eradication [14, 15]

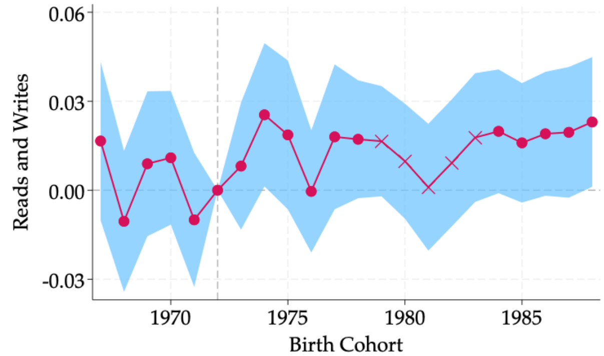
	(1)	(2)	(3)
Panel A. Formal Non-Agricultural Employment			
Treat × 1974-78 Cohorts	0.014	0.015	0.014
	(0.006)	(0.007)	(0.007)
Treat × 1984-88 Cohorts	-0.001	0.013	0.012
	(0.007)	(0.008)	(0.008)
1984-88 Cohorts' Effect / Pre-1973 High-GWD Cohorts' Mean	-1%	12%	11%
Panel B. Reads and Writes in Any Language			
Treat × 1974-78 Cohorts	0.014	0.014	0.016
	(0.008)	(0.011)	(0.010)
Treat × 1984-88 Cohorts	0.019	0.018	0.019
	(0.009)	(0.010)	(0.010)
1984-88 Cohorts' Effect / Pre-1973 High-GWD Cohorts' Mean	4%	4%	4%
Panel C. Lives in Urban Municipality			
Treat × 1974-78 Cohorts	0.023	0.035	0.035
	(0.008)	(0.010)	(0.009)
Treat × 1984-88 Cohorts	0.021	0.031	0.032
	(0.008)	(0.010)	(0.010)
1984-88 Cohorts' Effect / Pre-1973 High-GWD Cohorts' Mean	4%	6%	6%
Panel D. No Births Through Age 21			
Treat × 1974-78 Cohorts	0.011	0.035	0.034
	(0.012)	(0.015)	(0.015)
Treat × 1984-88 Cohorts	-0.016	0.028	0.027
	(0.013)	(0.016)	(0.016)
1984-88 Cohorts' Effect / Pre-1973 High-GWD Cohorts' Mean	-3%	5%	5%
Panel E. Man's Son Reads and Writes in Any Language, Ages 9-16			
Treat × 1974-78 Cohorts	0.019	0.032	0.026
	(0.014)	(0.018)	(0.017)
Treat × 1984-88 Cohorts	0.025	0.045	0.036
	(0.015)	(0.020)	(0.018)
1984-88 Cohorts' Effect / Pre-1973 High-GWD Cohorts' Mean	4%	6%	5%
Panel F. Man's Mother Still Alive			
Treat × 1974-78 Cohorts	0.015	0.022	0.022
	(0.011)	(0.014)	(0.014)
Treat × 1984-88 Cohorts	0.018	0.017	0.017
	(0.011)	(0.013)	(0.013)
1984-88 Cohorts' Effect / Pre-1973 High-GWD Cohorts' Mean	4%	4%	3%
Birth District FE and Birth Cohort FE	x	x	x
Birth Region FE × Birth Cohort FE		x	x
Additional FE			x
Observations in Panel A	502,526	502,526	500,877
Observations in Panel B	595,917	595,917	593,775
Observations in Panel C	598,204	598,204	596,021
Observations in Panel D	303,255	303,255	302,326
Observations in Panel E	98,708	98,708	98,413
Observations in Panel F	291,784	291,784	290,587
Birth Districts in Panels A-F	241	241	241

Notes: Data are the GSS 2021 census 10% sample. In Panels A-E, regressions use adults' observations and the additional fixed effects are for sex and ethnic group. In Panel F, regressions use sons' observations with fixed effects based on fathers' information and the additional fixed effects are for own age, sex, and ethnic group. Standard errors in parentheses are clustered by (father's) birth district.

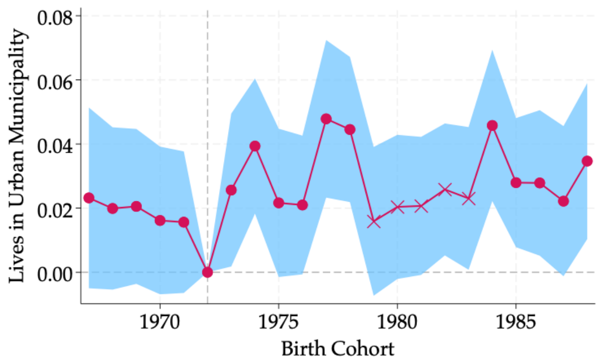
Figure 3: Plots for Individual-Level Effects [14, 15]



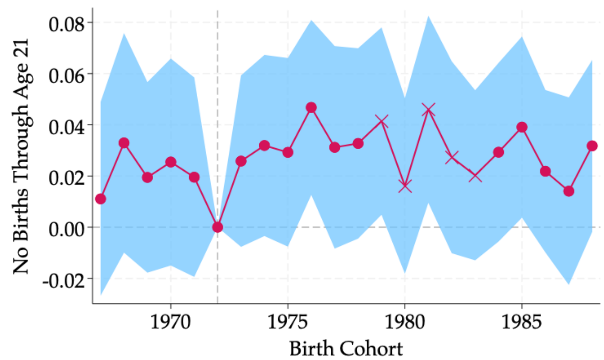
(a) Formal Non-Agricultural Employment



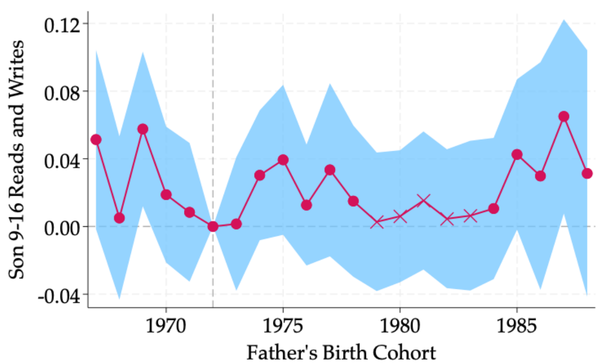
(b) Reads and Writes in Any Language



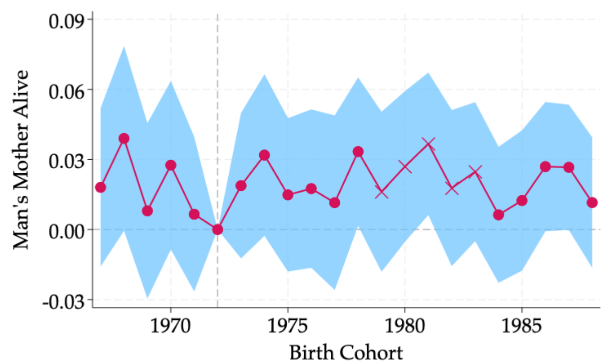
(c) Lives in Urban Municipality



(d) No Births Through Age 21



(e) Man's Son Reads and Writes in Any Language, Ages 9-16



(f) Man's Mother Is Still Alive

Notes: Graphs show estimates with 95% confidence intervals. Data are the GSS 2021 census 10% sample. An estimate shown with an X indicates a (father's) birth cohort that was aged 0-4 during Ghana's 1983 famine. As in Table 2 Column (3), regressions using adults' observations include own birth cohort, birth district, birth region-by-birth cohort, sex, and ethnic group fixed effects, and regressions using sons' observations include the analogous fixed effects based on their fathers' observations plus fixed effects for own age, sex, and ethnic group. Standard errors are clustered by (father's) birth district.

Online Appendix for:

Eradicating the Disease of the Empty Granary: Health, Structural Transformation, and Intergenerational Mobility in Ghana

Conor Carney
University of Chicago

Jon Denton-Schneider
Clark University

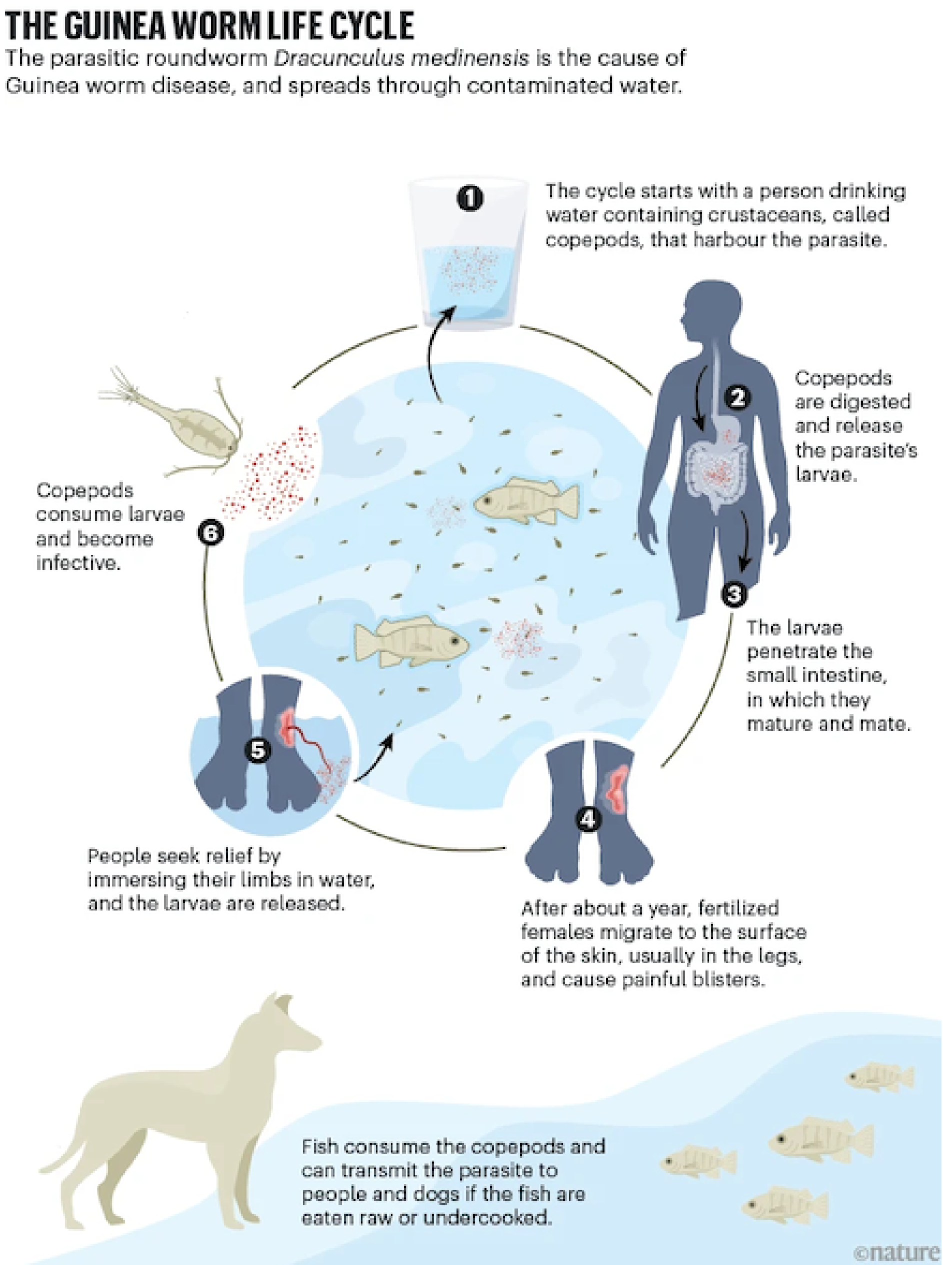
October 16, 2025

Contents

A. Additional Figures: Background

A1. D. medinensis Life Cycle

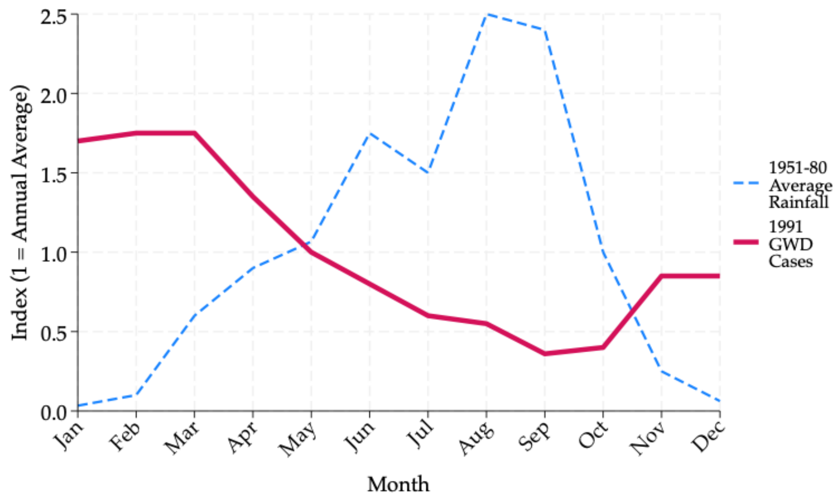
Figure A1: *D. medinensis* Life Cycle [3]



Notes: Figure taken from DeWeerdt (2024).

A2. Rainfall and GWD Cases in Tamale, Northern Region, 1991

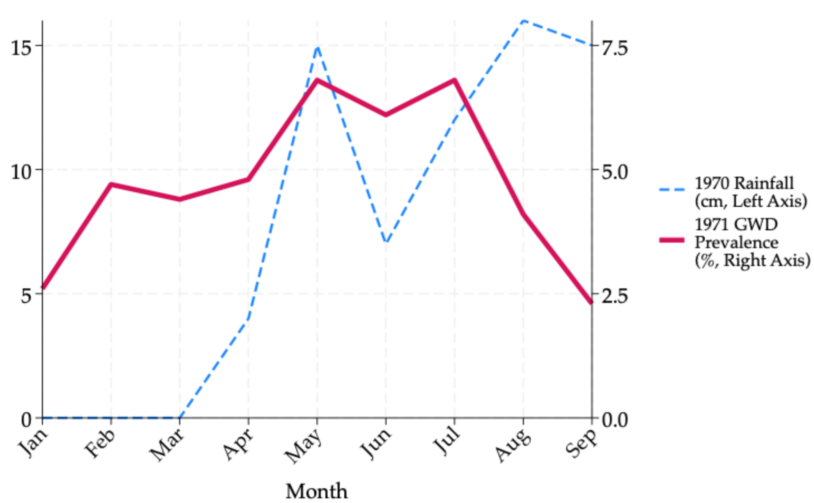
Figure A2: Rainfall and GWD Cases in Tamale, Northern Region, 1991 [3]



Notes: Figure adapted from Hunter (1997). Tamale is the capital of Ghana's Northern Region. Rainfall values are based on 1951-80 monthly averages from the World Meteorological Organization.

A3. Rainfall and GWD Cases in Wa District, Upper West Region, 1970-71

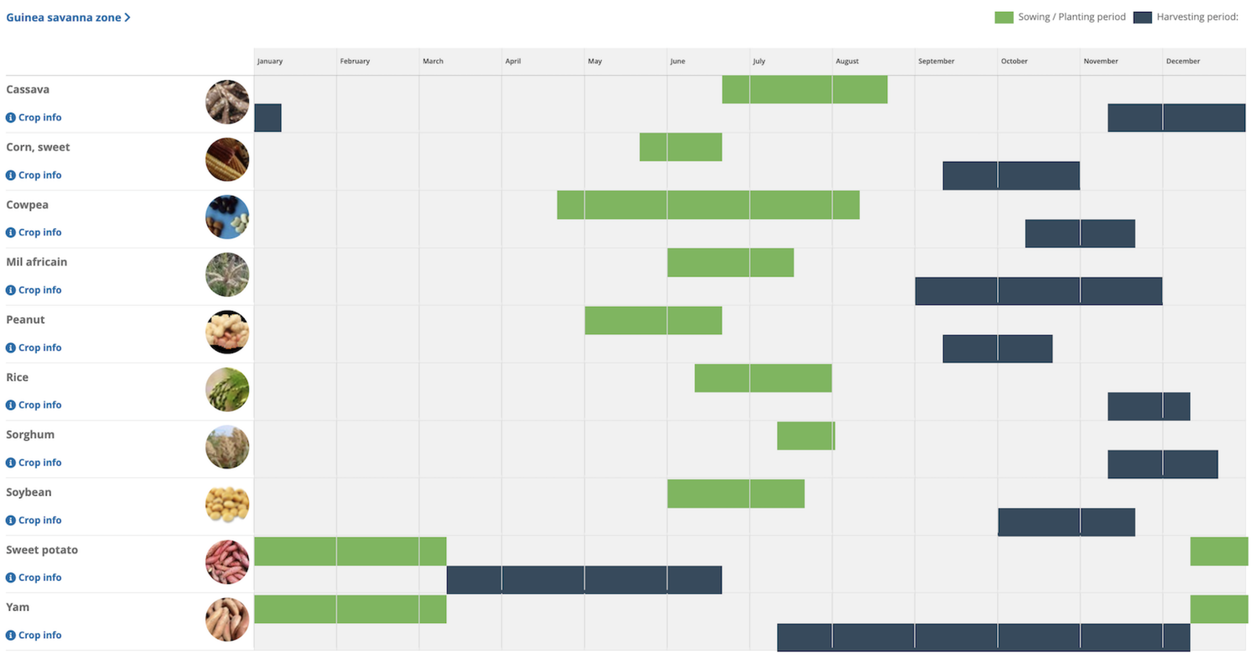
Figure A3: Rainfall and GWD Cases in Wa District, Upper West Region, 1970-71 [3]



Notes: Figure adapted from Lyons (1972). Data are for 5 selected villages in Wa District.

A4. Planting and Harvesting Calendars in Northern Ghana

Figure A4: Planting and Harvesting Calendars in Northern Ghana [3]

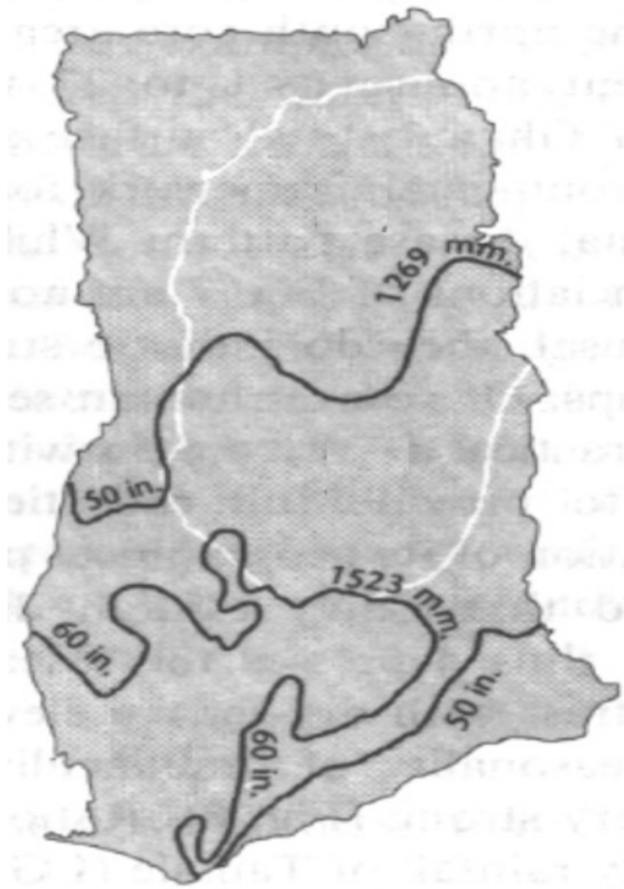


Notes: Figure shows the FAO Crop Calendar for the Guinea savanna zone in northern Ghana. Rows contain crops listed in the following order: casava, sweet corn, cowpea, millet, peanut, rice, sorghum, soybean, sweet potato, and yam. Columns correspond to months. Planting periods for each crop are denoted in light green and harvesting periods are denoted in dark blue.

B. Additional Figures: Differences-in-Differences Framework

B1. Rainfall Levels and Voltaian Sandstone

Figure B1: Rainfall Levels and Voltaian Sandstone [6]

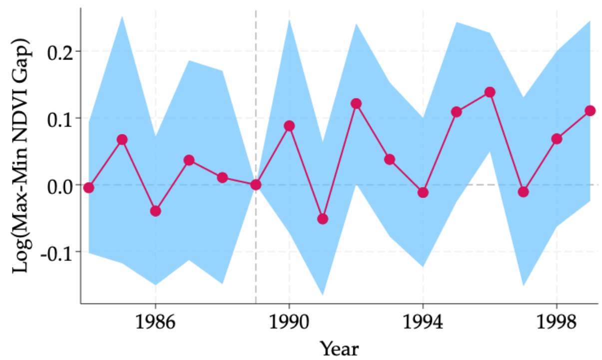


Notes: Map taken from Hunter (1997, p. 113) shows levels of rainfall (isohyets in black) and the basin of Voltaian sandstone (limits in white).

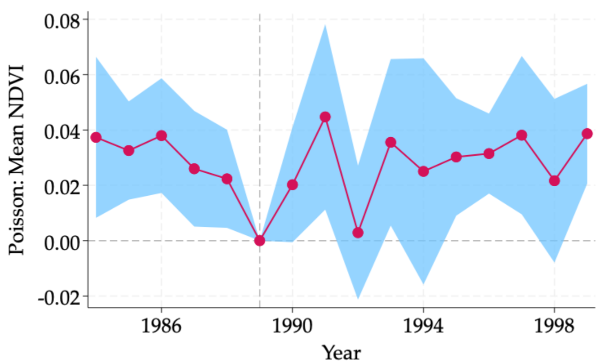
C. Additional Figures: Effects on Districts

C1. Alternative Measures of Agricultural Productivity

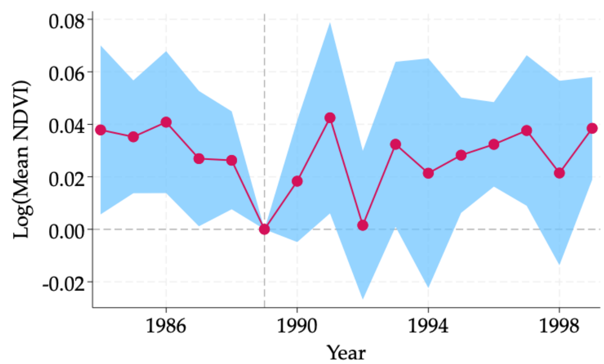
Figure C1: Alternative Measures of Agricultural Productivity [10]



(a) Log of Max-Min Gap in NDVI Values



(b) Poisson: Mean NDVI Value

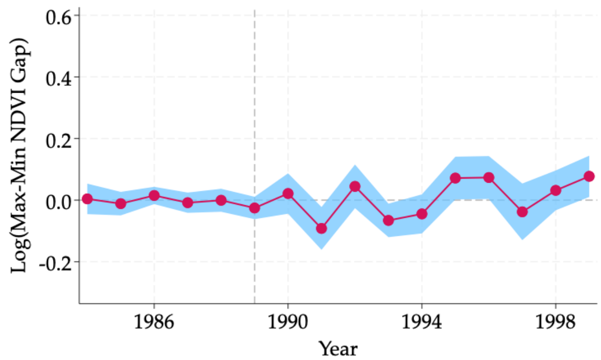


(c) Log of Mean NDVI Value

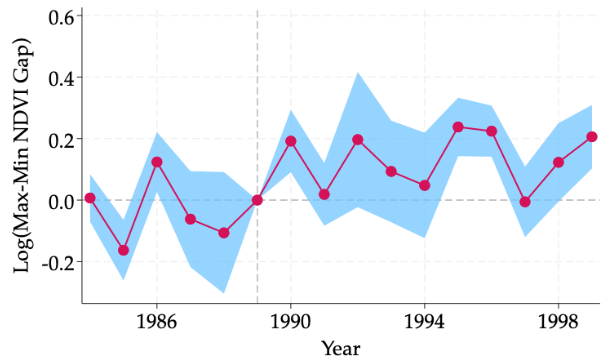
Notes: Graphs show estimates with 95% confidence intervals. Data are from GeoQuery. Top and bottom right panels use OLS and bottom left panel uses Poisson regression. All regressions include district, year, and region-by-year fixed effects with districts weighted by land area, as in Table 1 Panel A Column (2). Standard errors are clustered by district.

C2. Agricultural Productivity Results Using New Estimators

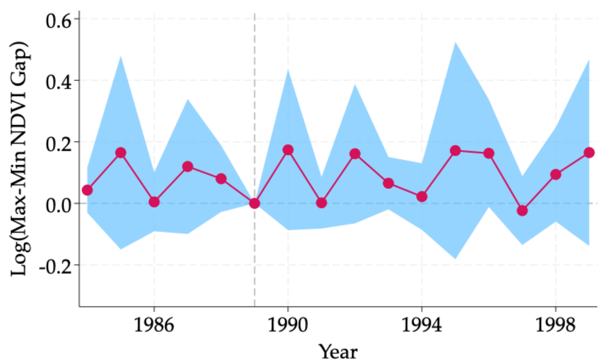
Figure C2: Agricultural Productivity Results Using New Estimators [10]



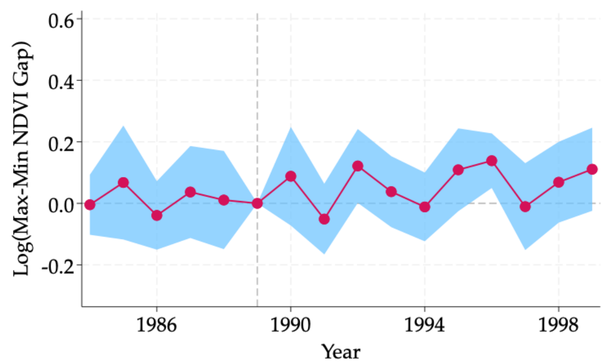
(a) Arkhangelsky et al. (2021)



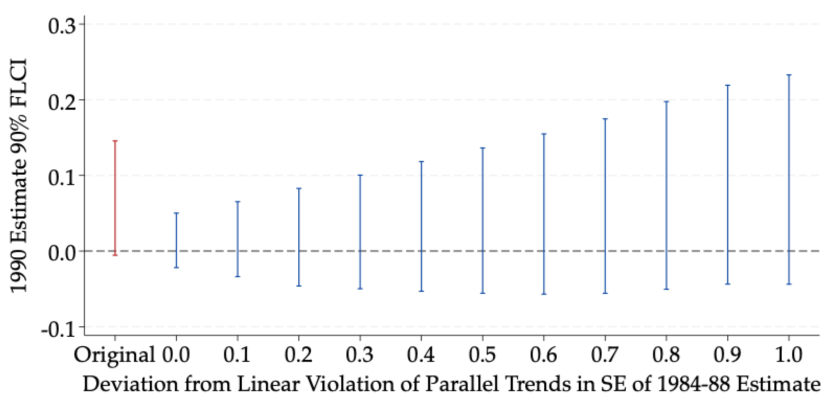
(b) Callaway and Sant'Anna (2021)



(c) de Chaisemartin and D'Haultfœuille (2020)



(d) Sun and Abraham (2021)

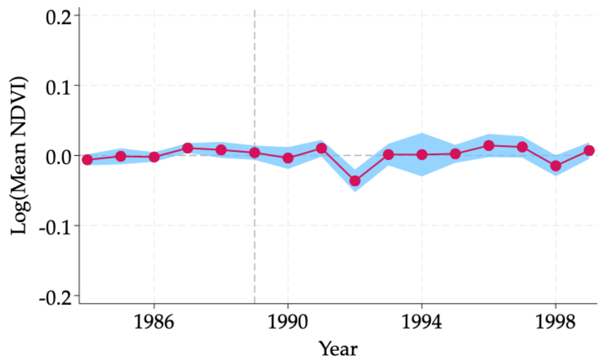


(e) Rambachan and Roth (2023)

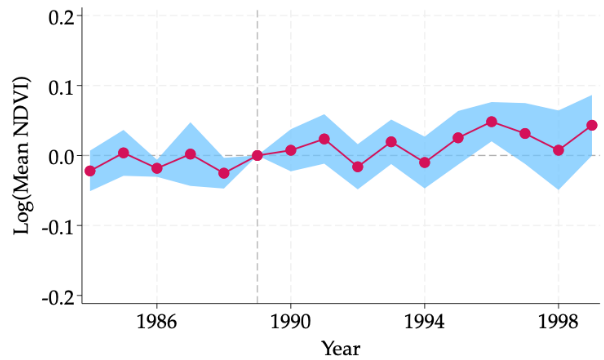
Notes: Top and middle panels show estimates with 95% confidence intervals and bottom panel shows 90% fixed length confidence intervals (FLCI). Data are from GeoQuery. Top and middle panels use OLS with the log-transformed outcome and bottom panel uses Poisson regression with the outcome in levels. All regressions include district, year, and region-by-year fixed effects with districts weighted by land area, as in Table 1 Panel A Column (2). Standard errors are clustered by district.

C3. Alternative Agricultural Productivity Results Using New Estimators

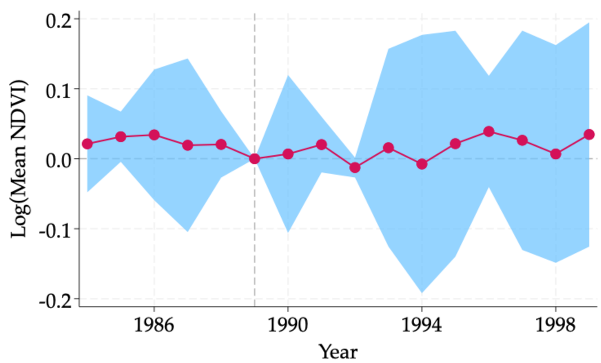
Figure C3: Alternative Agricultural Productivity Results Using New Estimators [10]



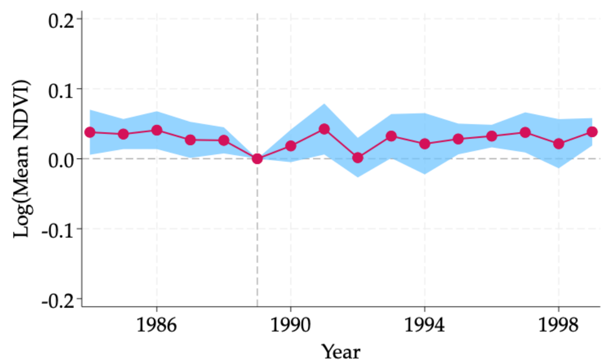
(a) Arkhangelsky et al. (2021)



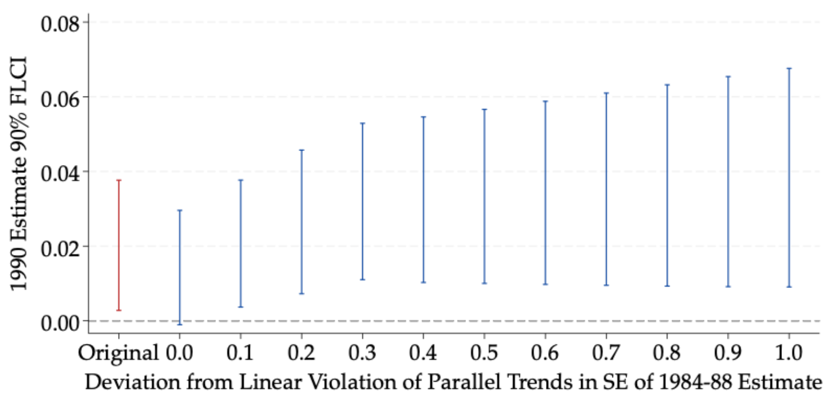
(b) Callaway and Sant'Anna (2021)



(c) de Chaisemartin and D'Haultfœuille (2020)



(d) Sun and Abraham (2021)

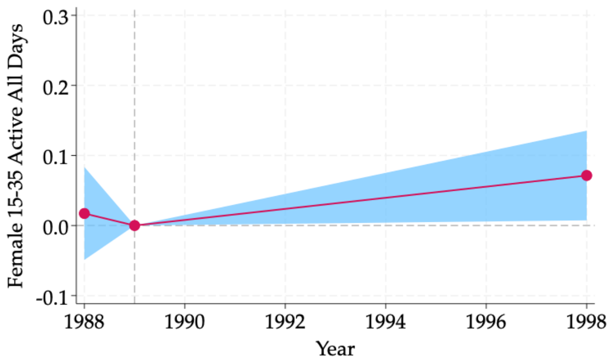


(e) Rambachan and Roth (2023)

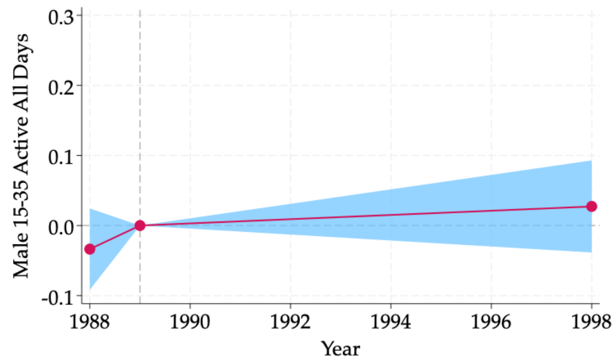
Notes: Top and middle panels show estimates with 95% confidence intervals and bottom panel shows 90% fixed length confidence intervals (FLCI). Data are from GeoQuery. Top and middle panels use OLS with the log-transformed outcome and bottom panel uses Poisson regression with the outcome in levels. All regressions include district, year, and region-by-year fixed effects with districts weighted by land area, as in Table 1 Panel A Column (2). Standard errors are clustered by district.

C4. Active All Days Results for Demographic Subgroups

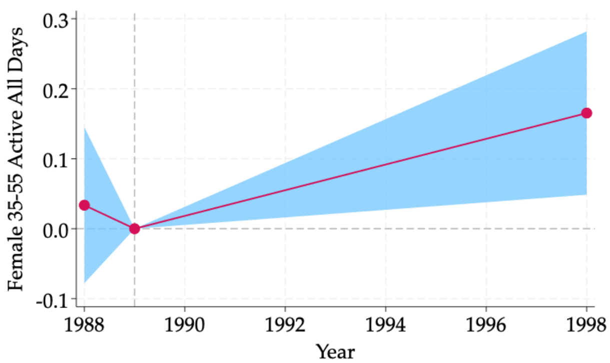
Figure C4: Active All Days Results for Demographic Subgroups [11]



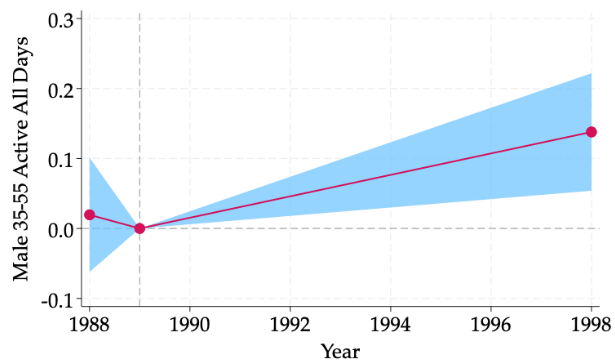
(a) Females 15-35



(b) Males 15-35



(c) Females 35-55

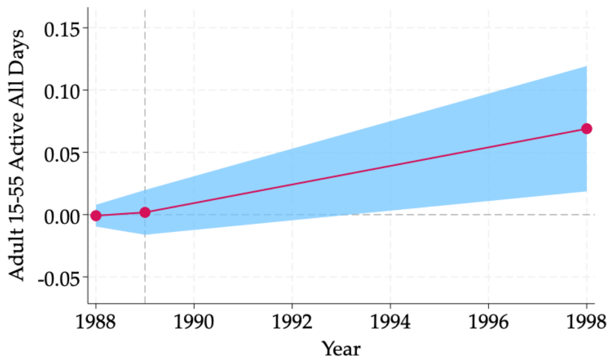


(d) Males 35-55

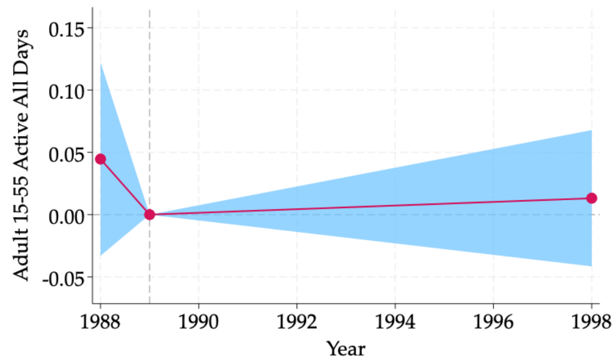
Notes: Panels show estimates with 95% confidence intervals. GLSS data (rounds 1, 2, and 4) are from the Ghana Statistical Service (GSS). Regressions include district, year, region-by-year, and age fixed effects, as in Table 1 Panel B Column (3). Standard errors are clustered by district.

C5. Active All Days Results Using New Estimators

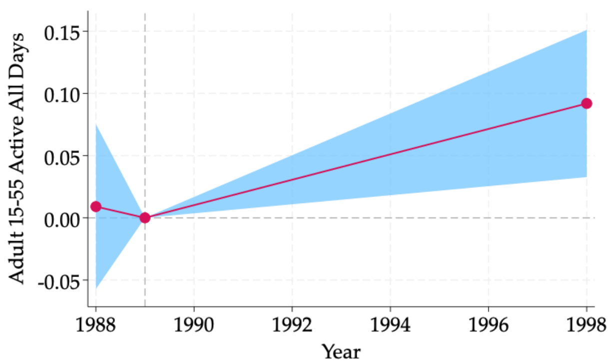
Figure C5: Active All Days Results Using New Estimators [11]



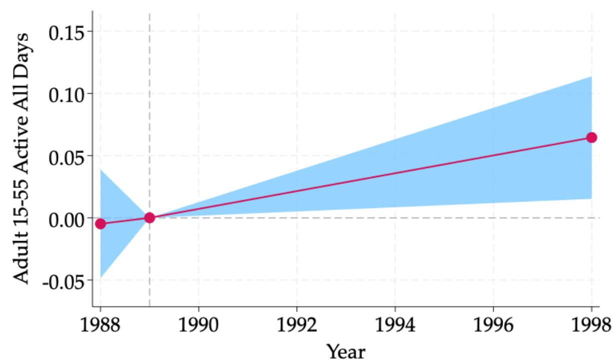
(a) Arkhangelsky et al. (2021)



(b) Callaway and Sant'Anna (2021)



(c) de Chaisemartin and D'Haultfœuille (2020)



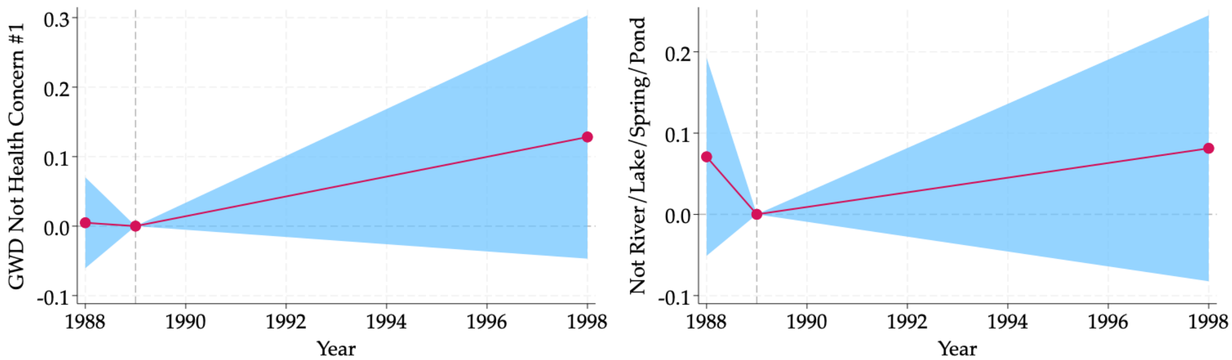
(d) Sun and Abraham (2021)

(e) Rambachan and Roth (2023)

Notes: Top and middle panels show estimates with 95% confidence intervals and bottom panel shows 90% fixed length confidence intervals (FLCI). GLSS data (rounds 1, 2, and 4) are from the GSS. Regressions include district, year, region-by-year, age, and sex fixed effects, as in Table 1 Panel B Column (3). Standard errors are clustered by district.

C6. Public Health Mechanism Results

Figure C6: Public Health Mechanism Results [11]



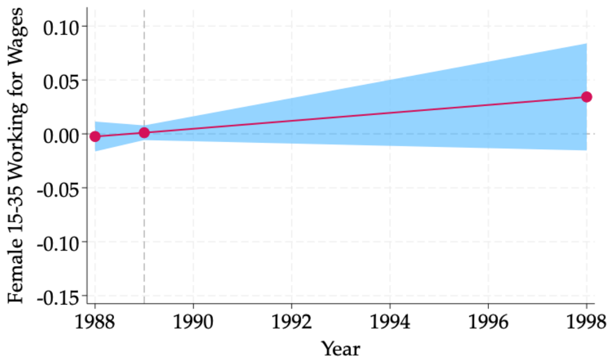
(a) Communities: Biggest Health Concern Not GWD

(b) Households: Water Source Not River, Lake, Spring, or Pond

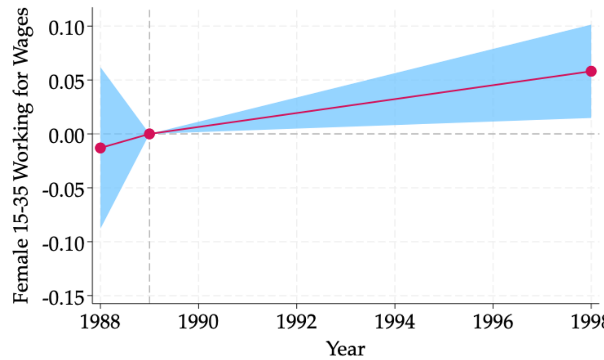
Notes: Panels show estimates with 95% confidence intervals. GLSS data (rounds 1, 2, and 4) are from the GSS. Regressions include district, year, and region-by-year fixed effects. Observations are weighted by the number of people in a community or household. Standard errors are clustered by district.

C7. Female 15-35 Working for Wages Results Using New Estimators

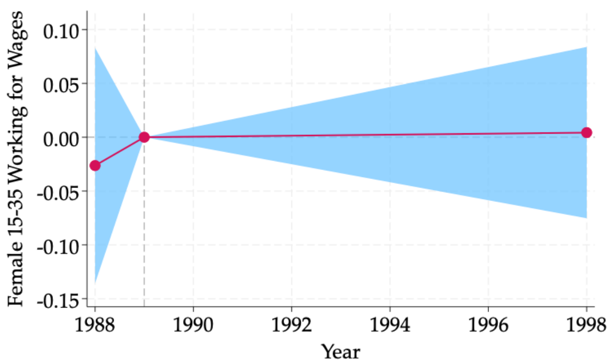
Figure C7: Female 15-35 Working for Wages Results Using New Estimators [11]



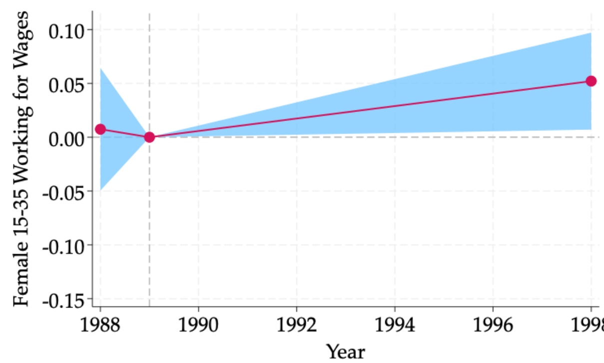
(a) Arkhangelsky et al. (2021)



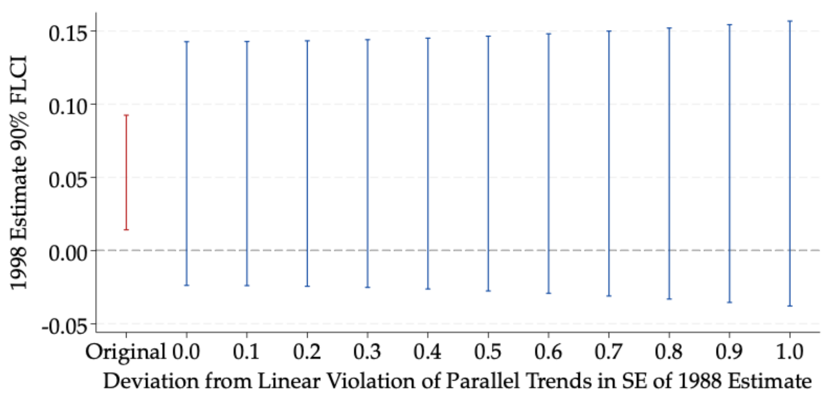
(b) Callaway and Sant'Anna (2021)



(c) de Chaisemartin and D'Haultfœuille (2020)



(d) Sun and Abraham (2021)

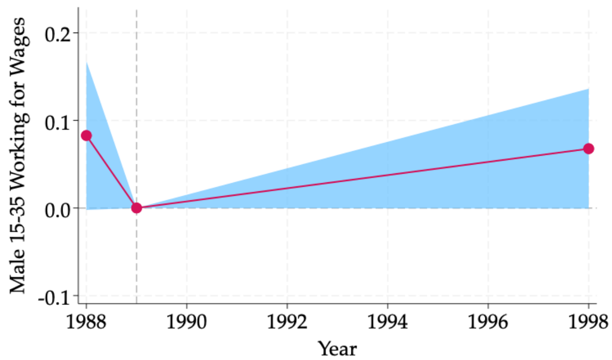


(e) Rambachan and Roth (2023)

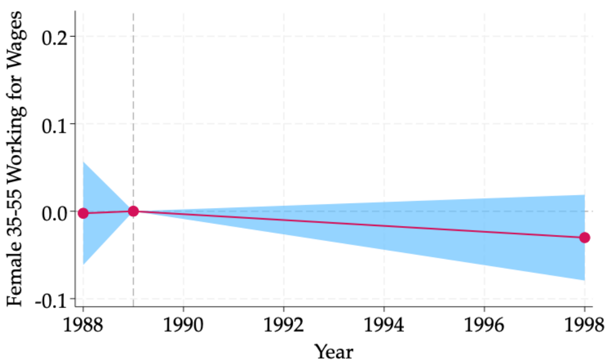
Notes: Top and middle panels show estimates with 95% confidence intervals and bottom panel shows 90% fixed length confidence intervals (FLCI). GLSS data (rounds 1, 2, and 4) are from the GSS. Regressions include district, year, region-by-year, and age fixed effects, as in Table 1 Panel C Column (3). Standard errors are clustered by district.

C8. Working for Wages Results for Demographic Subgroups

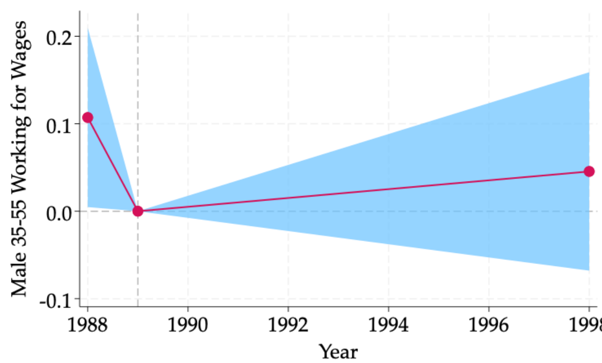
Figure C8: Working for Wages Results for Demographic Subgroups [11]



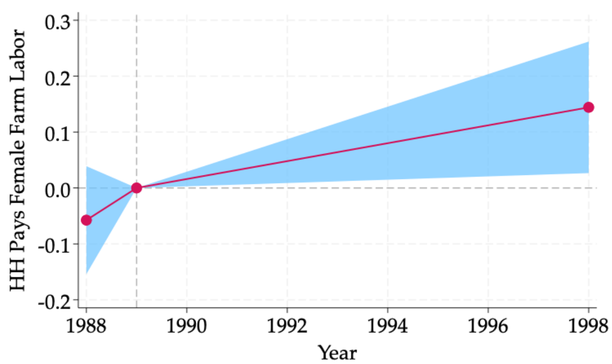
(a) Males 15-35



(b) Females 35-55



(c) Males 35-55

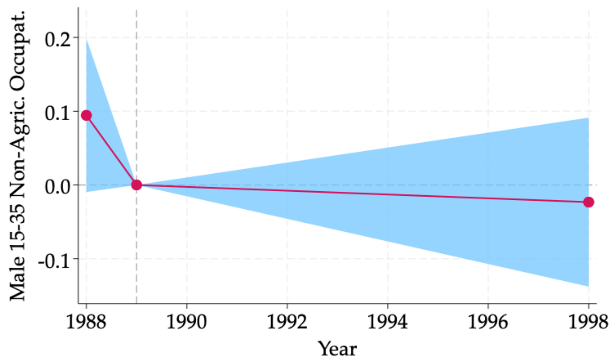


(d) Households Paid Female Farm Labor

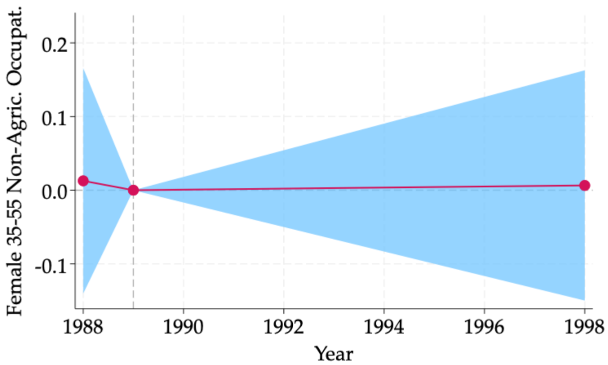
Notes: Panels show estimates with 95% confidence intervals. GLSS data (rounds 1, 2, and 4) are from the GSS. All regression include district, year, and region-by-year fixed effects, and regressions in top and middle panels include age fixed effects, as in Table 1 Panel C Column (3). Observations in bottom panel are households and are weighted by the number of members. Standard errors are clustered by district.

C9. Non-Agricultural Occupation Results for Demographic Subgroups

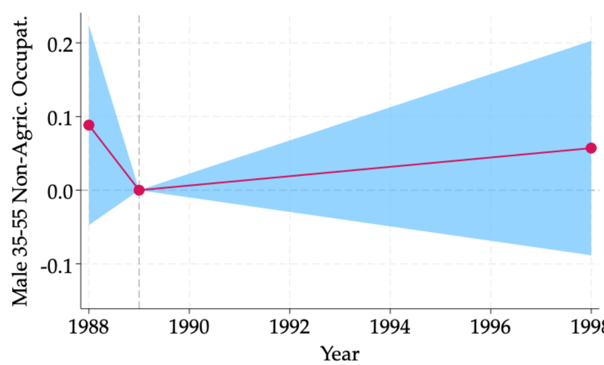
Figure C9: Non-Agricultural Occupation Results for Demographic Subgroups [11]



(a) Males 15-35



(b) Females 35-55

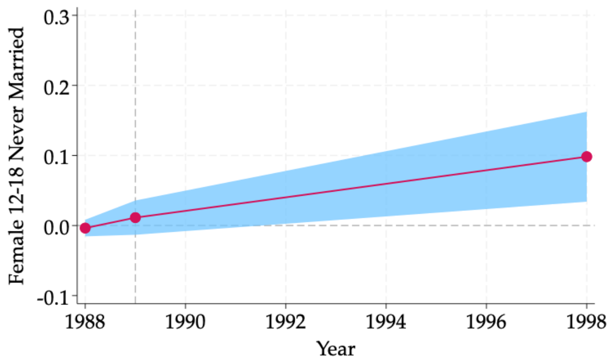


(c) Males 35-55

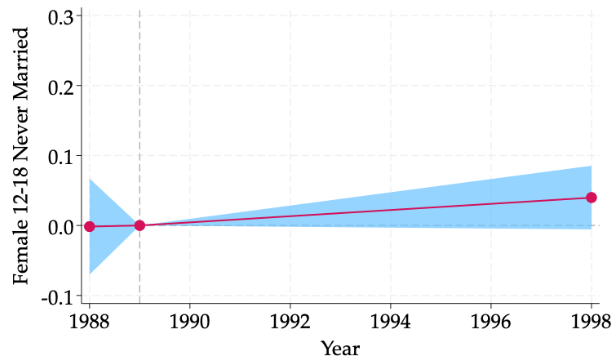
Notes: Panels show estimates with 95% confidence intervals. GLSS data (rounds 1, 2, and 4) are from the GSS. Regressions include district, year, region-by-year, and age fixed effects, as in Table 1 Panel D Column (3). Standard errors are clustered by district.

C10. Female 12-18 Never Married Results Using New Estimators

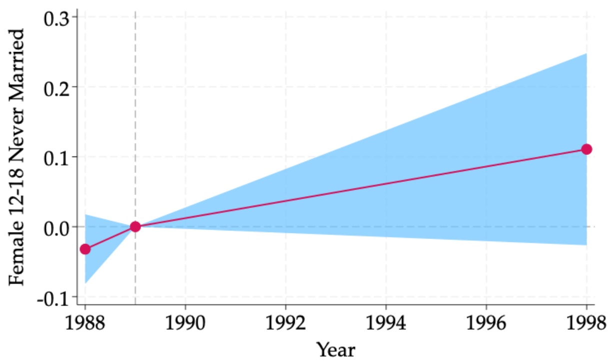
Figure C10: Female 12-18 Never Married Results Using New Estimators [12]



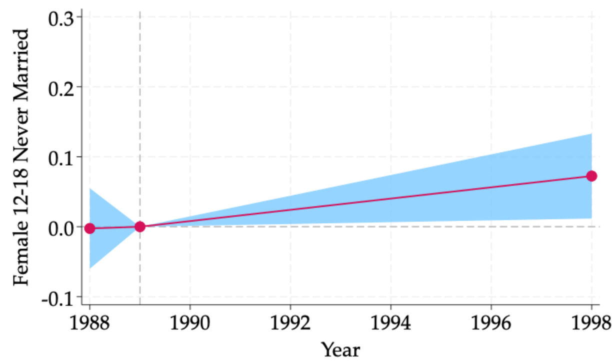
(a) Arkhangelsky et al. (2021)



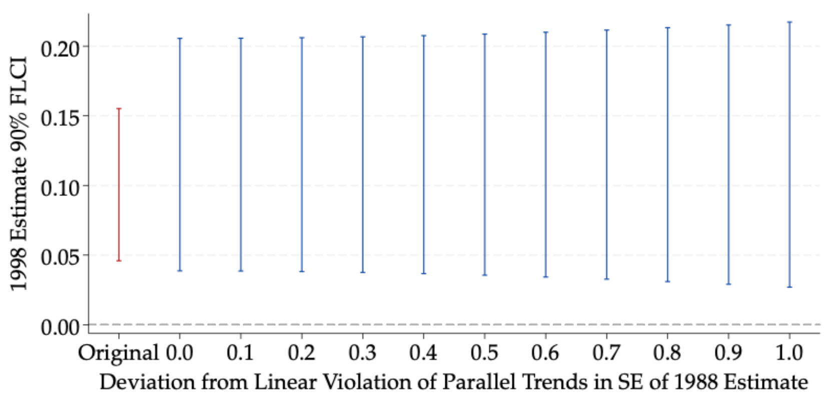
(b) Callaway and Sant'Anna (2021)



(c) de Chaisemartin and D'Haultfœuille (2020)



(d) Sun and Abraham (2021)

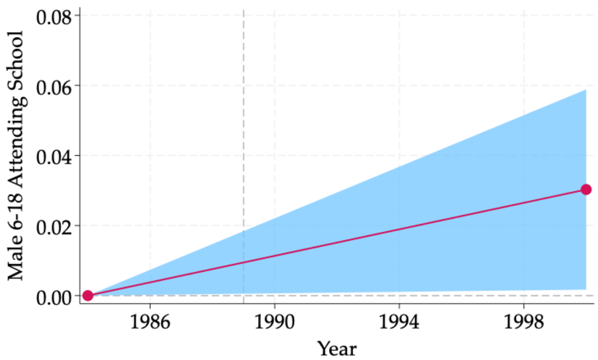


(e) Rambachan and Roth (2023)

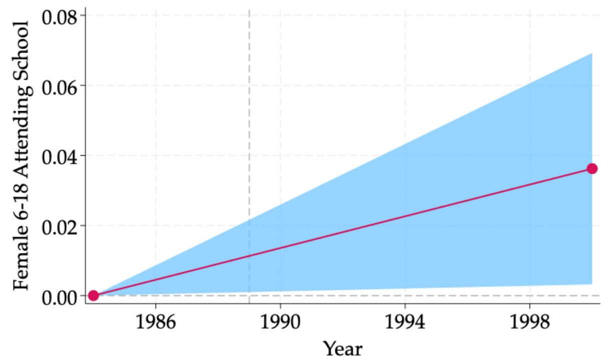
Notes: Top and middle panels show estimates with 95% confidence intervals and bottom panel shows 90% fixed length confidence intervals (FLCI). GLSS data (rounds 1, 2, and 4) are from the GSS. Regressions include district, year, region-by-year, and age fixed effects, as in Table 1 Panel E Column (3). Standard errors are clustered by district.

C11. Attending School Results Using GLSS Data and for Demographic Subgroups

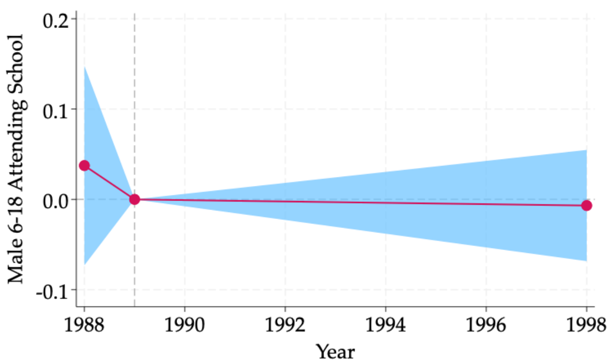
Figure C11: Attending School Results for Demographic Subgroups and Using GLSS Data [12]



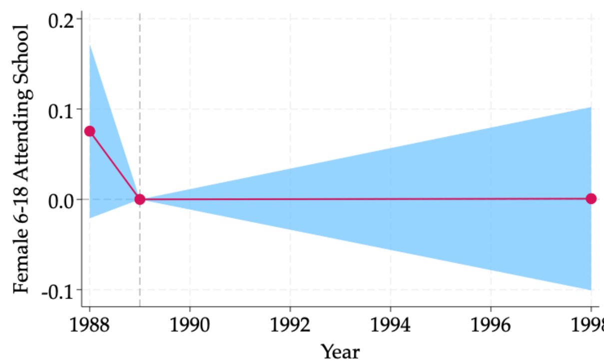
(a) Census: Males 6-18



(b) Census: Females 6-18



(c) GLSS: Males 6-18



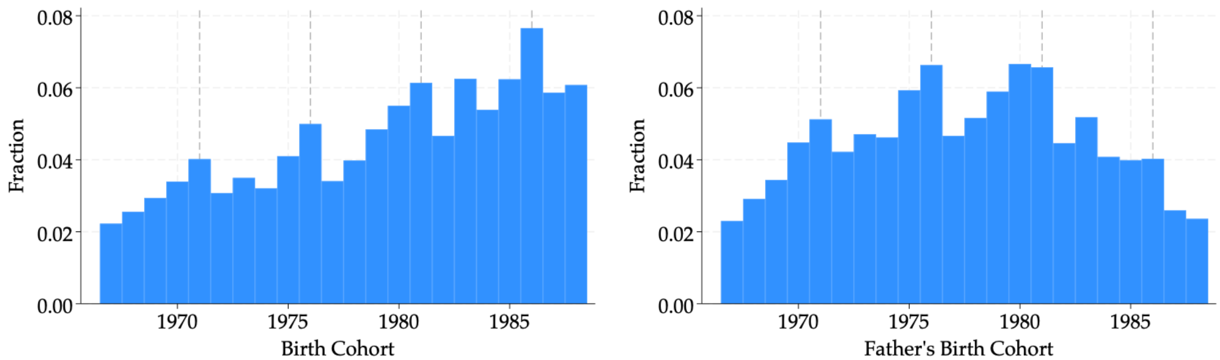
(d) GLSS: Females 6-18

Notes: Panels show estimates with 95% confidence intervals. GLSS data (rounds 1, 2, and 4) are from the GSS and census data (1984 and 2000) are the IPUMS 10% samples. Regressions include district, year, region-by-year, and age fixed effects, as in Table 1 Panel F Column (3). Standard errors are clustered by district.

D. Additional Figures: Effects on Individuals

D1. *Age Heaping in 2021 Census Data*

Figure D1: Age Heaping in 2021 Census Data [13]

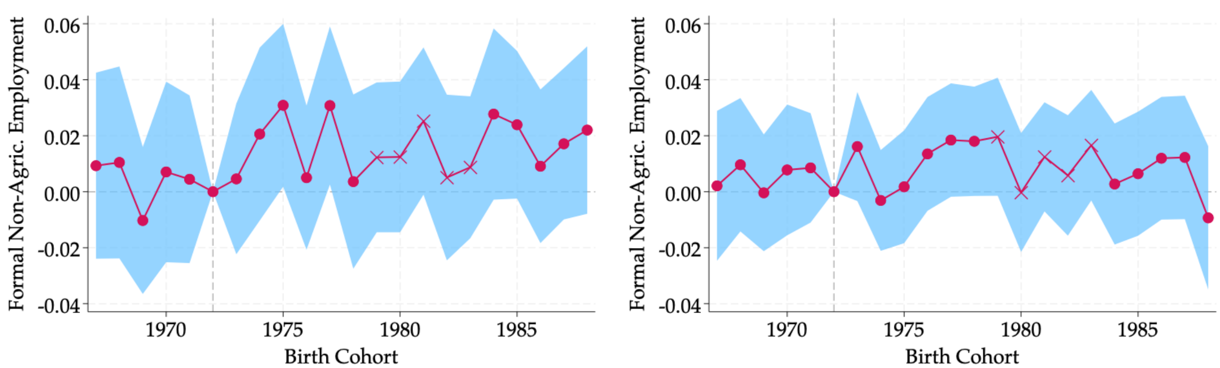


(a) Birth Cohorts 1967-88 **(b)** Fathers' Birth Cohorts 1967-88

Notes: Data are the 10% sample of the 2021 census from the GSS.

D2. *Formal Non-Agricultural Employment Results for Demographic Subgroups*

Figure D2: Formal Non-Agricultural Employment Results for Demographic Subgroups [14]

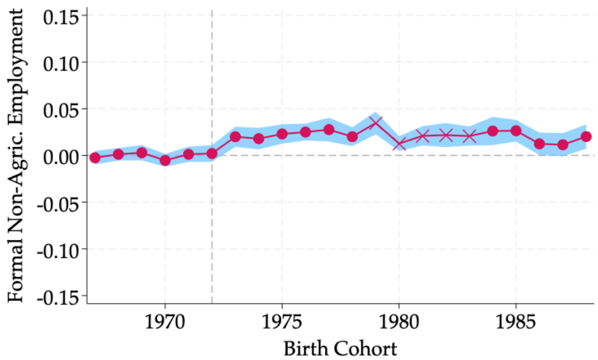


(a) Men **(b)** Women

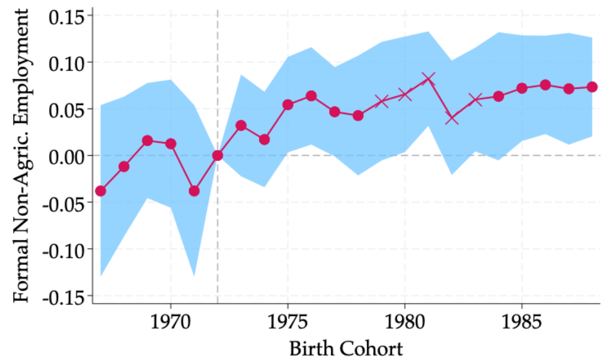
Notes: Panels show estimates with 95% confidence intervals for each sex. Data are the 10% sample of the 2021 census from the GSS. An estimate shown with an X indicates a birth cohort that was aged 0-4 during Ghana's 1983 famine. Regressions include birth district, birth year, birth region-by-year, and ethnic group fixed effects, as in Table 2 Panel A Column (3). Standard errors are clustered by birth district.

D3. *Formal Non-Agricultural Employment Results Using New Estimators*

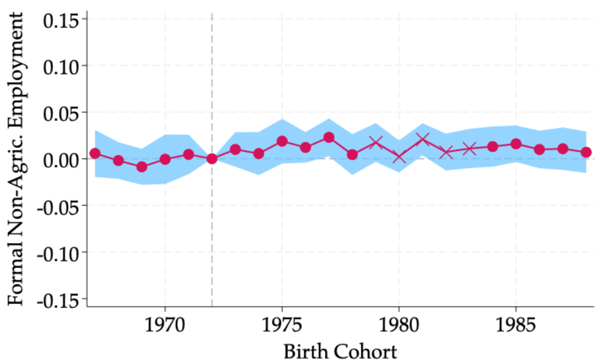
Figure D3: Formal Non-Agricultural Employment Results Using New Estimators [14]



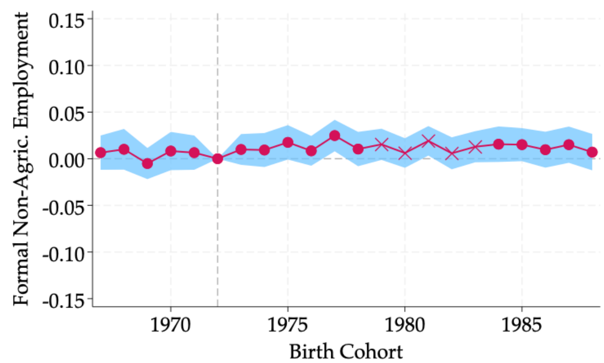
(a) Arkhangelsky et al. (2021)



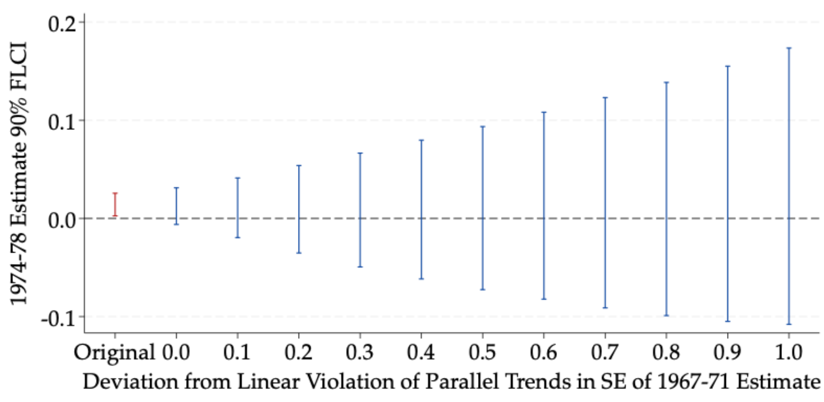
(b) Callaway and Sant'Anna (2021)



(c) de Chaisemartin and D'Haultfœuille (2020)



(d) Sun and Abraham (2021)

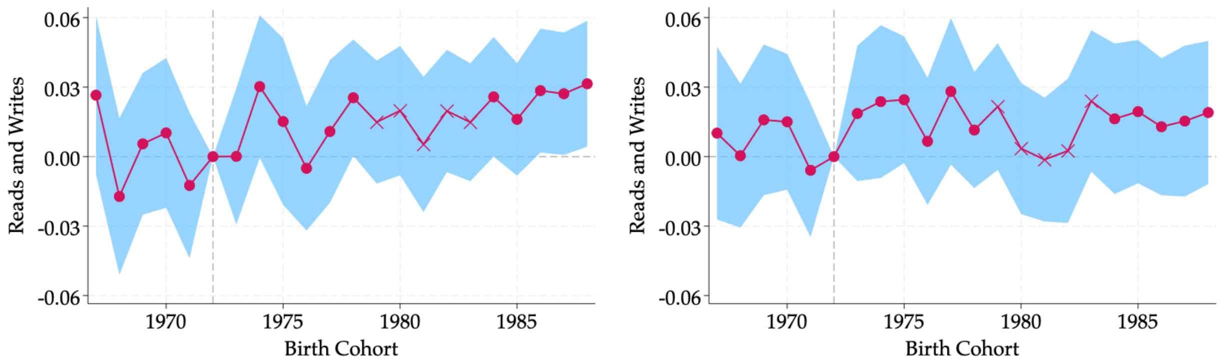


(e) Rambachan and Roth (2023)

Notes: Top and middle panels show estimates with 95% confidence intervals and bottom panel shows 90% fixed length confidence intervals (FLCI). Data are the 10% sample of the 2021 census from the GSS. An estimate shown with an X indicates a birth cohort that was aged 0-4 during Ghana's 1983 famine. Regressions include birth district, birth year, birth region-by-year, sex, and ethnic group fixed effects, as in Table 2 Panel A Column (3). Standard errors are clustered by birth district.

D4. Literacy Results for Demographic Subgroups

Figure D4: Literacy Results for Demographic Subgroups [14]

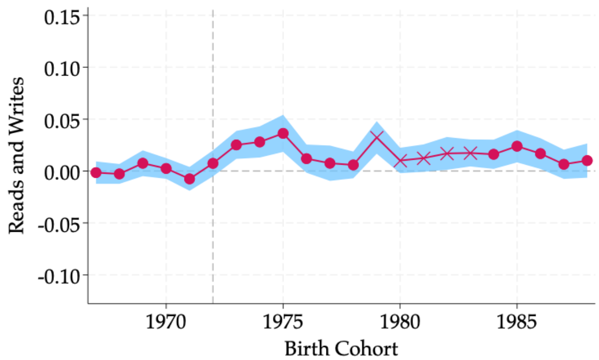


(a) Men **(b)** Women

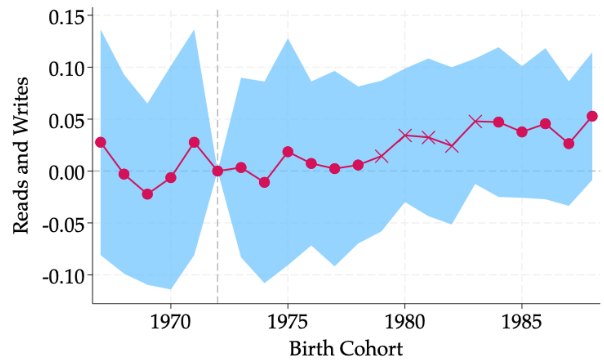
Notes: Panels show estimates with 95% confidence intervals for each sex. Data are the 10% sample of the 2021 census from the GSS. An estimate shown with an X indicates a birth cohort that was aged 0-4 during Ghana's 1983 famine. Regressions include birth district, birth year, birth region-by-year, and ethnic group fixed effects, as in Table 2 Panel B Column (3). Standard errors are clustered by birth district.

D5. Literacy Results Using New Estimators

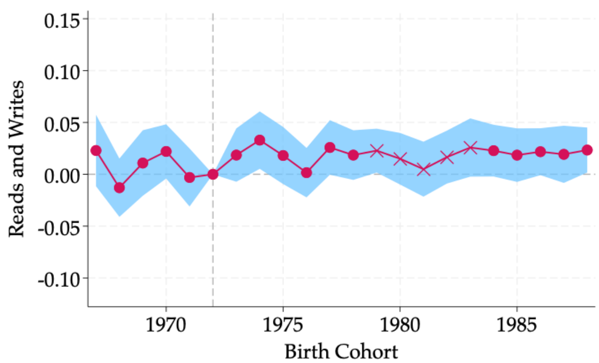
Figure D5: Literacy Results Using New Estimators [14]



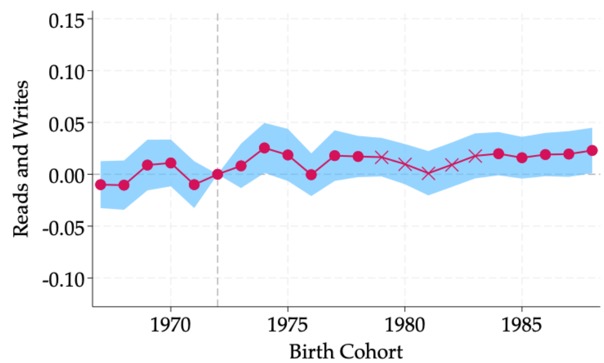
(a) Arkhangelsky et al. (2021)



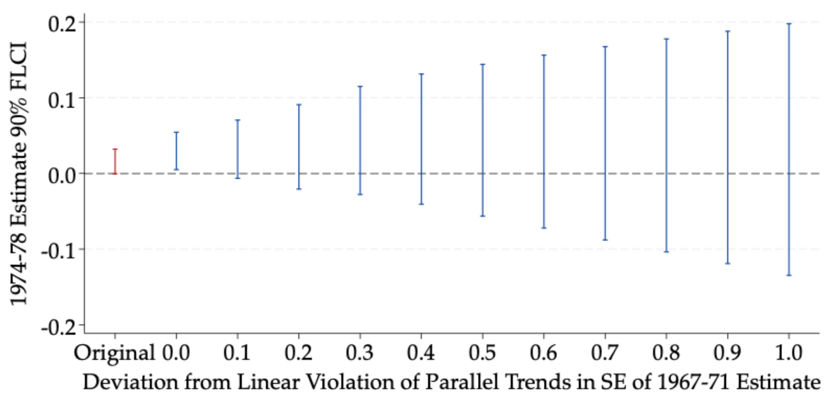
(b) Callaway and Sant'Anna (2021)



(c) de Chaisemartin and D'Haultfœuille (2020)



(d) Sun and Abraham (2021)

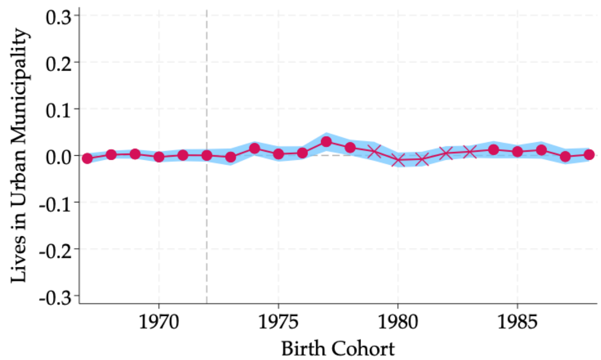


(e) Rambachan and Roth (2023)

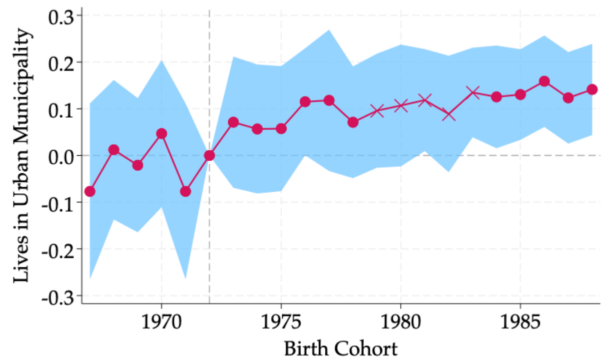
Notes: Top and middle panels show estimates with 95% confidence intervals and bottom panel shows 90% fixed length confidence intervals (FLCI). Data are the 10% sample of the 2021 census from the GSS. An estimate shown with an X indicates a birth cohort that was aged 0-4 during Ghana's 1983 famine. Regressions include birth district, birth year, birth region-by-year, sex, and ethnic group fixed effects, as in Table 2 Panel B Column (3). Standard errors are clustered by birth district.

D6. *Urban Residence Results Using New Estimators*

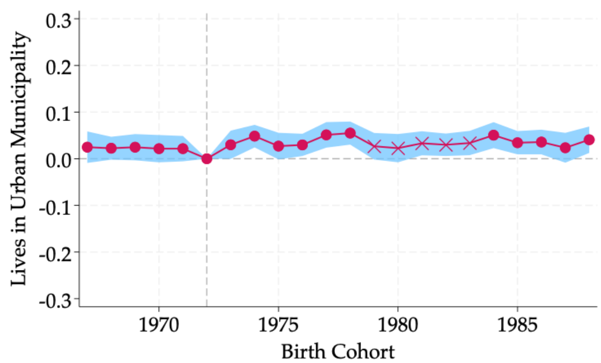
Figure D6: Urban Residence Results Using New Estimators [14]



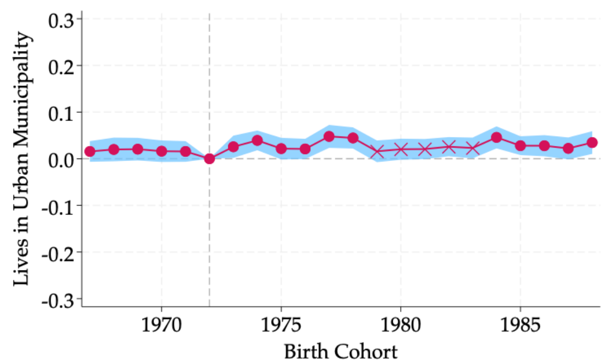
(a) Arkhangelsky et al. (2021)



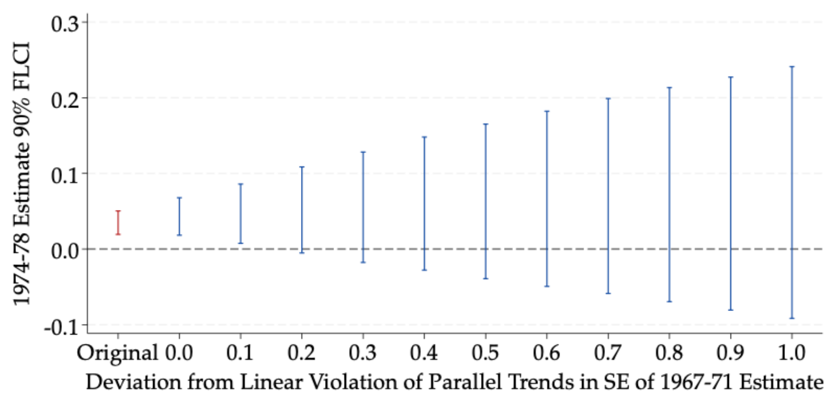
(b) Callaway and Sant'Anna (2021)



(c) de Chaisemartin and D'Haultfœuille (2020)



(d) Sun and Abraham (2021)

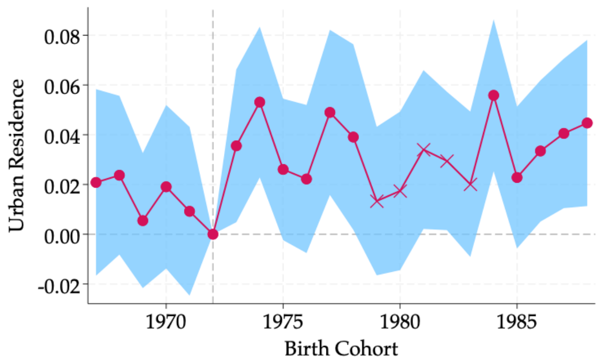


(e) Rambachan and Roth (2023)

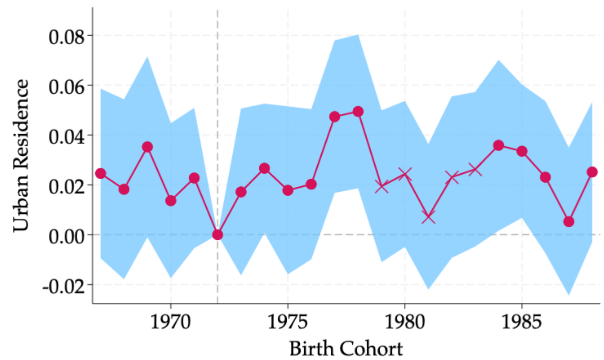
Notes: Top and middle panels show estimates with 95% confidence intervals and bottom panel shows 90% fixed length confidence intervals (FLCI). Data are the 10% sample of the 2021 census from the GSS. An estimate shown with an X indicates a birth cohort that was aged 0-4 during Ghana's 1983 famine. Regressions include birth district, birth year, birth region-by-year, sex, and ethnic group fixed effects, as in Table 2 Panel C Column (3). Standard errors are clustered by birth district.

D7. Urban Residence and Migration Results for Demographic Subgroups

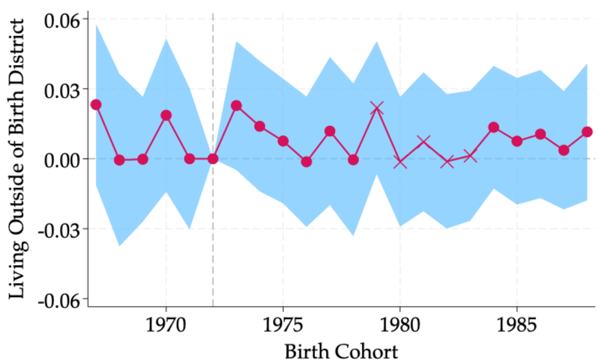
Figure D7: Urban Residence and Migration Results for Demographic Subgroups [14]



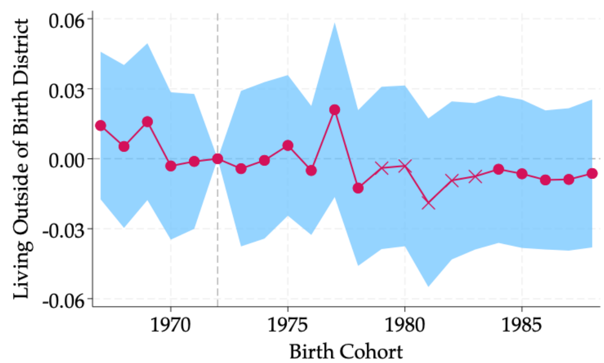
(a) Men: Urban Residence



(b) Women: Urban Residence



(c) Men: Living Outside of Birth District

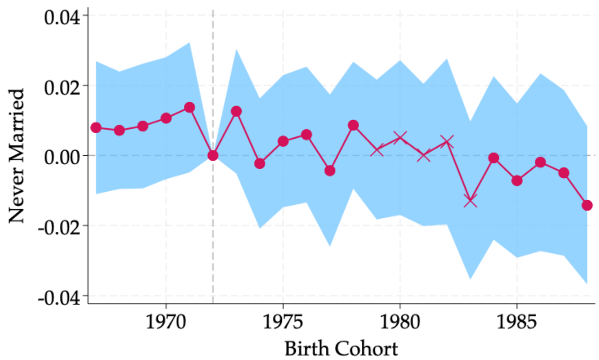


(d) Women: Living Outside of Birth District

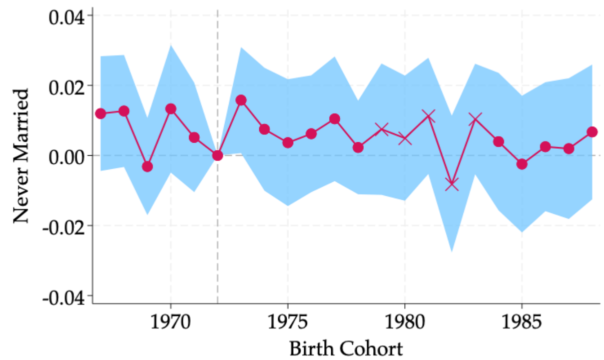
Notes: Panels show estimates with 95% confidence intervals for each sex. Data are the 10% sample of the 2021 census from the GSS. An estimate shown with an X indicates a birth cohort that was aged 0-4 during Ghana's 1983 famine. Regressions include birth district, birth year, birth region-by-year, and ethnic group fixed effects, as in Table 2 Panel C Column (3). Standard errors are clustered by birth district.

D8. *Marriage Results for Demographic Subgroups and Additional Fertility Results*

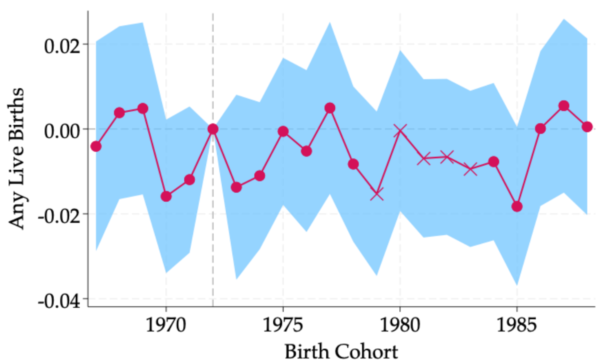
Figure D8: Marriage Results for Demographic Subgroups and Additional Fertility Results [15]



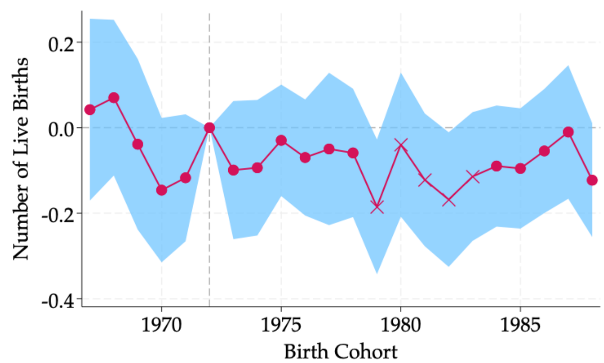
(a) Men: Never Married



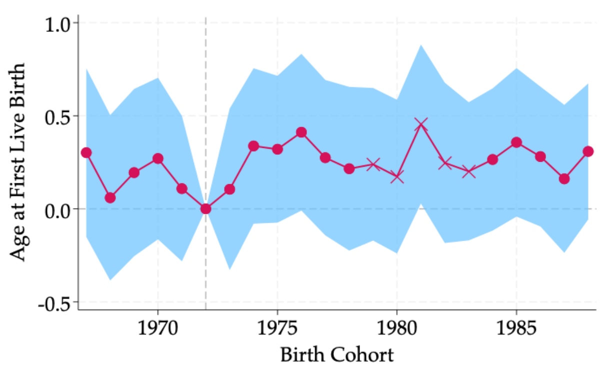
(b) Women: Never Married



(c) Any Live Births



(d) Number of Live Births

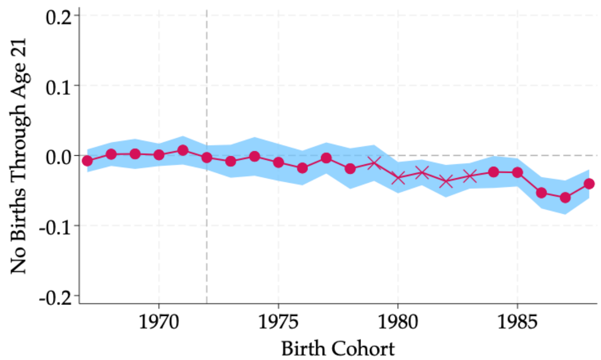


(e) Age at First Live Birth

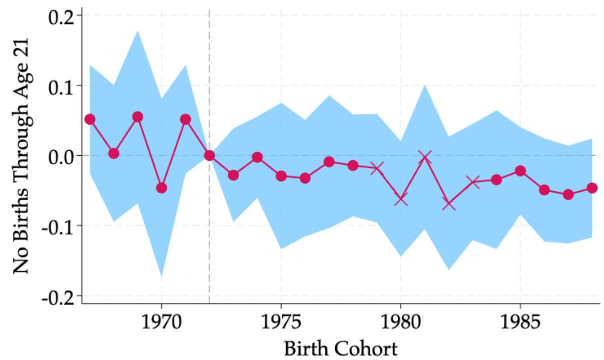
Notes: Panels show estimates with 95% confidence intervals. Data are the 10% sample of the 2021 census from the GSS. An estimate shown with an X indicates a birth cohort that was aged 0-4 during Ghana's 1983 famine. Regressions include birth district, birth year, birth region-by-year, and ethnic group fixed effects, as in Table 2 Panel D Column (3). Standard errors are clustered by birth district.

D9. No Births Through Age 21 Results Using New Estimators

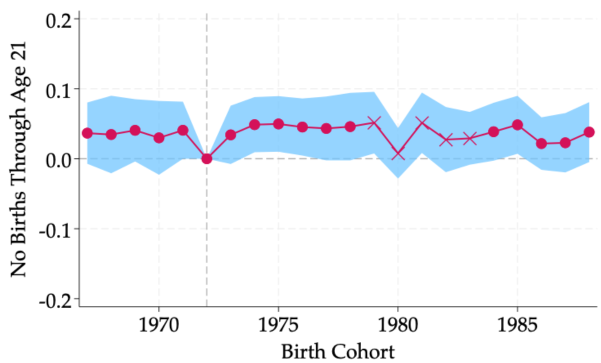
Figure D9: No Births Through Age 21 Results Using New Estimators [15]



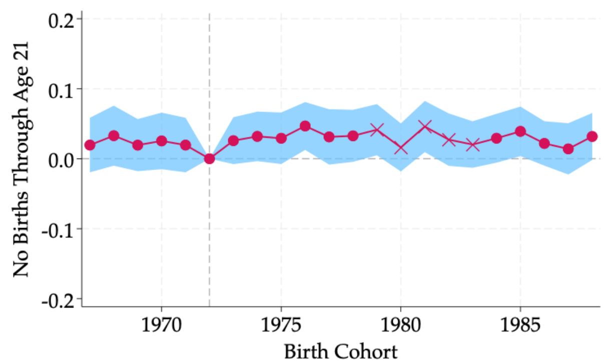
(a) Arkhangelsky et al. (2021)



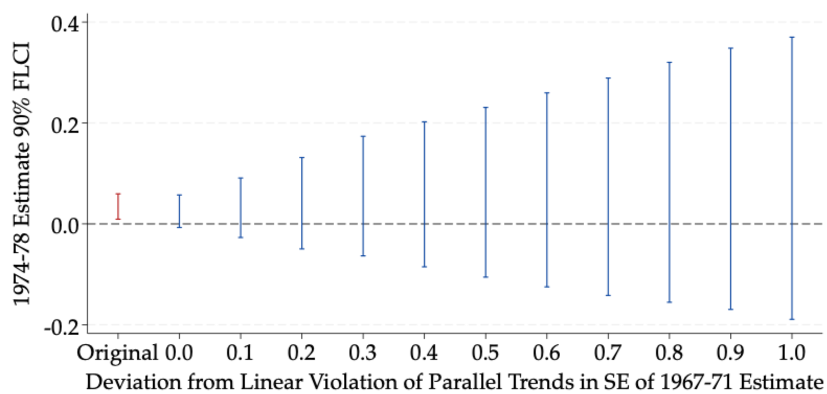
(b) Callaway and Sant'Anna (2021)



(c) de Chaisemartin and D'Haultfœuille (2020)



(d) Sun and Abraham (2021)

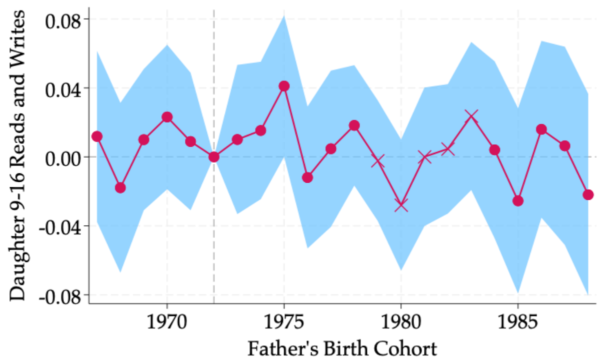


(e) Rambachan and Roth (2023)

Notes: Top and middle panels show estimates with 95% confidence intervals and bottom panel shows 90% fixed length confidence intervals (FLCI). Data are the 10% sample of the 2021 census from the GSS. An estimate shown with an X indicates a birth cohort that was aged 0-4 during Ghana's 1983 famine. Regressions include birth district, birth year, birth region-by-year, and ethnic group fixed effects, as in Table 2 Panel D Column (3). Standard errors are clustered by birth district.

D10. Daughter 9-16 Literacy Result

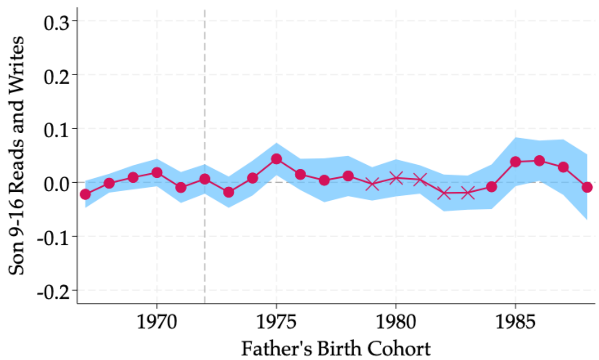
Figure D10: Daughter 9-16 Literacy Result [15]



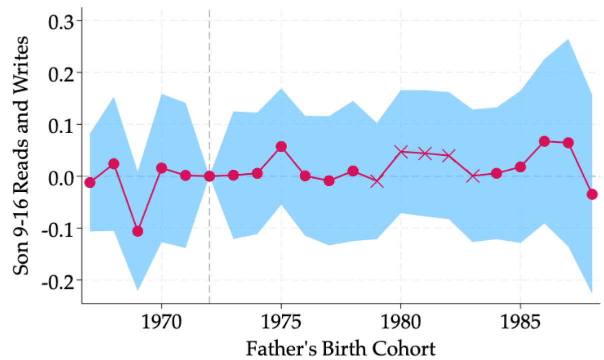
Notes: Panel shows estimates with 95% confidence intervals. Data are the 10% sample of the 2021 census from the GSS. An estimate shown with an X indicates a father's birth cohort that was aged 0-4 during Ghana's 1983 famine. Regression includes father's birth district, father's birth year, father's birth region-by-year, own age, and own ethnic group fixed effects, as in Table 2 Panel E Column (3). Standard errors are clustered by father's birth district.

D11. Son 9-16 Literacy Results Using New Estimators

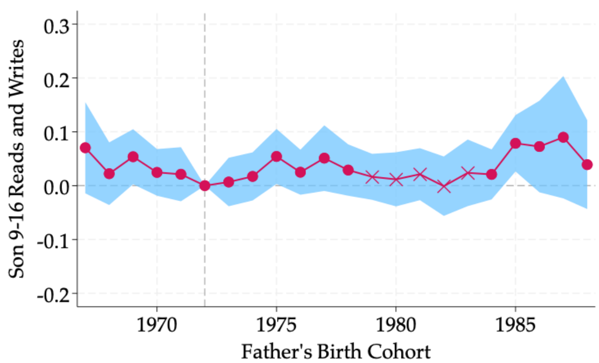
Figure D11: Son 9-16 Literacy Results Using New Estimators [15]



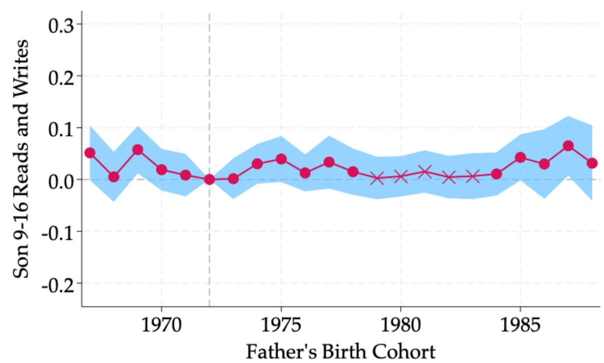
(a) Arkhangelsky et al. (2021)



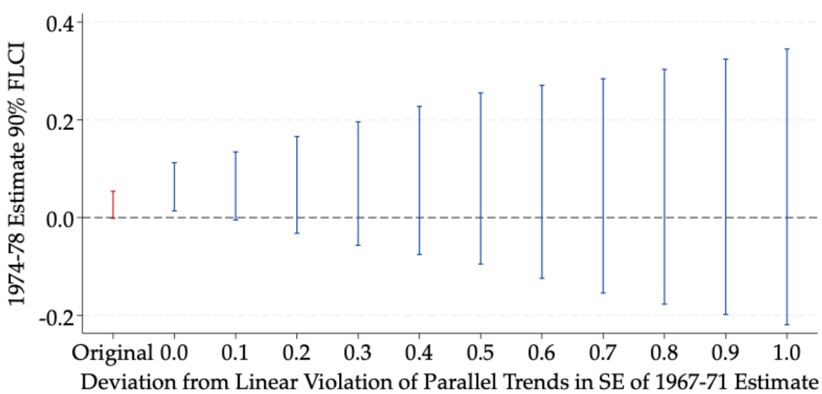
(b) Callaway and Sant'Anna (2021)



(c) de Chaisemartin and D'Haultfœuille (2020)



(d) Sun and Abraham (2021)

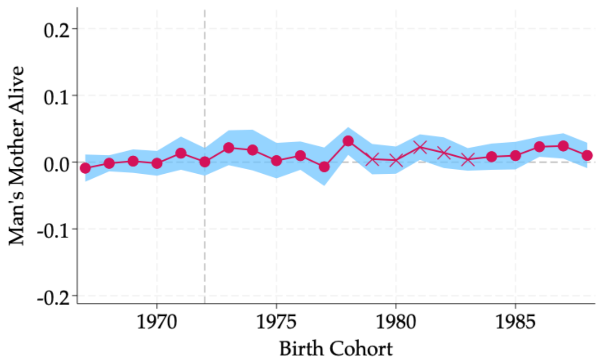


(e) Rambachan and Roth (2023)

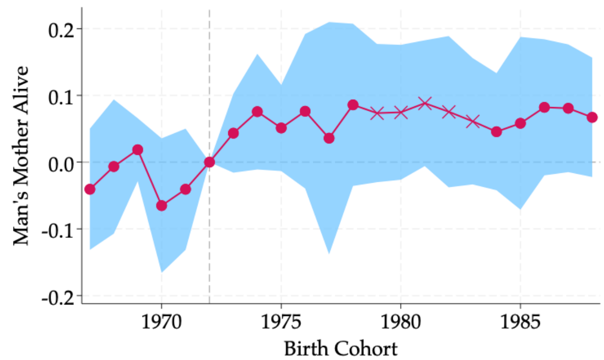
Notes: Top and middle panels show estimates with 95% confidence intervals and bottom panel shows 90% fixed length confidence intervals (FLCI). Data are the 10% sample of the 2021 census from the GSS. An estimate shown with an X indicates a father's birth cohort that was aged 0-4 during Ghana's 1983 famine. Regressions include father's birth district, father's birth year, father's birth region-by-year, own age, and own ethnic group fixed effects, as in Table 2 Panel E Column (3). Standard errors are clustered by father's birth district.

D12. Man's Mother Alive Results Using New Estimators

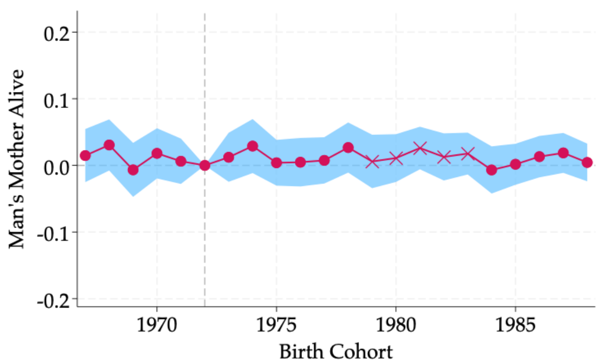
Figure D12: Man's Mother Alive Results Using New Estimators [15]



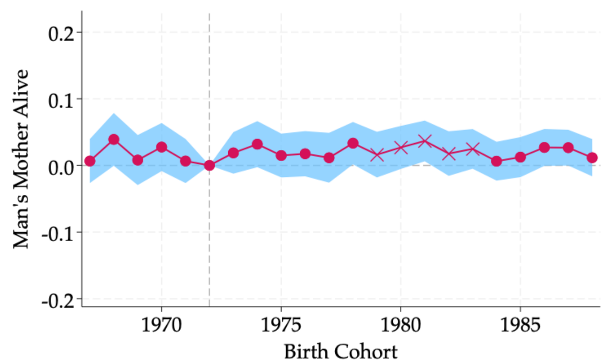
(a) Arkhangelsky et al. (2021)



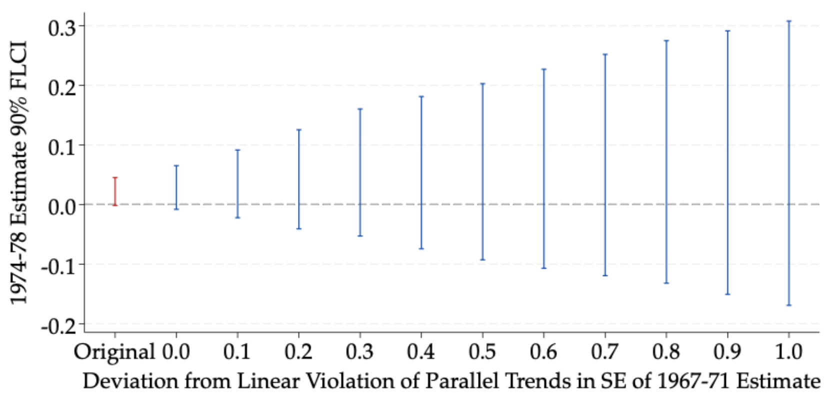
(b) Callaway and Sant'Anna (2021)



(c) de Chaisemartin and D'Haultfœuille (2020)



(d) Sun and Abraham (2021)

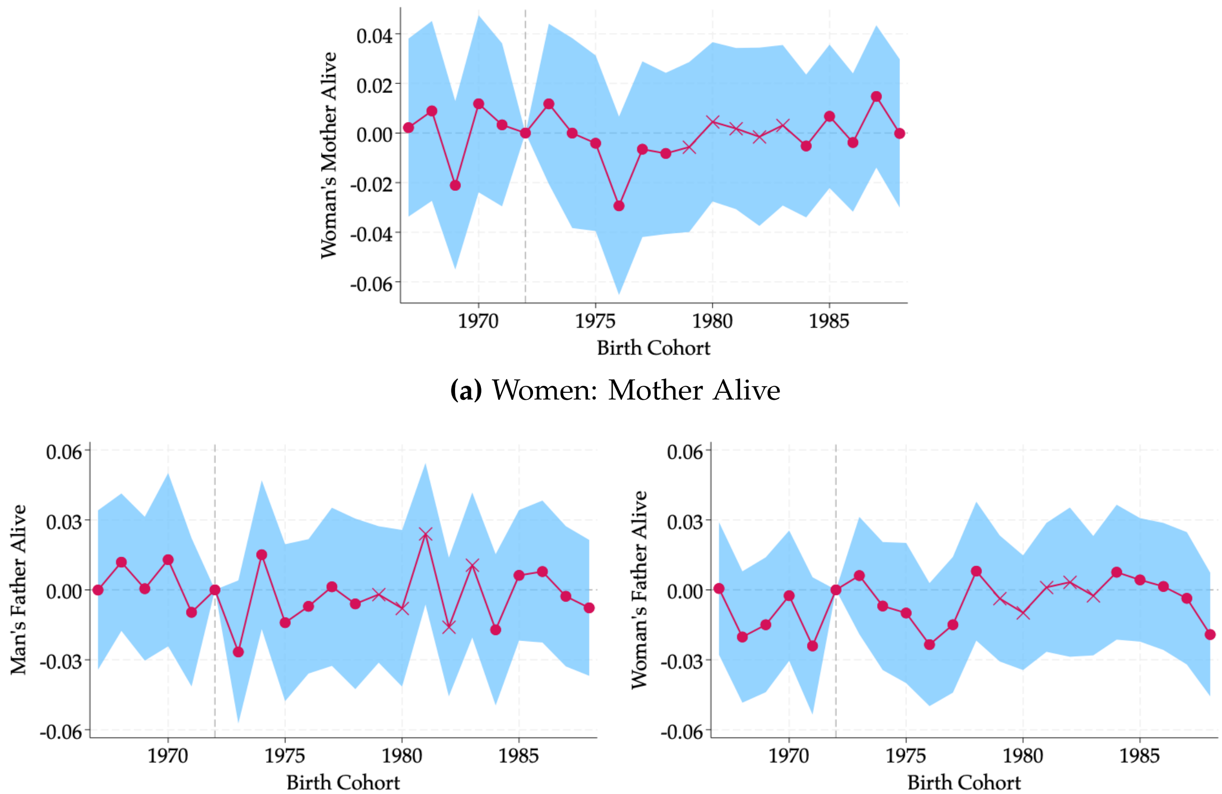


(e) Rambachan and Roth (2023)

Notes: Panels show estimates with 95% confidence intervals. Data are the 10% sample of the 2021 census from the GSS. An estimate shown with an X indicates a birth cohort that was aged 0-4 during Ghana's 1983 famine. Regression includes birth district, birth year, birth region-by-year, and ethnic group fixed effects, as in Table 2 Panel F Column (3). Standard errors are clustered by father's birth district.

D13. Additional Parent Alive Results

Figure D13: Additional Parent Alive Results [15]



(a) Women: Mother Alive

(b) Men: Father Alive

(c) Women: Father Alive

Notes: Top and middle panels show estimates with 95% confidence intervals and bottom panel shows 90% fixed length confidence intervals (FLCI). Data are the 10% sample of the 2021 census from the GSS. An estimate shown with an X indicates a birth cohort that was aged 0-4 during Ghana's 1983 famine. Regressions include birth district, birth year, birth region-by-year, and ethnic group fixed effects, as in Table 2 Panel F Column (3). Standard errors are clustered by birth district.