Demographic Transition and Structural Transformation*

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Abstract

We explore the effect of demographic transition on structural transformation. When fertility declines, a larger share of the population may remain in farming due to agriculture's reliance on a fixed factor of production, land. We test this hypothesis at the household, state, and country levels. A quasi-experimental family planning program provided to Bangladeshi households, and abortion policy changes around the world in the last 60 years and across U.S. states in the 19th century, generate plausibly exogenous variation in fertility. In each of these three empirical analyses, lower fertility raises the agricultural employment share. Improving human capital can therefore offset the effect of fertility declines on the agricultural employment share.

Keywords: Economic growth, fertility, human capital, industrialization.

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1 Introduction

Economic growth is characterized by two fundamental processes: the demographic transition, in which fertility and mortality fall, and structural transformation, in which workers leave agriculture for manufacturing and service jobs. A large literature examines how growth and structural transformation drive demographic transition (Galor and Weil 1996, 2000; Chatterjee and Vogl 2018; Ager et al. 2020). Little is known, however, about how demographic transition drives structural transformation. Given farmers' reliance on a fixed factor of production, land, a decline in population may result in more workers staying in agriculture as land congestion eases (Malthus 1798; Lewis 1954).

Unified models of the growth process typically hold, however, that endogenous technological change will swamp the Malthusian force of diminished land congestion keeping workers in agriculture as fertility falls (Boserup 1965; Galor and Weil 2000). But if the pace of technological advancement is slowing (Bloom et al. 2020) or frictions restrict some countries' access to the technological frontier (Gancia and Zilibotti 2009; Buera and Oberfield 2020), Malthusian forces may once again become salient. With fertility declining in virtually every country on earth today (Delventhal et al. 2021) and world population expected to peak within the next 60 years (United Nations 2024), understanding the impact of fertility decline on structural transformation is crucial.

Lower fertility may affect human capital, and therefore structural transformation, via the quality-quantity tradeoff (Barro and Becker 1989). If nonagriculture more intensively uses human capital, then an increase in human capital may raise nonagricultural employment. The net effect of a fertility reduction on structural transformation—depending on both the Malthusian force of land in agriculture and the quality-quantity tradeoff—is therefore ambiguous. We formalize this logic in a stylized two-sector, overlapping generations model in Section 2.

Testing models relating fertility and structural transformation is challenging for three reasons. First, fertility changes endogenously with a region's economic growth and structural transformation. Second, there will be a substantial lag between changes in fertility and resulting impacts, as cohorts must grow up before entering the labor market. This requires consistent data for a lengthy period of time. Third, understanding the mechanisms by which fertility affects structural transformation is difficult when using regionally aggregated data.

We test whether fertility drives subsequent structural transformation in three distinct, complementary empirical contexts. In each approach, we find that falling fertility slows down structural transformation. Hence, the population size effect dominates the quantity-quality induced human capital improvements. Our results imply that governments seeking to transform their economy away from agriculture and to reduce fertility should pair family planning programs with investments in human capital.

We begin our empirical analysis in Section 3 by estimating the long-run impact of a quasi-random intervention in Bangladesh that distributed modern contraception and childhood vaccines nearly 50 years ago. The intervention accelerated the demographic transition by first inducing a fall in birth rates inside the treatment area during the program period (Joshi and Schultz 2007). Several years into the program vaccines were rolled out, reducing early-childhood death rates and raising the cognitive abilities and education of treated cohorts (Barham 2012; Barham et al. 2021b). Treatment was assigned by village, with treatment and comparison villages well-balanced across a wide range of pre-intervention characteristics. We leverage highly detailed microdata collected across four decades in rural Bangladesh to understand the long-run effect on structural transformation and the corresponding mechanisms of population size and the child quality-quantity tradeoff.

We find that the faster demographic transition induced by the program slowed down the movement of workers out of agriculture 35 years later. Treated households allocated a 19 percent higher share of work hours to agriculture and 12 percent less to manufacturing.

We consider two key mechanisms: population size and human capital. We find that household size is a crucial mechanism through which the program affects structural transformation. We use the program's quasi-experimental variation to quantify the effect of adding a household male to an average household. Doing so more than doubles the fraction of work time spent in agriculture, while the share of work time spent in the manufacturing sector falls substantially. In levels, a marginal male substantially raises total hours worked in manufacturing and services while leaving agricultural largely unchanged.

Second, households on average sent higher human capital sons to work outside of agriculture. We obtain quasi-exogenous variation in human capital by comparing those born during the intensive child health phase of the intervention to those born before it. Vaccines raised affected cohorts' human capital. Treatment area men born during the intensive child health phase of the program worked more in the service sector where human capital returns are higher.

The preceding analysis only identifies a partial equilibrium response. To understand whether the same effect of fertility changes that we see in the quasi-experiment persists in the face of general equilibrium forces, such as endogenous changes in prices, wages, and technology, we conduct two exercises using aggregate data in Section 4.

We first leverage cross-country variation since 1960 to estimate an event study relating changes in abortion policies to the agricultural employment share. A nearly one standard deviation increase in abortion accessibility, which reduces fertility rates, increases agricultural employment share by about 5 percentage points three decades later, consistent with our quasi-experimental results. This result implies that the population size mechanism outweighs the strength of the child quality-quantity tradeoff channel.

The cross-country analysis has the advantage of estimating the key relationship of interest: how fertility changes affect an economy's agricultural employment share in the face of general equilibrium effects, such as changes in wages and prices. Cross-country regressions, however, have well-known difficulties, including harmonizing data across countries (Durlauf et al. 2005). We therefore turn to a within-country analysis.

We estimate the long-run effect of abortion restrictions passed by U.S. states in the 19th century. Event study estimates reveal that abortion restrictions accelerate structural transformation in subsequent decades. On average, 19th century abortion restrictions, which increased fertility rates, decreased the agricultural employment share by about 5 percentage points three decades later, consistent with our cross-country results.

How much human capital investment is required to escape the "Malthusian trap" highlighted by our empirical analysis, and how does this investment vary across the development spectrum? In Section 5, we provide a first step towards answering these questions, leveraging our model and the estimated elasticities to conduct back-of-the-envelope calculations. The model suggests that human capital would need to be three times higher in Matlab in order to completely offset Malthusian population size effects. Moreover, a low-income country like Bangladesh would need to raise human capital over 3.5 times as much as a high-income country to offset the effect of a given population decrease on agricultural employment share.

This paper contributes to a growing literature on the consequences of fertility decline for economic growth (Ashraf et al. 2013; Cavalcanti et al. 2021; Jones 2022; Hopenhayn et al. 2022).[1] Unified growth models emphasize that declining fertility raises per capita income growth by freeing up resources to invest more in human capital (the quality-quantity tradeoff) and raising the ratios of labor-to-capital and labor-to-land (Galor and Weil 2000; Galor 2005). Relative to previous work, we emphasize the role of the fixed factor of land in agriculture as a countervailing force against the growth-enhancing effects of fertility decline.[2] We provide direct evidence that the Malthusian force of land in agriculture outweighs the offsetting effect of the quality-quantity tradeoff in keeping workers in agriculture as fertility

[1] Li and Zhang (2007) estimate the effect of fertility decline on economic growth in the context of China's one child policy. Their identification strategy relies on regional changes in ethnic minorities, which itself is likely to be endogenous as workers migrate to faster growing regions.

[2] We implicitly assume that moving workers out of agriculture is growth-enhancing. This is consistent with extensive empirical evidence on productivity wedges between agriculture and non-agricultural sectors (see, for example, Gollin et al. (2014)). In our model in Section 2 we capture this misallocation with a reduced-form wage wedge, in which workers are paid above their marginal product in agriculture but not in non-agriculture.

falls.

We are the first to empirically establish a causal link leading from the demographic transition to structural transformation, two central features of economic development (Kuznets 1957). Many studies focus on how structural transformation and productivity growth lead to demographic transition (Greenwood and Seshadri 2002; Wanamaker 2012; Ager et al. 2020). A couple notable exceptions which quantitatively explore how population growth shapes structural transformation in economic history are Voigtländer and Voth (2013) and Leukhina and Turnovsky (2016). Gollin and Rogerson (2014) and Herrendorf et al. (2012) quantitatively explore the role of transportation infrastructure facilitating population movements and thereby structural transformation. These studies rely, however, on calibrated macroeconomic models and aggregate data moments, inhibiting an analysis of mechanisms at the level of decision making and clear causal identification.[3]

We contribute to the literature on the child quality-quantity tradeoff by quantifying the net effect of fertility decline and the associated human capital increase on structural transformation. Consistent with Rosenzweig and Zhang (2009), we estimate that the endogenous human capital investment response to declining fertility is modest. A quantitative analysis by Cheung (2023) on the importance of fertility decline and the associated human capital rise does not feature land in agricultural production, and hence abstracts away from the Malthusian mechanism that we focus on in this paper.

2 Model

In this section we present a simple model of structural transformation. There are two sectors, agriculture and manufacturing, and two factors of production: land and labor. Overlapping generations live together in households in which parents decide the quantity and education of children. Parents enjoy engaging in sex, but can reduce the likelihood of having children by purchasing contraception. We consider the effects of reducing the cost of accessing contraception on human capital investment and agricultural employment share.

[3]Fertility and agricultural employment share may commove due to changes in skill-biased technical change, which affect the returns to child quality investments (relative to quantity) and the returns to employment in agriculture.

2.1 Setup

2.1.1 Production

Consider a small open economy that trades agricultural and manufacturing goods with the world economy.[4] In total there are T units of land, which is only used in agriculture.

Production of agricultural output is Cobb-Douglas:

$$Q_{at} = A_{at} L_{at}^{\theta} T_a^{1-\theta} \tag{1}$$

where Q_{at} is the quantity of agricultural output at time t, A_{at} is Hicks-neutral agricultural productivity, L_{at} is the quantity of labor employed in agriculture, and T_a is the quantity of land used in agriculture (equal to T in equilibrium). $\theta \in (0, 1)$ is the labor income share in agriculture. Land rents are paid to absentee landlords.

Production in manufacturing is linear in labor:

$$Q_{mt} = A_{mt} h_t L_{mt} \tag{2}$$

where Q_{mt} is the quantity of manufacturing output, A_{mt} is Hicks-neutral manufacturing productivity, L_{mt} is the quantity of labor employed in manufacturing.[5] As in Caselli and Coleman (2001) and Porzio et al. (2022), per household human capital h_t only yields returns outside of agriculture.[6]

We assume that labor markets are distorted by a wage wedge, such that agricultural wages are lower than nonagricultural wages:

$$w_{at} = \xi w_{mt}$$

where $\xi \in (0, 1)$. We simplify notation by setting $w_{mt} \equiv w_t$, so $w_t = w_{at}/\xi$. As a result, there will be inefficiently high employment in agriculture, a common feature in developing economies (Gollin et al. 2014).

[4] The small open economy assumption implies prices are exogenous and therefore unaffected by local demand. We discuss the implications of adding trade costs to our model at the end of Section 2.3 and in Appendix Section A.3. We also show in Table D.9 that the quasi-experimental intervention in Bangladesh that we study in Section 3 induced only modest changes in consumption shares across sector, suggesting that demand-side factors are not driving sectoral reallocations in our Bangladesh context.

[5] We consider alternative manufacturing production functions in Appendices A.1 and A.2.

[6] A less restrictive assumption would allow human capital to boost output in both sectors, but moreso in manufacturing. Doing so does not change the main predictions of the model.

2.1.2 Households

To characterize households, we extend the model of Strulik (2017). Preferences are defined as

$$U = \log c_t^a + \delta \log c_t^m + \alpha \log n_t + \gamma \log w_{t+1} + \sigma \log s_t,$$

where w_{t+1} is each child's potential income when they enter the labor force in the following period, s_t is the amount of sex had by the household, σ is the desire for sex, n_t is the number of births per household, c_t^a is consumption of the agricultural good, and c_t^m is consumption of the manufacturing good per household.[7] We assume $\alpha > \gamma$ to ensure parents have children even if they could be costlessly avoided.

Define the number of births as

$$n_t = \min\{s_t - \mu u_t, \bar{n}\}$$

where u_t represents the quantity of family planning technologies used. Households may use contraception or abortion to limit their childbearing. μ is the effectiveness of family planning technologies such that a unit of u_t prevents the birth of μ children. Sex is proportional to births according to some constant that we normalize to 1. $\bar{n}$ is the biological maximum reproduction for a given female; in what follows, we consider only interior solutions.

Human capital is produced according to

$$h_{t+1} = A_{ht} e_{t+1} h_t,$$

where e_{t+1} is the time spent on educating each child and A_{ht} is exogenous human capital production productivity. Households have one unit of time per adult and therefore face the budget constraint

$$w_t[1 - (\phi + e_{t+1})n_t] = p_{ft} u_t + p_{at} c_{at} + p_{mt} c_{mt}$$

given child rearing costs ϕ and price of a unit of the family planning technology p_{ft}. The world price of agriculture is p_{at} and of manufacturing is p_{mt}. Each household works a fraction of their time endowment equal to $\ell_t = 1 - (\phi + e_{t+1})n_t$. Aggregate labor supply is a product of the adult population in time t, n_{t-1}, and the per adult labor supply ℓ_t:

$$L_t = n_{t-1} \ell_t. \tag{3}$$

[7] Note that because we have assumed a small open economy, introducing nonhomotheticity in the demand for agricultural goods would have no effect on our equilibrium results. Strulik (2017) in his appendix shows that Stone-Geary preference for consumption would not change the effect of reducing family planning price p_{ft} on fertility and education.

2.2 Equilibrium

Labor markets clear so

$$L_t = L_{at} + L_{mt}.$$

The equilibrium wage comes out of the manufacturing firm's marginal product:

$$w_t = \xi p_{mt} A_{mt} h_t.$$

The equilibrium agricultural employment share is

$$\frac{L_{at}}{L_t} = \left(\frac{\theta p_{at} A_{at}}{\xi p_{mt} A_{mt} h_t} \right)^{\frac{1}{1-\theta}} \frac{T}{L_t}. \tag{4}$$

Assuming an interior solution, each household's optimal choice of fertility and child education are as follows:

$$n_t = \frac{(\alpha - \gamma)\mu w_t}{(1 + \delta + \alpha + \sigma)(\mu w_t \phi - p_{ft})}$$

$$e_{t+1} = \frac{\gamma(\mu w_t \phi - p_{ft})}{(\alpha - \gamma)\mu w_t}$$

2.3 Effects of Abortion and Contraception Access

We assess the effect of the fertility transition on sectoral employment through the lens of our model. We consider a reduction of the price of the family planning technology p_{ft}. The price includes both monetary and non-monetary costs associated with accessing the family planning technology. Reducing p_{ft} decreases fertility and increases education of the next generation:

$$\frac{\partial n_t}{\partial p_{ft}} > 0, \qquad \frac{\partial e_{t+1}}{\partial p_{ft}} < 0.$$

Hence both current human capital h_t and current adult population n_{t-1} are unchanged as a result of the program. The only contemporaneous variable that changes is labor hours, ℓ_t:

$$\frac{\partial \ell_t}{\partial p_{ft}} = -(e_{t+1} + \phi)\frac{\partial n_t}{\partial p_{ft}} - n_t \frac{\partial e_{t+1}}{\partial p_{ft}}.$$

That is, the direction of the change in labor hours depends on the relative strength of quality-quantity tradeoff. On the one hand, parents have fewer children to raise and therefore less demand on their parenting time. On the other, parents invest more time educating each child. The net effect is theoretically ambiguous. Empirically, Aaronson et al. (2021) estimate that the effect of fertility on women's labor supply is negligible at low levels of development but significantly negative for more developed countries. Lundberg and Rose (2002) finds that men increase their labor supply with fertility. Hence, the aggregate net effect is also ambiguous but the small or offsetting estimated effects suggest that the magnitude may not be very large.

In subsequent generations, more accessible family planning technologies has two additional effects. First, human capital (h_t) rises, thereby pulling workers into the manufacturing sector. Second, the adult population (n_{t-1}) falls. The net effect on total labor supply is

$$\frac{\partial L_t}{\partial p_{ft-1}} = n_{t-1}\frac{\partial \ell_t}{\partial p_{ft-1}} + \ell_t \frac{\partial n_{t-1}}{\partial p_{ft-1}}.$$

Relative to the prior period in which only ℓ_t may change, the land-labor ratio rises, increasing the returns to labor in agriculture, as seen in equation (4). The net effect of more accessible family planning technology on agricultural employment share depends on the relative strength of the human capital channel versus the labor supply channel.

We show that our predictions are robust to alternative production functions in Appendix A. In Appendix Section A.1, we show our results hold when adding an additional factor of production, imported intermediate inputs.[8]

We discuss when our results hold if trade is costly in Appendix Section A.3. If trade costs are sufficiently high, the economy becomes closed and must rely on local production. Hence, the food problem (Schultz 1953) becomes salient and reverses our baseline model's prediction: a larger population raises demand for agriculture, thus shifting a greater share of workers into that sector. Hence the relative closedness of the agricultural sector in many developing economies (Gollin et al. 2007) works against our hypothesized population size effect. If every country's agricultural sector was perfectly closed, in our model declining fertility would decrease agricultural employment share, so long as the per-household effect on labor supply ℓ_t is sufficiently small. Tombe (2015), however, shows a wide range of openness among countries' agricultural sectors, including for developing countries. A growing literature emphasizes an open-economy perspective on structural change (Uy et al. 2013; Sposi 2019; Fajgelbaum and Redding 2022; Farrokhi and Pellegrina 2023; Gollin et al. 2025). Moreover, we show in our subsequent empirical analyses that the demographic transition slows down the movement of workers out of agriculture, implying that agricultural sectors are on average sufficiently open to drive open economy effects.

[8] One can instead think of this additional factor as capital when the economy is open to the global capital market. We further show in Appendix Section A.2 that our main results hold if we allow intermediate inputs and labor to be arbitrarily substitutable. Introducing capital to the model makes it intractable, as noted by Galor (2005).

3 Bangladesh Quasi-Experiment

The Maternal and Child Health and Family Planning (MCH-FP) program was introduced in the Matlab subdistrict in Bangladesh in 1977 to a subset of local villages by icddr,b (formerly known as the International Centre for Diarrhoeal Disease Research, Bangladesh). The program included family planning and maternal and child health services.

3.1 Program Details

Program interventions were rolled out over time during two main periods. Between October 1977 and December 1981, the focus was family planning and maternal health. Local female community health workers provided access to and advice on using modern contraception, tetanus toxoid vaccines for pregnant women, and iron and folic acid supplementation for women in their third trimester of pregnancy Bhatia et al. (1980). Intensive child health interventions started in 1982 with the provision of the measles vaccine to children under age five.

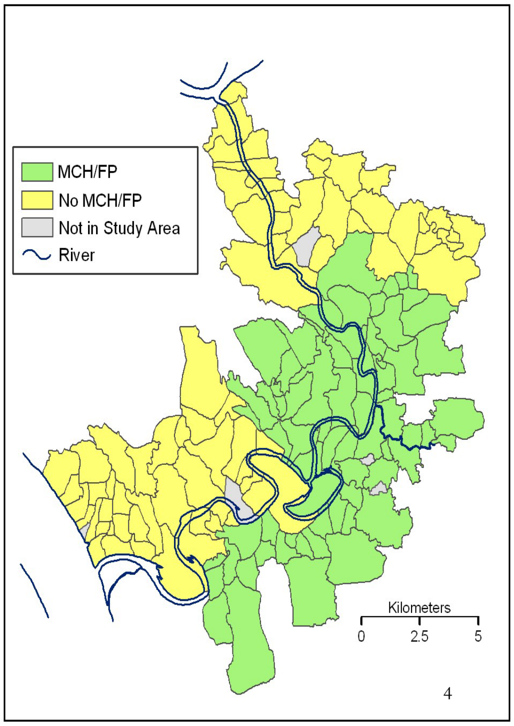
The MCH-FP program was introduced to a subset of the villages in Matlab, with the remaining villages serving as an untreated comparison area (Figure 1).[9] While the treatment area received in-home delivery of program services, the comparison area continued to have access to then-standard government health and family planning services available only at clinics. Some of the childhood services, such as vaccinations, were not readily available in clinics until 1989 or later, providing a period, 1977–1988, during with access to family planning and health services differed substantially between the two areas.

At the time the program was introduced, the Matlab subdistrict included about 200,000 people across 149 villages, with the population split evenly between the two areas. Treatment and comparison villages were socially and economically similar and geographically insulated from outside influences (Phillips et al. 1982) and households in both areas faced a similar distance to transportation and health infrastructure. Our analysis assumes that outcomes in these two areas would have evolved similarly in the absence of the MCH-FP program, and we provide support for this identification strategy in Section 3.3.1 by documenting balance in pre-program household characteristics as well as similarities in birth rates between the two areas during the two decades before program rollout.

The program was successful in driving rapid take up of the two key interventions: family planning and the measles vaccine (see Appendix Figure D.7). Prior to the program, the

[9] The program was placed in a single block of contiguous villages, with a block of comparison villages on either side. The design was intended to reduce potential information spillovers about the family planning intervention (Huber and Khan 1979) and any positive externalities generated by the vaccinations.

Figure 1: Map of Matlab Study Area



Notes: The map plots villages in the Matlab subdistrict in Bangladesh. Villages in green are within the treatment area while those in yellow are in the comparison area. Taken from Barham (2012).

contraceptive prevalence rate for married women 15–49 was low (less than 6 percent) in both the treatment and comparison areas. It rose by over 25 percentage points in the treatment area in the first year, then rose steadily thereafter. Contraceptive use rose much more slowly in the comparison area. The measles vaccination rate rose substantially to 60 percent after it was introduced in the second half of the program; rates for vaccination coverage for diseases targeted by the program increased throughout the program duration. Rates for the comparison area were much lower throughout the period. We provide additional details about the MCH-FP in Appendix Section C.

The staggered rollout of program components led to differential treatment of children depending on their year of birth. However, children of all ages may have experienced some effects as parents shift child-specific investments in response to the program. Moreover, the program affected all participants in the labor market, as the intervention significantly affected cohort size.

Previous research demonstrates that the MCH-FP program had significant effects on fertility and human capital. Barham et al. (2021a) show that completed family size was between 0.52 and 0.67 smaller in the treatment than the comparison area depending on the number of reproductive years a woman was exposed to the MCH-FP Program. Joshi and Schultz (2007) use a different research design and also find schooling increased for boys. Regarding human capital, Barham (2012) finds that adolescent boys born during the vaccine phase of the program in the treatment area experienced significant improvements in height, cognitive functioning, and schooling. There was no effect on those born prior to the introduction of intensive child health interventions for those born between 1977–1981. In a follow-up paper, Barham et al. (2021b) show that effects on height and education persisted into adulthood for those born between 1982–88. The persistence of the effect on human capital is strongest for affected men.

3.2 Data and Treatment Assignment

Data Sources. We draw on the extraordinarily rich data available for the Matlab study area. We focus on household- and individual-level sectoral employment measured in both the 1996 Matlab Health and Socioeconomic Survey (MHSS1) (Rahman et al. 1999) and the second wave of the Matlab Health and Socioeconomic Survey (MHSS2), which was collected in 2012–2014.[10] Questions changed significantly between survey rounds, and the MHSS2 offers a richer set of questions about sectoral employment (see Appendix Section B.1 for more details on our sectoral employment classification). In particular, we measure the share of months worked by sector in MHSS1 and the share of annual hours worked by sector in MHSS2.

MHSS2 exhibits low attrition rates, with the loss of less than 10 percent of the target sample.[11] Respondents were tracked throughout Bangladesh and intensive efforts were made to interview international migrants and difficult-to-track migrants when they returned to the study area to visit family.

We use two supplementary data sources: periodic censuses from 1974 and 1982 (icddr,b 1974, 1982), and 1974–2014 Matlab demographic surveillance site (DSS) data on the universe of vital events (e.g., births, marriages, deaths, in and out migrations) collected by icddr,b.

[10]Fieldwork occurred across multiple years with increasing effort in order to maximize response rates among difficult-to-track migrants. Migrants were identified as a part of the survey and tracked throughout the country. Beginning in October 2013, rapid-response teams were put in place in major city centers in Bangladesh so that interviews could take place once a migrant was found via family members in Matlab. In-person surveys were collected during the two Eid festivals in July and October 2014 when migrants returned to their villages in Matlab. Finally, some international and distant domestic migrants were interviewed via a phone survey in late 2014.

[11]The MHSS2 is a panel followup of all individuals in the MHSS1 primary sample and their descendants. The MHSS1 primary sample is representative of the study area's 1996 population, but does not include individuals who migrated between program start and 1996. To address this unrepresentativeness, MHSS2 introduces to the panel individuals born in an MHSS1 household between 1972 and 1989 but who had migrated out of Matlab between 1977 and 1996, which we refer to as pre-1996 migrants.

The MHSS1 and MHSS2 are a panel of a random sample of households from the study area, while the census and DSS data cover the entire study area. A key feature of all these data is that individuals can be linked across different data sources over time by a unique individual identifier. There are few, if any, other study sites that have similarly rich data availability to allow for this type of long-term evaluation.

We provide additional details about the Matlab data in Appendix Section B.1.

Analysis Sample and Attrition. We select individual and household responses from MHSS1 and MHSS2 by focusing on the MHSS1 household as our unit of analysis and using data from the members of that household from both survey waves. In Bangladesh, households typically make joint education, migration, and employment decisions.

We restrict our sample to households where the MHSS1 household head was a primary respondent to the MHSS1 survey. Because the MCH-FP program could have drawn households into the treatment area Barham and Kuhn (2014), we use DSS data to further restrict our sample to households in which the household head was present in Matlab prior to the start of the program (i.e., October 1977). These restrictions result in a sample of 2,534 MHSS1 households.

When measuring individual outcomes in MHSS1, we use data of household members who responded to the individual-level adult survey. In MHSS2, we rely on data from these same individuals, and further include the MHSS2 panel members who migrated out of Matlab from our sample households prior to MHSS1 (i.e., the pre-1996 migrants) as well as any children of the MHSS1 respondents who were adults at the time of the MHSS2 survey. Appendix Section B.1 discusses in detail how we aggregate outcomes measured across multiple households and individuals in MHSS2 to the MHSS1 household level. Due to the low attrition in MHSS2, fewer than 2 percent of MHSS1 households have no members who were tracked to the MHSS2 survey round, and our household-level analysis using MHSS2 data include the 2,484 households tracked to this second round.

When assessing the role of human capital in the MCH-FP's total effect, we analyze employment outcomes at the individual level. This analysis relies on the same set of individuals that underlie our household-level analysis. Because we are focused on employment outcomes, we restrict our sample to individuals born in 1947 or later, and were thus 65 or younger at the start of MHSS2 surveying, and those who were born in 1988 or earlier, to focus on the set of individuals born before or during the MCH-FP program. Including death and other types of non-response, the attrition rate is 16 percent among all men in our sample, and 11 percent among men born during the program interventions. This is a low attrition rate compared to other long-term effects studies with shorter follow-up periods despite a migration rate of approximately 60 percent for men (25 percent international) in this highly-mobile population.

Intent-to-Treat and Baseline Variables. Access to the MCH-FP program was based on the village of residence of the individual/household during the program period. We cannot use the area where the household or individual lived at the time of survey or even when some of the individuals in our individual sample were born because the household's location decision may have been affected by the program (Barham and Kuhn 2014).

We create an individual-level intent-to-treat (ITT) indicator by tracing each individual back to their village of residence at the time of the 1974 census to determine eligibility status. If the person was not alive or present in the DSS in 1974, we find the residency of their first DSS household head (or that person's first DSS household head, etc.) present in the 1974 census. For an individual, the ITT variable takes the value of 1 if the 1974 census-linked individual or household head was living in a village in the treatment area in the 1974 census or first migrated into a village in the treatment area from outside Matlab between 1974 and 1977 (using the DSS), and 0 otherwise. For our primary household-level analysis, the treatment indicator for the MHSS1 household is derived from the individual treatment indicator of the household head.

3.3 Empirical Strategy

We now discuss how we leverage the quasi-experimental variation induced by the MCH-FP program to estimate the causal effect of the program on structural transformation. Our empirical strategy compares the post-intervention outcomes of households from the treatment and comparison areas. For the difference in average outcomes to identify the causal effect of the MCH-FP program, we assume that average post-program outcomes among treatment area households, conditional on pre-intervention controls, would have been the same as the average outcomes in the comparison area. Below we show that birthrates were similar across the two areas in the nearly two decades leading up to program rollout and document that a wide-range of pre-intervention covariates were balanced between the two areas.

3.3.1 Baseline Balance and Trends

Because our identification strategy uses variation between treatment and comparison villages, we provide evidence that pre-intervention characteristics were well balanced between these two areas and were trending similarly in the years leading up to the program's rollout.

Prior studies have documented balance between treatment and control villages across a range of variables including mortality rates, fertility rates, and pre-intervention household and household head characteristics (Koenig et al. 1990; Menken and Phillips 1990; Barham 2012; Joshi and Schultz 2013). Additionally, migration stocks and flows were similar between the treatment and comparison area at the start of the program and through to 1982, for the cohort of individuals most likely to migrate at the start of the program (Barham and Kuhn 2014). Barham et al. (2023) further show that men born between 1977 and 1988 come from households experiencing similar labor market outcomes in 1974 (DSS census), 1982 (DSS census), and 1996 (MHSS1). Finally, Barham (2012) shows that cognitive functioning, height, and years of education were similar across the treatment and comparison areas in 1996 for those who were old enough that their human capital and height were not likely to have been affected by the program.

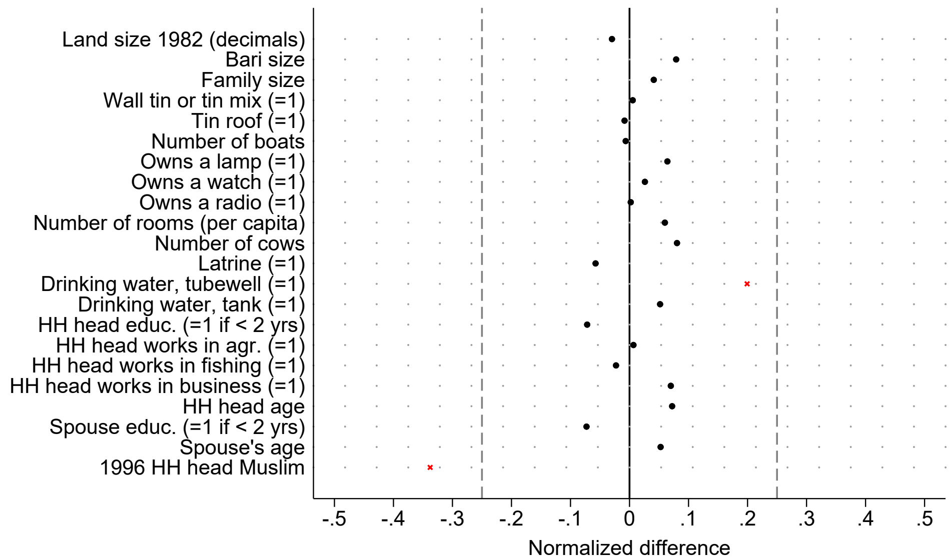
We demonstrate that this balance persists in our analysis sample of MHSS1 households, complementing previous work examining individual differences among the panel of MHSS1 respondents (e.g., Barham 2012; Barham et al. 2023). Figure 2 depicts the normalized differences in means (difference in the means divided by the standard deviation of the comparison area) of pre-intervention household characteristics measured in the 1974 census.[12] These normalized differences provide an indication of the economic significance of the differences that do not depend on sample sizes, normalized differences bigger than 0.25 standard deviations are generally considered to be economically meaningful (Imbens and Wooldridge 2009). In Figure 2, any difference which is statistically significant at the 5% level is indicated with a red X.

Differences in means are statistically insignificant at the five percent level for all variables except whether the household head is Muslim and a dummy for the household using tubewell water for drinking. Because we test balance across 22 variables, it is unsurprising that two are statistically different. With the exception of religion and the use of tubewell drinking water, the normalized differences are less than 0.12 standard deviations suggesting that the differences that do exist are relatively small. In our main specification, we control for all these baseline characteristics.

The difference in tubewell access is close to the cut off at 0.20 standard deviations. There is widespread groundwater arsenic contamination in the tubewells in Bangladesh (Chowdhury et al. 2000) and arsenic is a health concern and has been shown to reduce IQ among school aged Bangladeshi children (Wasserman et al. 2006). Barham (2012) explores the potential for tubewell access to bias estimates of the program's effect on human capital and does not find any evidence for this. In sum, our baseline balance results mimic previous research and

[12]Appendix Table D.1 presents the means for the treatment and comparison group separately and the level differences in means between the two groups.

Figure 2: Baseline Balance in Normalized Differences



Notes: The chart plots normalized differences in baseline variables. Each variable, unless otherwise specified, is measured using the 1974 census. The normalized difference is the difference in means divided by the comparison area's standard deviation. Any difference between treatment and comparison average which is statistically significant at the 5% level is indicated with a red X.

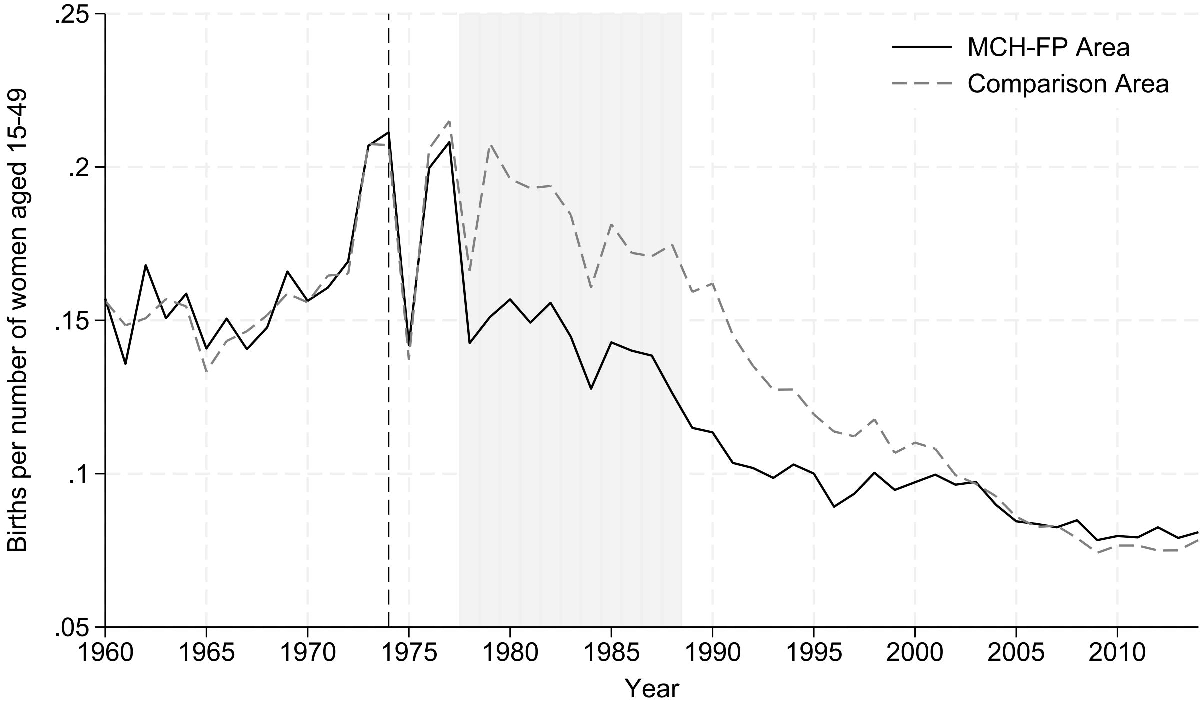
show that the two areas are similar across a wide variety of household and household head characteristics.

Finally, because this paper focuses on the demographic transition, we document the similarity in birth rates during the nearly two decades before program rollout. Figure 3 plots the number of births relative to the population of adult women of childbearing age (15–49) for both the treatment and comparison area using data from the DSS.[13] Prior the the implementation of the program in 1977, the levels and trend of birth rates were nearly identical, including the severe drop in the birth rate in 1975 around the time of the Bangladesh famine.[14] During the experimental period, which is shaded in gray, there is a substantial divergence in birth rates. The comparison area experienced nearly 30% higher birth rates than the treatment area.

[13]The DSS began tracking demographic events in April 30, 1974. In years prior to 1974, we construct birth rates using the population of women aged 15–49 present in the DSS at the time of the initial census on April 30, 1974 divided by the number of individuals born in the given year still residing in the DSS on that same date. In counting the number of births in 1974, we count the number of children born before April 30, 1974 and residing in the DSS, as well as any new births recorded later that year. For later years, the denominator includes the population of women 15–49 present in the DSS on January 1 of that year.

[14]Note that birth rates prior to 1974 undercount the actual number of live births as the estimates are based on individuals who survived to 1974.

Figure 3: Trends in Birthrates 1960–2014, MCH-FP Treatment Area and Comparison Area



Notes: The figure reports birth rate estimates across the Matlab Demographic Surveillance Site (DSS) from 1960 through 2014. DSS records begin April 30, 1974 (denoted by the vertical dashed line). In 1974 and earlier, we construct birth rates by counting the number of individuals who resided in the DSS area on April 30, 1974 who were born in a given year and dividing by the number of women aged 15–49 residing in the DSS on April 30, 1974. In later years, birth rates are constructed by counting the number of individuals residing in the DSS on the day of their birth in a given year and dividing by the number of women aged 15–49 residing in the DSS area on January 1 of that year. The shaded gray area marks the period (1978–1988) when the MCH-FP intervention was available in the treatment area, but not the comparison area.

3.3.2 Empirical Specification

To examine the effect of the program on sectoral employment and agricultural outcomes, we take advantage of the well-balanced treatment and comparison areas and use a single-difference intent-to-treat (ITT) models. We estimate the household-level specification,

$$Y_h = \omega_0 + \omega_1 T_h + \zeta X_h + \varepsilon_h \tag{5}$$

where T_h is an indicator for whether household h is considered treated (as defined in Section 3.2) and X_h is the vector of demographic and baseline characteristics detailed in Table D.1. The coefficient of interest, ω_1, measures the difference in average outcomes between treatment and comparison area households conditional on the set of 1974 household characteristics. To adjust our inference for the village-level treatment assignment, we cluster standard errors by the 1974 village of the household head of h or his antecedents.

3.4 Main Results

We first estimate the effects of the MCH-FP on the share of time spent working in each sector at the household level. Results are shown in Table 1. We separate the estimates into medium-run effects (columns 1 and 2) measured in the 1996 MHSS1 survey, and long-run effects (columns 3 through 6) measured in the 2012–2015 MHSS2 survey. The dependent variable measured in MHSS1 is the share of months spent per year in each sector.[15] In MHSS2, the dependent variables are the share of total annual hours worked by household members in each sector (columns 3 though 5), and the average annual number of hours worked by household members (column 6).

As of 1996, 19 years after the MCH-FP program started, we find no significant effect of the program on sectoral employment (columns 1 and 2). The estimated treatment effect on the agriculture share is 0.7 percentage points (SE=2.1). The effect of the program on non-agricultural employment is similarly small, with an estimated effect of 0.4 p.p. (SE=2.1).

Next, we turn to the long-run effects of the MCH-FP, 35 years after it started. Columns 3 through 6 of Table 1 report our results at the time of the 2012–2015 MHSS2 survey. The MCH-FP raised the share of time household adults spent working in agriculture by 4.1 p.p. (SE=1.4 p.p), representing a 20 percent increase over the comparison area mean (column 3). The share of time household members spent working in manufacturing falls by 3.2 p.p. (SE=1.4), a 16 percent reduction relative to comparison area households (column 4). In services, we find a very small effect of -1.3 p.p. (SE=1.8), a 3 percent reduction relative

[15]Because we measure time at the monthly level, share spent working in agriculture and non-agriculture may sum to more than one if individuals worked in both sectors in the same month.

Table 1: ITT Effects of MCH-FP on Work Time Shares by Sector: Household-Level

	MHSS1 (1996)		MHSS2 (2012–2014)			
	(1) Agriculture Share	(2) Non-Agriculture Share	(3) Agriculture Share	(4) Manufacturing Share	(5) Services Share	(6) Annual Hours Per Person
Treatment	0.007	0.004	0.041***	-0.032**	-0.013	-27.083
	(0.021)	(0.021)	(0.014)	(0.014)	(0.018)	(35.457)
% chg. rel. to mean	1.1	1.2	19.9	-15.8	-2.8	-1.9
Mean	0.68	0.36	0.21	0.20	0.48	1445.47
Baseline controls	Y	Y	Y	Y	Y	Y
Observations	2534	2534	2484	2484	2484	2484

Notes: The table presents estimates of equation (5) for outcomes at the MHSS1 household-level. Variable means refer to the comparison group. Standard errors are clustered by the 1996 household head's pre-program village. Columns (1) and (2) measure outcomes in the 1996 MHSS1, while columns (3) through (6) measure outcomes in the 2012–2015 MHSS2. The MHSS1 dependent variable is the share of working months in the year allocated to each sector. MHSS2 dependent variables are the share of hours worked by sector within the household (columns 3–5) and the average annual hours worked per person (column 6). MHSS2 regressions are weighted to account for household-level attrition between the MHSS1 and MHSS2 surveys. See Appendix B.1 for more details on how we classify workers into sectors. Due to changes between survey waves, sectors are constructed differently in the MHSS1 and MHSS2, and therefore are not directly comparable. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

to comparison households (column 5). In aggregate, the typical adult household member worked similar hours between the treatment and comparison areas—we find only a 27-hour difference during the previous 12 months (column 6). Hence, the MCH-FP program reduced the speed of structural transformation.

We separately explore the MCH-FP's effect on the extensive margin of farming. Columns 1 and 3 of Appendix Table D.2 show results consistent with our baseline in Table 1. In the medium run, the program had negligible effects on farming in 1996 (column 1). By contrast, in the long-run the program kept more households in farming relative to control households. By 2014, treatment area households were 4 percentage points more likely to have a household member engaged in farming relative to comparison area households (column 3).

Population pressure is determined by the land-to-labor ratio, with land being fixed at the local level. At the household level, by contrast, households may buy or sell land in response to changes in household size. We find no evidence the program changed the amount of acres owned by households (columns 2 and 4 of Appendix Table D.2). Moreover, land transactions outside the family are quite rare (less than 6% of households engage in them annually as of MHSS1) and are typically modest in size.

Given the importance of entrepreneurship for development (McMillan and Woodruff 2003; Buera et al. 2011, 2021), we explore whether the patterns observed in employment are matched by sector-specific entrepreneurship. We report the results in Appendix Table D.3. Columns 1 through 3 show a similar pattern as in Table 1: increased agricultural enterprise, with no change in manufacturing or service entrepreneurship.

As large firms, especially factories, drive structural change and growth (Buera and Kaboski 2012), we also explore how the MCH-FP affected employment across firm types in columns 4–6 of Appendix Table D.3. Employment at factories among treated households lagged behind comparison area households (columns 4 and 5), as did employment at large firms (column 6).

Finally, given the importance of rural-to-urban migration in the development process (Lagakos 2020; Lagakos et al. 2023), we explore its role in shaping our baseline estimates. We re-estimate equation (5) by sector, but further split the dependent variable of work hours share by rural and urban location of employment. We report results in Appendix Table D.4, with the effect on hours worked share in urban areas reported in columns 1–3, and in rural areas in columns 4–6. Our main results are driven by treated households engaging more in rural agriculture and less in urban manufacturing relative to comparison households, underlining the importance of rural-to-urban migration in structural transformation in Bangladesh.

Robustness. We explore the robustness of our main results above to variations in sampling, specification, and variable construction.

We assess the concern that information spillovers along the border of the treatment and control zones may reduce our estimated effect. To do so, we restrict our sample to those living in a village prior to the intervention which has a centroid within 3km of the border. In Panel B of Appendix Table D.5, we show that our results are very similar in magnitude to our baseline estimates when applying this restriction.

Given our finding in Section 3.3.1 that Muslims are disproportionately represented in control villages, we re-estimate our main results using only Muslim households. We find that results are virtually unchanged with this sample restriction, as shown in Panel C of Appendix Table D.5. Since Matlab is about 85% Muslim, we do not have sufficient statistical power to estimate program effects for the Hindu population on its own.

Finally, we address one other asymmetry between treatment and control areas: the only urban center in the study area, Pourashava, exists in the treatment area. In Panel C of Appendix Table D.5, we show that our results are largely unchanged when we remove households who resided in Pourashava prior to the intervention.

3.5 Mechanisms

We take advantage of the richness of the household data from Matlab to examine the mechanisms driving the main effects. We focus on two key mechanisms which may work in opposite directions: population size and human capital.

3.5.1 Family Size

We start by testing how household size shapes our results. Fauveau (1994), Joshi and Schultz (2013), and Barham et al. (2023) have all found significant effects of the MCH-FP in reducing fertility. We also estimate the effect of the program on the number of men and women born during the experimental period, with results shown in Table D.6. Consistent with earlier research, we find the program reduced household size. In particular, we find the program reduced the number of males per household aged 24 to 34 by 16 percent, and decreased the number of females per household in the same age range by 11 percent.[16]

Next, to understand how population pressures within the household contributed to structural transformation, we estimate how the number of male children per household born during the experimental period affected those children's later-life sectoral employment choices. We focus on males because of their stronger labor market attachment. In particular, we estimate an equation of the form

$$Y_h = \alpha_0 + \alpha_1 Num.\ males\ age\ 24\ to\ 34_h + \gamma X_h + \epsilon_h \tag{6}$$

where Y_h is either the share of household work hours by sector or the number of hours by sector. Because the number of males born during the experimental period is an outcome of the program, we instrument for $Num.\ males\ age\ 24\ to\ 34_h$ using the treatment dummy.

We present our results in Table 2, with estimates for the share of hours by sector appearing in Panel A and for the number of hours by sector in Panel B.

Starting with Panel A, we find that larger households spend a smaller share of their adults working in agriculture (column 1). One more male born during the program period reduces the share of household work time spent in agriculture by nearly 40 percentage points. Conversely, larger households are more likely to have a member working in manufacturing (column 2) or services (column 3), though the effect is less precisely estimated for services.

In Panel B we explore the effect on the number of hours worked by sector. Doing so allows us to quantify how much of the decrease in available son labor corresponds to a change in the level of agricultural labor relative to the level of non-agricultural labor. We find a negative but imprecisely estimated effect on agricultural hours worked due to having an additional son. By contrast, we observe a substantial increase in hours worked in both manufacturing

[16] The difference in number of 24-34 year olds by gender is statistically indistinguishable. The effect size on fertility is smaller than what is reported by Joshi and Schultz (2013) and Barham et al. (2023). This is because for the present estimation at the household level, we are not subsetting to families most likely to have children, i.e., by the age of the household head. Therefore, we have some households, for example, with exclusively older individuals in the MHSS1 who had no children, and this drives down the average effect we estimate.

Table 2: ITT Effects of MCH-FP on Long-term Work Hour Shares by Sector and Household-Size: Household-Level

	(1) Agriculture	(2) Manufacturing	(3) Services
Panel A: Work Time Shares by Sector			
No. males aged 24–34	-0.260**	0.201*	0.085
	(0.101)	(0.105)	(0.110)
% chg. rel. to mean	-125.8	100.2	17.5
Mean	0.21	0.20	0.48
First-stage F-stat.	14.2	14.2	14.2
Baseline controls	Y	Y	Y
Observations	2484	2484	2484
Panel B: Total Work Time by Sector			
No. males aged 24–34	-426	2,507***	2,001*
	(574)	(955)	(1,108)
% chg. rel. to mean	-31.1	141.8	49.9
Mean	1368	1769	4007
First-stage F-stat.	14.2	14.2	14.2
Baseline controls	Y	Y	Y
Observations	2484	2484	2484

Notes: The table presents 2SLS estimates for outcomes measured in the 2012–2015 MHSS2 aggregated at the MHSS1 household-level. Variable means refer to the comparison group. Standard errors are clustered by the 1996 household head's pre-program village. The dependent variable in Panel A is the share of hours worked within the household by sector. The dependent variable in Panel B is the total hours worked within the household by sector. See Appendix B.1 for more details on how we classify workers into sectors. Regressions are weighted to account for household-level attrition between the MHSS1 and MHSS2 surveys. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

and services. Our results are therefore consistent with a story in which the marginal son is sent to work in the non-agricultural sector.

3.5.2 Human Capital

When returns to human capital are higher outside agriculture, an increase in human capital draws workers out of agriculture. We test this hypothesis by leveraging the rollout of the vaccine arm of the MCH-FP and cross-cohort variation in exposure.

First, we confirm that returns to human capital are in fact higher outside agriculture. We show this by estimating a Mincer equation relating the log wage to education and potential experience by sector. Appendix Table D.10 displays the results. Consistent with Caselli and Coleman (2001) and Porzio et al. (2022), returns to education are lower in agriculture relative to non-agriculture, and highest in the service sector.

Past research on the effects of the MCH-FP by Barham (2012) and Barham et al. (2021b) have found pronounced effects on human capital for the cohorts born between 1982 and 1988 and negligible effects for those born between 1977 and 1981. Effects were strongest among men. We estimate the effect of the MCH-FP on years of education as of the MHSS2 within our household sample, with results shown in Appendix Table D.11. We estimate a negligible effect of the program on all adults. In light of the program's focus on vaccinating only young children, this is unsurprising. As expected, and consistent with earlier research, we find that adults born during the vaccine period of the MCH-FP obtained 5.7% higher years of education than the average comparison household member born during the same period. The effect is stronger for men than for women. In what follows, we therefore take as given that cohorts born into the vaccine arm of the MCH-FP (between 1982 and 1988) experience a significant human capital boost relative to other cohorts.

We estimate a single-difference equation at the individual level of the form:

$$Y_i = \alpha_{y(i)} + \gamma_1(T_i \times Born_i^{77-81}) + \gamma_2(T_i \times Born_i^{82-88}) + \gamma_3(T_i \times Born_i^{Pre-77}) + \nu X_i + \epsilon_i \quad (7)$$

where T_i is an indicator for whether i is treated as defined in Section 3.2; $\alpha_{y(i)}$ is a set of indicator variables for i's birth year; and X_i is the vector of pre-intervention demographic and baseline characteristics detailed in Table D.1.[17] We cluster standard errors by the 1974 village of i (or i's antecedents if i was not born by 1974).

The coefficients γ_1, γ_2, and γ_3 represent the intent-to-treat single-difference coefficients of interest. In particular, they capture the difference in conditional means for the outcome for the relevant age group. γ_1 captures the effects of the family planning and maternal health interventions combined with any spillovers of having younger siblings exposed to the intensive child health interventions, and γ_2 is the combined effect of all program interventions, including the childhood vaccination programs. γ_3 captures any indirect spillover effects of the program on older generations. For each cohort, we also report the cohort's mean outcome in the comparison area, and the percent change relative to the cohort comparison mean.

Table 3 reports results at the individual level among men.[18] We find that, consistent with our household-level estimates, treated individuals increase the share of hours worked in

[17] We additionally control for dummy variables indicating whether i was born (i) prior to the intervention starting in October 1977, (ii) during the first phase of the intervention October 1977 to February 1982, and during the second phase of the intervention March 1982 to December 1988. Because we define our cohort dummies $Born_i^{77-81}$, $Born_i^{82-88}$, and $Born_i^{Pre-77}$ using these year-month cutoffs, they are not collinear with the vector of birth year cohort dummies $\alpha_{y(i)}$.

[18] We show results for women in Appendix Table D.7. The program did not affect hours worked for women. Vaccine-treated women work more in agriculture and less in non-market activities. Given women's much lower labor supply, we focus on men in our analysis.

agriculture (column 1) and reduce it in manufacturing (column 2).

Table 3: ITT Effects of MCH-FP on Long-term Work Hour Shares by Sector: Individual-Level

	Share hours by sector			
	(1)	(2)	(3)	(4)
	Agriculture	Manufacturing	Services	Hours worked
Treatment × Born 1982–1988	0.01	-0.08**	0.05	-24.20
	(0.02)	(0.03)	(0.04)	(87.49)
Treatment × Born 1977–1981	0.05*	-0.06**	-0.01	-64.32
	(0.02)	(0.03)	(0.04)	(85.68)
Treatment × Born Pre-1977	0.04*	-0.00	-0.04	-145.84**
	(0.02)	(0.01)	(0.02)	(61.92)
% chg. (1982–88)	12.6	-30.4	10.3	-0.8
% chg. (1977–81)	56.5	-30.5	-2.0	-2.0
% chg. (Pre-1977)	13.2	-0.7	-6.9	-5.1
Comparison mean (1982–88)	0.08	0.25	0.51	3040.01
Comparison mean (1977–81)	0.08	0.21	0.59	3184.98
Comparison mean (Pre-1977)	0.29	0.10	0.52	2857.40
Observations	4744	4744	4744	4744

Notes: The table presents estimates of the effect of the MCH-FP on 2014 outcomes for men at the individual level. Means by age group refer to the comparison area. Standard errors are clustered by pre-program village. Regressions are weighted to adjust for attrition between the MHSS1 and MHSS2 surveys. All variables control for the baseline controls listed in Table D.1 as well as erosion exposure. The dependent variable in columns (1) through (3) is the fraction of total hours worked by sector. See Appendix B.1 for more details on how we classify workers into sectors. Employment shares do not sum to 1 for two reasons. First, we do not report results for two small sectors, construction and mining. Second, a small set of respondents do not work and are coded as spending 0 percent of their time working in each of the given sectors. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

There is, however, considerable heterogeneity in program effects across cohorts. To interpret these differences across cohorts, recall that the 1977–81 cohort in the treatment area only directly experienced the effects of smaller family sizes via the contraception arm of the MCH-FP. By contrast, the cohorts born between 1982 and 1988 experienced both smaller family sizes and improved early-life health from vaccinations, which translated into higher later-life human capital (Barham 2012; Barham et al. 2021b).

We find that men born during the human-capital building phase of the program, between 1982 and 1988, worked more in the service sector and less in manufacturing (first row of coefficients). However, this increase in service sector employment was offset by reductions in the share of hours worked by all other cohorts of men (column 3). These other cohorts of men (born before 1982 or after 1988) increased their agricultural employment. Our results can be understood to the extent that the returns to human capital are higher in the service sector than in agriculture or manufacturing, and that families optimally allocated sons to sectors based on their human capital.

3.5.3 Agricultural Adjustment

We next examine household-level effects of the program on agriculture. Since treated households are smaller, less family labor is available for use on the farm. Farming households may therefore switch into growing less labor-intensive crops. We estimate the effect of the MCH-FP on crop choice and show the results in Figure Table D.1. The program induced a shift towards crops which produce more revenue per unit of labor input. Roughly put, farmers shifted away from rice and into potatoes.

We finally assess whether observable measures of farm productivity change as a result of the program. With the human capital rising due to the vaccine component of the MCH-FP, farmers may raise their per-acre farm productivity if they increasingly use more complex inputs. As we show in Appendix Table D.8, we see no evidence of the program raising farm productivity per acre.

Our proxy for per acre productivity is revenue and profit per acre. To compute the value of output, we first need data on crop prices. Lacking farmgate prices for each household in the MHSS2 data, we instead draw upon the Bangladesh statistical yearbooks for 2012 through 2014. These yearbooks list prices at the variety level (e.g., coarse paddy boro or fine paddy boro), not the crop level (e.g., paddy boro). Hence we take prices in two ways: either the minimum price within crop across varieties, or the maximum.

We estimate the effect of the MCH-FP for the subset of households which grow crops. In columns 1 and 2 we look at the effect on potential revenue per acre, while we estimate the effect on profits per acre in columns 3 and 4. Across all outcomes, we can not statistically rule out a null effect. This result is consistent with our individual-level estimates in Table 3 which shows that the men whose human capital was improved most by the program (i.e., were born during the vaccine arm of the MCH-FP) left agriculture to work in services.

While the MCH-FP Matlab quasi-experiment sheds light on the partial equilibrium effects of fertility changes and vaccine accessibility, it cannot on its own be informative about the general equilibrium effects. In particular, wages, prices, and technology may change as a result of large, widespread changes in fertility and human capital Acemoglu (2010). To understand the general equilibrium effect of fertility changes, taking into account general equilibrium forces, we first leverage cross-country and cross-state variation in the next section, and then rationalize our results with a model in Section 2 and do some rough back-of-the-envelope calculations.

4 Aggregate Analyses

We next explore whether the relationship between fertility and structural transformation estimated in Section 3 holds when general equilibrium forces are salient. We do so with two exercises using aggregate data. First, we leverage cross-country data and changes in abortion policies over the last 60 years. Second, we use cross-U.S. state data and changes in abortion restrictions in the 19th century.

4.1 Cross-Country Analysis

We leverage variation across countries in abortion policies to assess how fertility affects the agriculture employment share. The cross-country analysis has two main advantages. First, we assess whether the relationship estimated in partial equilibrium in Section 3 holds even when accounting for general equilibrium forces at the country level, such as changing prices. Second, we can establish whether this relationship holds for a broad set of countries at different points on the development path and with widely varying cultural norms around fertility.

4.1.1 Cross-Country Data

We construct a cross-country panel dataset of agricultural employment share and abortion policy changes. To measure agricultural employment share we rely primarily on Wingender (2014b), who compiles and harmonizes data for an unbalanced panel of 169 countries between 1900 and 2010. Additional data details are provided in Wingender (2014a).

We use abortion policy changes across countries between 1960 and 2006 collected by the United Nations Population Division following Bloom et al. (2001).[19] We collapse specific policy changes into an index that varies between 1 and 5 as in Elías et al. (2017). A value of 1 indicates that there is no law regulating abortion; an index value of 2 indicates that abortion is prohibited unless it would save the mother's life; a value of 3 that abortion is only allowed to protect the mother's physical or mental health; a value of 4 that additionally abortion is allowed if there are fetal abnormalities and in the case of rape or incest; and a value of 5 indicates that abortion is freely permitted. Hence, a higher value of the index indicates that abortion is more accessible. The median value of the index is 3, indicating

[19] The UN discontinued updating their abortion policy database in 2007.

that the typical country only allows abortion to protect the mother's health; the standard deviation is 1.3. 56 countries make at least one abortion policy change during the sample period; 6 countries experienced two abortion policy changes, with no countries experiencing more than two changes.

4.1.2 Cross-Country Specification

Fertility rates and agricultural employment share are very likely endogenously determined, each influencing the other. For example, an improvement in nonagricultural productivity may pull workers away from the farm and raise the returns to human capital, inducing parents to switch away from child quantity and into child quality (Galor 2005). We therefore need an exogenous shifter of fertility rates which is uncorrelated with factors shaping the agricultural employment share, conditional on controls.

We leverage variation in country policy changes to abortion access. Specifically, we estimate an event study of the effect of abortion policies on the agricultural employment share. Our specification is

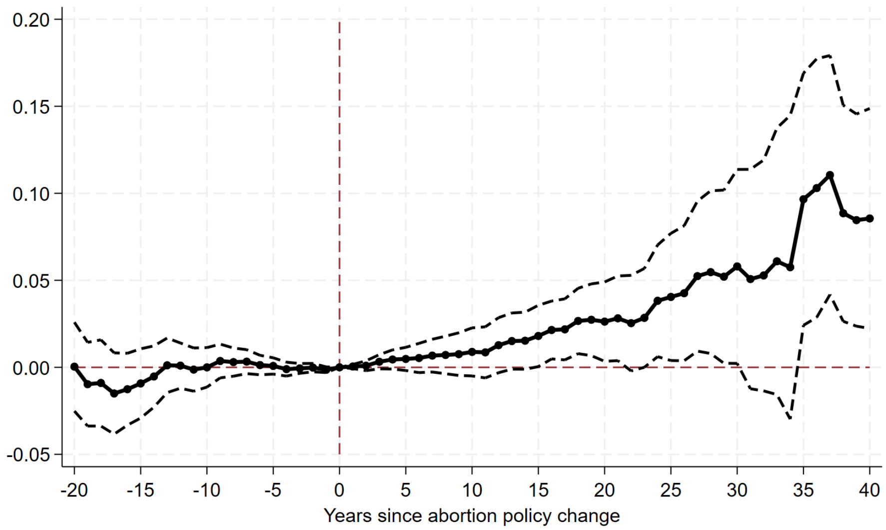
$$AES_{ct} = \alpha_c + \alpha_t + \sum_{\tau=T_0}^{T} \beta_\tau Abortion_{ct} + \epsilon_{ct} \tag{8}$$

where AES_{ct} is country c's agricultural employment share in year t. $Abortion_{ct}$ is equal to the magnitude of the change in the abortion policy index in country c in year t. β_τ then traces out the dynamic effect of abortion policy changes on the birth rate and agricultural employment share. α_c is a vector of country fixed effects and α_t a vector of year fixed effects. Given the continuous nature of the treatment—since multiple abortion policies may change at once, and abortion may become more or less accessible—we estimate equation (8) following De Chaisemartin and d'Haultfoeuille (2024). As robustness, we estimate the effect of abortion using a binary indicator when that equals one when the index is 5 and zero otherwise, with the results shown in Appendix Figure D.3.

4.1.3 Cross-Country Results

We show the results of estimating equation (8) in Figure 4, which shows the event study plot. We do not find evidence of pretrends. The effect of abortion policy changes on agricultural employment share takes a number of years to manifest, suggesting that the immediate effect of fertility reduction on labor force participation is modest. The average effect of a policy making abortion more accessible 15 to 40 years later is a 5 percentage point increase in agricultural employment share. Relative to a mean share of 0.37, this represents a 14 percent

Figure 4: Effect of Abortion Policy Changes on Agricultural Employment Share



Notes: The figure shows event study coefficient estimates for the effect of abortion policy changes on the agricultural employment share. 95% confidence intervals depicted with standard errors clustered at the country level. Data on country-level agricultural employment shares 1960–2020 comes from Wingender (2014b). Abortion policy change database compiled by Bloom et al. (2009). Estimated using the Stata command `did_multiplegt_dyn` by de Chaisemartin et al. (2024).

drop.[20]

We also estimate the effect of abortion policy on the birth rate using equation (8). Appendix Figure D.2 shows the result. We do not find strong evidence of pretrends, with 8 of 10 pre-policy change coefficients statistically insignificantly different from 0. A relaxation of abortion restrictions reduces the birth rate immediately and persistently. The average cumulative effect of a one point increase in the policy index (corresponding to abortion becoming more accessible) reduces the birth rate by 0.33 children per 1,000 population. Relative to a mean birth rate of 30, this implies a 1.3% reduction. This magnitude is very close to the 1.1 percent decline estimated by Bloom et al. (2009), whose sample differs slightly from ours.

Our cross-country results therefore suggest that the demographic transition slows down structural transformation. This is consistent with the modest human capital effects driven by the quality-quantity tradeoff found by Rosenzweig and Zhang (2009) and Bhalotra and Clarke (2020). Hence, the population size effect dominates.

There are two main drawbacks to our cross-country analysis. First, data may not be directly comparable across countries, and may require various assumptions and imputations to harmonize (see, for example, Behrman and Rosenzweig 1994 and Durlauf et al. 2005). To

[20] Appendix Figure D.3 depicts similar results using the binary abortion indicator for free abortion.

address this concerns, we turn next to a within-country analysis. Of course, disaggregating is not without drawbacks of its own as smaller regions are less likely to influence prices and hence we may miss out on some general equilibrium effects that we captured in the cross-country analysis.

4.2 U.S. State-level Analysis

We next consider a subnational analysis of the long-run effect of abortion policy changes on agricultural employment share. We do so leveraging the tightening of abortion access in the United States during the 19th century.[21]

As surgical abortions became more prevalent in the U.S. in the 1800s, a backlash followed, driving widespread implementation of abortion restrictions across the country. Lahey (2014) finds that the passage of these laws was not correlated to the immigrant population share, literacy rate, pre-law child-to-woman ratio, and, importantly for the present study, the urbanization rate. Lahey (2014) leverages the staggered rollout of these laws across U.S. states to estimate that abortion restrictions increased fertility by about 10 percent.[22]

To measure agricultural employment share, we use the decadal data compiled by Craig and Weiss (1998) for the period 1800 to 1900. These data are drawn from decennial census tabulations computed by the U.S. Census as well as estimates based on the Census microdata for the 1870 to 1900 waves. Imputations were necessary, especially in earlier census periods.[23] The dependent variable drawn from these data is the ratio of male agricultural workers ages 10 and older to the total population.[24] We provide additional details on the data and their construction in Appendix Section B.2.

We estimate the causal effect of abortion restrictions on agricultural employment share

[21] Other U.S. reproductive policy changes may come to mind but are not suitable for our analysis. The liberalization of abortion access in the 1960s and 1970s yields too little across-state variation over time, as most states were treated all at once with the 1973 Roe v. Wade Supreme Court decision. Regarding the 'power of the pill,' Myers (2017) argues that the rollout of oral contraception across the U.S. had little impact on fertility.

[22] Measures of abortion use across states and over time does not exist for 19th century America, unfortunately. Still, the responsiveness of fertility that Lahey (2014) finds is similar to magnitudes in other studies. For example, Fischer et al. (2018) estimate that policies reducing funding to family planning clinics and imposing burdensome regulations on abortion providers in Texas reduced abortions by 16.7% and increased fertility by 1.3%. Myers (2021) estimates that mandatory waiting periods for abortion reduced abortion takeup by almost 9% and raised fertility by 1.5%. Given the lack of alternative modern contraceptive options available to women in the 19th century, it is unsurprising that the fertility elasticity estimated by Lahey (2014) is larger than those estimated in modern contexts.

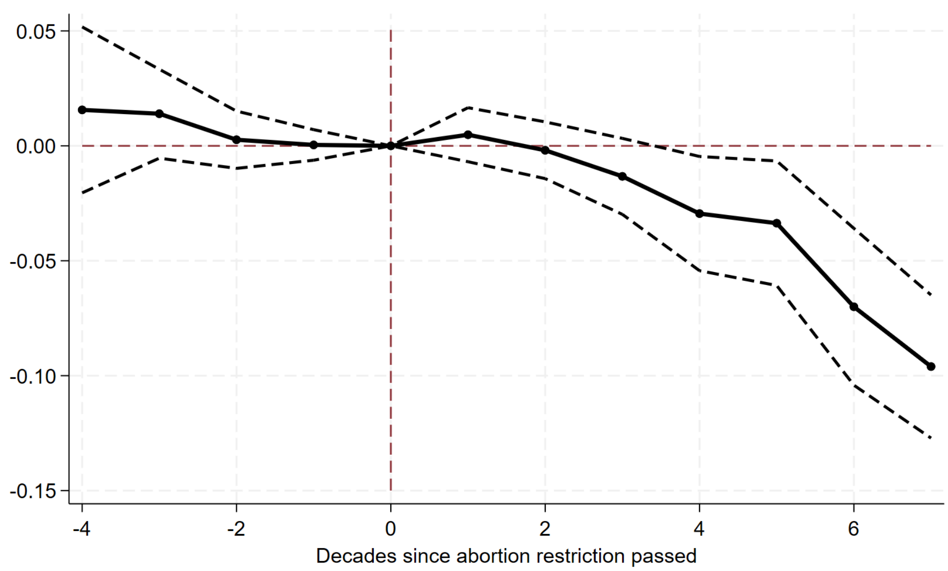
[23] We redo the estimation using the 1850–1900 full count census waves to construct agricultural employment share and our results do not change; see Appendix Figure D.4. See Appendix Section B.2 for more on the imputations implemented by Craig and Weiss (1998).

[24] We focus on male employment since female farm employment, primarily unpaid, was substantially undermeasured in official Census tabulations which focused on paid work (Ngai et al. 2024).

over time. Specifically, we estimate the staggered dynamic difference-in-differences following De Chaisemartin and d'Haultfoeuille (2020). Each abortion policy's passage is associated to the subsequent decennial census wave.

Figure 5 shows the resulting event study plot of our estimates. There are no differential trends in agricultural employment share prior to the implementation of abortion restrictions. After restrictions are in place, a negative effect on agricultural employment share begins to emerge, becoming statistically significantly negative four decades later. The delayed effect is consistent with the fact that affected cohorts must age into the labor market, and mirrors our findings in the cross-country estimates shown in Section 4.1. The implication is that increased fertility—a slower demographic transition—speeds up the movement of workers out of agriculture. In terms of the magnitude, agricultural employment share falls by almost 5 percentage points four decades after abortion was restricted, a 27% reduction. If the average abortion policy reduced fertility by 10% as suggested by Lahey (2014), then the resulting long-run fertility-agricultural employment share elasticity is 2.7.

Figure 5: Effect of Abortion Restriction on Agricultural Employment Share, U.S. States



Notes: Data on state-level agricultural employment shares 1800-1900 comes from Craig and Weiss (1998). Timing of abortion restrictions come from Lahey (2014) and Lahey and Wanamaker (2025). 95% confidence intervals depicted with standard errors clustered at the state level. Estimated using the Stata command `did_multiplegt_dyn` by de Chaisemartin et al. (2024).

We conduct two additional robustness checks of our main results. First, Appendix Figure D.5 shows the event study plot when excluding states that passed abortion restriction laws prior to 1840. Laws passed prior to 1840 were often part of larger bills and not enforced until much later. While fewer states and years are included, we still see a statistically and economically significantly negative effect of abortion restrictions on agricultural employment share four decades later.

Second, given the westward expansion of the U.S. throughout the 19th century, we cannot observe the agricultural employment shares for all states for all Census waves. In our baseline, we included an unbalanced panel of states. To gauge the degree to which our sampling composition of states drives our results, we show the event study plot when including only states that we observe in 1800 in Appendix Figure D.6. As in our baseline analysis, we observe no pretrend and a significantly negative effect of abortion restrictions three plus decades after passage. Because we only observe 20 states as of 1800, we bootstrap the clustered standard errors.

5 Back-of-the-Envelope Quantification

How much human capital investment would be needed to offset a fertility reduction's effect on agricultural employment share? And how does the effect of fertility reduction vary by country income? We take a first step towards answering these questions using our stylized framework and making back-of-the-envelope calculations.

Take equation (4) and substitute equation (3) for L_t. Define $\hat{x}$ as the proportional change in a variable x due to a change in parameters, such as the accessibility of family planning technologies. Then we have that changes in the agricultural employment share can be decomposed as follows:

$$\widehat{L_a/L} = -\frac{\hat{h}}{1-\theta} - \widehat{n_{-1}} - \hat{\ell}.$$

where we removed t subscripts for clarity. We consider three scenarios.

First, we compute the model's predicted agricultural employment share change in Matlab in the medium run, in which human capital is unaffected: $\widehat{L_a/L} = -\widehat{n_{-1}} - \hat{\ell}$. As shown in Appendix Table D.11, the program induced no change in average years of education across all adults 35 years later, as the treated cohorts are only a small fraction of the total population.

We assume the change in fertility $\widehat{n_{-1}}$ to be -15% (column 1 of Appendix Table D.6) and the change in labor supply $\hat{\ell}$ to be -1.9% (the average decline observed in column 6 of Table 1). The resulting predicted rise in agricultural employment share is 18.1%, slightly smaller than the percent change that we estimated in column 3 of Table 1.

Second, we consider the long-run effect of the program, i.e., allowing population average human capital to change. As the fraction of the population treated by vaccines approaches 1, we would expect years of education to rise in line with Barham (2012), Barham et al. (2021b), and Appendix Table D.11. We therefore consider a $\hat{h}$ equal to 0.057, the percent change in years of education induced by the program for vaccine recipients (column 4 of Appendix Table D.11). We also must calibrate the land cost share in agricultural production, $1 - \theta$. Using data from ICRISAT's Village Dynamics in South Asia project, Boppart et al. (2023) compute the land share to be 0.35 in Bangladesh. Adding in human capital substantially reduces the model's predicted impact of the program on the agricultural employment share to an 1.8% increase, as wages in nonagriculture rise with higher human capital. Hence our results suggest that in the long-run, the combined effect on agriculture employment share of fertility and early-childhood vaccines will dissipate. Still, a transitional period will occur in the meantime in which the Malthusian population size effect dominates the human capital effects.

Finally, we explore how our quantitative results would change for more developed countries. Boppart et al. (2023) show that the land cost share in agriculture decreases as income per capita rises, and that the highest income countries' value added share of land in agriculture is about 0.1. A high-income country would therefore only need a human capital increase of about 1.8% to offset a 16% reduction in population size. By contrast, a less-developed country like Bangladesh with a 0.35 agricultural land cost share requires 6.3% higher human capital to offset an equivalent fertility drop. Hence, a low-income country would have to raise human capital by 3.5 times more than a high-income country in order to offset an equal fertility reduction's effect on the agricultural employment share.

6 Conclusion

Fertility decline is an essential process by which countries escape the "Malthusian trap" of excess population growth, economic stagnation and poverty (Galor 2012). Yet technological progress raising the returns to human capital, and thus the investments in children by parents, is necessary to achieve sustained growth. In this paper, we show that fertility decline without sufficient accompanying technological advancement slows down structural transformation out of agriculture. We demonstrate this empirical relationship in varying contexts, using distinct sources of exogenous variation and levels of aggregation.

Our findings do not suggest that developing countries should avoid investing in family planning policies. Instead the modest effects of fertility decline on slowed structural transformation can be offset by investment in human capital. Policymakers should therefore take care to pair family planning programs with education and public health investments that raise human capital.

References

Daniel Aaronson, Rajeev Dehejia, Andrew Jordan, Cristian Pop-Eleches, Cyrus Samii, and Karl Schulze. The effect of fertility on mothers' labor supply over the last two centuries. *Economic Journal*, 131(633):1–32, 2021.

Daron Acemoglu. Theory, general equilibrium, and political economy in development economics. *Journal of Economic Perspectives*, 24(3):17–32, 2010.

Philipp Ager, Benedikt Herz, and Markus Brueckner. Structural change and the fertility transition. *Review of Economics and Statistics*, 102(4):806–822, 2020.

Quamrul H Ashraf, David N Weil, and Joshua Wilde. The effect of fertility reduction on economic growth. *Population and Development Review*, 39(1):97–130, 2013.

Tania Barham. Enhancing cognitive functioning: Medium-term effects of a health and family planning program in Matlab. *American Economic Journal: Applied Economics*, 4(1):245–73, 2012.

Tania Barham and Randall Kuhn. Staying for benefits: The effect of a health and family planning program on out-migration patterns in Bangladesh. *Journal of Human Resources*, 49(4):982–1013, 2014.

Tania Barham, Brachel Champion, Andrew D Foster, Jena D Hamadani, Warren C Jochem, Gisella Kagy, Randall Kuhn, Jane Menken, Abdur Razzaque, Elisabeth Dowling Root, et al. Thirty-five years later: Long-term effects of the Matlab maternal and child health/family planning program on older women's well-being. *Proceedings of the National Academy of Sciences*, 118(28):e2101160118, 2021a.

Tania Barham, Gisella Kagy, Brachel Champion, and Jena Hamadani. Early childhood health and family planning: Long-term and intergenerational effects on human capital. April 2021b.

Tania Barham, Randall Kuhn, and Patrick S Turner. No place like home: Long-run impacts of early child health and family planning on labor and migration outcomes. *Journal of Human Resources*, 2023.

Robert J Barro and Gary S Becker. Fertility choice in a model of economic growth. *Econometrica: journal of the Econometric Society*, pages 481–501, 1989.

Jere R Behrman and Mark R Rosenzweig. Caveat emptor: Cross-country data on education and the labor force. *Journal of Development Economics*, 44(1):147–171, 1994.

Sonia Bhalotra and Damian Clarke. The twin instrument: Fertility and human capital investment. *Journal of the European Economic Association*, 18(6):3090–3139, 2020.

Shushum Bhatia, W Henry Mosley, Abu SG Faruque, and Jotsnamoy Chakraborty. The Matlab family planning-health services project. *Studies in Family Planning*, 11(6):202–212, 1980.

David E Bloom, David Canning, and JP Sevilla. Economic growth and the demographic transition. Technical report, National Bureau of Economic Research Cambridge, Mass., USA, 2001.

David E Bloom, David Canning, Günther Fink, and Jocelyn E Finlay. Fertility, female labor force participation, and the demographic dividend. *Journal of Economic Growth*, 14:79–101, 2009.

Nicholas Bloom, Charles I Jones, John Van Reenen, and Michael Webb. Are ideas getting harder to find? *American Economic Review*, 110(4):1104–1144, 2020.

Timo Boppart, Patrick Kiernan, Per Krusell, and Hannes Malmberg. The macroeconomics of intensive agriculture. Technical report, National Bureau of Economic Research, 2023.

Ester Boserup. *The conditions of agricultural growth: The economics of agrarian change under population pressure*. George Allen & Unwin Ltd., 1965.

Francisco J Buera and Joseph P Kaboski. Scale and the origins of structural change. *Journal of Economic Theory*, 147(2):684–712, 2012.

Francisco J Buera and Ezra Oberfield. The global diffusion of ideas. *Econometrica*, 88(1): 83–114, 2020.

Francisco J Buera, Joseph P Kaboski, and Yongseok Shin. Finance and development: A tale of two sectors. *American Economic Review*, 101(5):1964–2002, 2011.

Francisco J Buera, Joseph P Kaboski, and Yongseok Shin. The macroeconomics of microfinance. *Review of Economic Studies*, 88(1):126–161, 2021.

Francesco Caselli and Wilbur John Coleman. The US structural transformation and regional convergence: A reinterpretation. *Journal of Political Economy*, 109(3):584–616, 2001.

Tiago Cavalcanti, Georgi Kocharkov, and Cezar Santos. Family planning and development: Aggregate effects of contraceptive use. *The Economic Journal*, 131(634):624–657, 2021.

Shoumitro Chatterjee and Tom Vogl. Escaping Malthus: Economic growth and fertility change in the developing world. *American Economic Review*, 108(6):1440–67, 2018.

T Terry Cheung. Schooling, skill demand, and differential fertility in the process of structural transformation. *American Economic Journal: Macroeconomics*, 15(4):305–330, 2023.

Uttam K Chowdhury, Bhajan K Biswas, T Roy Chowdhury, Gautam Samanta, Badal K Mandal, Gautam C Basu, Chitta R Chanda, Dilip Lodh, Khitish C Saha, Subhas K Mukherjee, et al. Groundwater arsenic contamination in Bangladesh and West Bengal, India. *Environmental Health Perspectives*, 108(5):393–397, 2000.

Lee A Craig and Thomas Weiss. Rural agricultural workforce by county, 1800 to 1900. Technical report, University of Kansas, 1998. URL https://eh.net/database/u-s-agricultural-workforce1800-1900/.

Clément De Chaisemartin and Xavier d'Haultfoeuille. Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–2996, 2020.

Clément De Chaisemartin and Xavier d'Haultfoeuille. Difference-in-differences estimators of intertemporal treatment effects. *Review of Economics and Statistics*, pages 1–45, 2024.

Clément de Chaisemartin, Diego Ciccia, Xavier D'Haultfœuille, Felix Knau, Mélitine Malézieux, and Doulo Sow. Did_multiplegt_dyn: Stata module to estimate event-study difference-in-difference (did) estimators in designs with multiple groups and periods, with a potentially non-binary treatment that may increase or decrease multiple times. Technical report, Boston College Department of Economics, 2024.

Matthew J Delventhal, Jesús Fernández-Villaverde, and Nezih Guner. Demographic transitions across time and space. Technical report, National Bureau of Economic Research, 2021.

Steven N Durlauf, Paul A Johnson, and Jonathan RW Temple. Growth econometrics. *Handbook of economic growth*, 1:555–677, 2005.

Julio J Elías, Nicola Lacetera, Mario Macis, and Paola Salardi. Economic development and the regulation of morally contentious activities. *American Economic Review*, 107(5):76–80, 2017.

Pablo Fajgelbaum and Stephen J Redding. Trade, structural transformation, and development: Evidence from argentina 1869–1914. *Journal of political economy*, 130(5):1249–1318, 2022.

Farid Farrokhi and Heitor S Pellegrina. Trade, technology, and agricultural productivity. *Journal of Political Economy*, 131(9):2509–2555, 2023.

Vincent Fauveau. *Matlab: Women, Children and Health*. Dhaka; ICDDR, B, 1994.

Stefanie Fischer, Heather Royer, and Corey White. The impacts of reduced access to abortion and family planning services on abortions, births, and contraceptive purchases. *Journal of Public Economics*, 167:43–68, 2018.

Oded Galor. From stagnation to growth: unified growth theory. *Handbook of economic growth*, 1:171–293, 2005.

Oded Galor. The demographic transition: causes and consequences. *Cliometrica*, 6(1):1–28, 2012.

Oded Galor and David N Weil. The gender gap, fertility, and growth. *American Economic Review*, 86(3):374, 1996.

Oded Galor and David N Weil. Population, technology, and growth: From Malthusian stagnation to the demographic transition and beyond. *American Economic Review*, 90(4): 806–828, 2000.

Gino Gancia and Fabrizio Zilibotti. Technological change and the wealth of nations. *Annual Review of Economics*, 1(1):93–120, 2009.

Douglas Gollin and Richard Rogerson. Productivity, transport costs and subsistence agriculture. *Journal of Development Economics*, 107:38–48, 2014.

Douglas Gollin, Stephen L Parente, and Richard Rogerson. The food problem and the evolution of international income levels. *Journal of Monetary Economics*, 54(4):1230–1255, 2007.

Douglas Gollin, David Lagakos, and Michael E Waugh. The agricultural productivity gap. *The Quarterly Journal of Economics*, 129(2):939–993, 2014.

Douglas Gollin, David Lagakos, Xiao Ma, and Shraddha Mandi. The dynamics of agricultural productivity gaps: An open-economy perspective. Technical report, National Bureau of Economic Research, 2025.

Jeremy Greenwood and Ananth Seshadri. The US demographic transition. *American Economic Review*, 92(2):153–159, 2002.

Berthold Herrendorf, James A Schmitz, Jr, and Arilton Teixeira. The role of transportation in us economic development: 1840–1860. *International Economic Review*, 53(3):693–716, 2012.

Hugo Hopenhayn, Julian Neira, and Rish Singhania. From population growth to firm demographics: Implications for concentration, entrepreneurship and the labor share. *Econometrica*, 90(4):1879–1914, 2022.

Douglas H Huber and Atiqur Rahman Khan. Contraceptive distribution in bangladesh villages: The initial impact. *Studies in Family Planning*, 10(8/9):246–253, 1979.

icddr,b. Matlab 1974 census, 1974.

icddr,b. Health and demographic surveillance system - Matlab, 1982.

Guido W Imbens and Jeffrey M Wooldridge. Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, 47(1):5–86, 2009.

Charles I Jones. The end of economic growth? Unintended consequences of a declining population. *American Economic Review*, 112(11):3489–3527, 2022.

Shareen Joshi and T Paul Schultz. Family planning as an investment in development: Evaluation of a program's consequences in Matlab, Bangladesh. *Yale University Economic Growth Center Discussion Paper*, (951), 2007.

Shareen Joshi and T. Paul Schultz. Family planning and women's and children's health: Long-term consequences of an outreach program in Matlab, Bangladesh. *Demography*, 50 (1):149–180, 2013.

Michael A. Koenig, Mehrab Ali Khan, Bogdan Wojtyniak, John D. Clemens, Jyotsnamoy Chakraborty, Vincent Fauveau, James F. Phillips, Jalaluddin Akbar, and Uday S. Barua. Impact of measles vaccination on childhood mortality in rural Bangladesh. *Bulletin of the World Health Organization*, 68(4):441, 1990.

Simon Kuznets. Quantitative aspects of the economic growth of nations: II. Industrial distribution of national product and labor force. *Economic Development and Cultural Change*, 5(S4):1–111, 1957.

David Lagakos. Urban-rural gaps in the developing world: Does internal migration offer opportunities? *Journal of Economic Perspectives*, 34(3):174–192, 2020.

David Lagakos, Ahmed Mushfiq Mobarak, and Michael E Waugh. The welfare effects of encouraging rural–urban migration. *Econometrica*, 91(3):803–837, 2023.

Joanna N Lahey. Birthing a nation: The effect of fertility control access on the nineteenth-century demographic transition. *Journal of Economic History*, 74(2):482–508, 2014.

Joanna N Lahey and Marianne H Wanamaker. Effects of restrictive abortion legislation on cohort mortality evidence from 19th century law variation. *Journal of Public Economics*, 243:105329, 2025.

Oksana M Leukhina and Stephen J Turnovsky. Population size effects in the structural development of England. *American Economic Journal: Macroeconomics*, 8(3):195–229, 2016.

W. Arthur Lewis. Economic development with unlimited supplies of labour. *The Manchester School*, 22(2):139–191, 1954.

Hongbin Li and Junsen Zhang. Do high birth rates hamper economic growth? *Review of Economics and Statistics*, 89(1):110–117, 2007.

Shelly Lundberg and Elaina Rose. The effects of sons and daughters on men's labor supply and wages. *Review of Economics and Statistics*, 84(2):251–268, 2002.

Thomas R. Malthus. *An Essay on the Principle of Population*. Online Library of Liberty, reprint, 1798. URL https://oll.libertyfund.org/titles/malthus-an-essay-on-the-principle-of-population-1798-1st-ed.

John McMillan and Christopher Woodruff. The central role of entrepreneurs in transition economies. *Journal of Economic Perspectives*, 16(3):153–170, 2003.

Jane Menken and James F. Phillips. Population change in a rural area of Bangladesh, 1967-87. *The Annals of the American Academy of Political and Social Science*, 510(1):87–101, 1990.

Caitlin Knowles Myers. The power of abortion policy: Reexamining the effects of young womenâs access to reproductive control. *Journal of Political Economy*, 125(6):2178–2224, 2017.

Caitlin Knowles Myers. Cooling off or burdened? the effects of mandatory waiting periods on abortions and births. 2021.

L Rachel Ngai, Claudia Olivetti, and Barbara Petrongolo. Gendered change: 150 years of transformation in US hours. Technical report, National Bureau of Economic Research, 2024.

James F. Phillips, Wayne S. Stinson, Shushum Bhatia, Makhlisur Rahman, and Jyotsnamoy Chakraborty. The demographic impact of the family planning–health services project in Matlab, Bangladesh. *Studies in Family Planning*, pages 131–140, 1982.

Tommaso Porzio, Federico Rossi, and Gabriella V. Santangelo. The human side of structural transformation. *American Economic Review*, 112(8):2774–2814, 2022.

O Rahman, J Menken, A Foster, C Peterson, MN Khan, R Kuhn, and P Gertler. The Matlab health and socio-economic survey: Overview and user's guide, 1999, 1999.

Mark R Rosenzweig and Junsen Zhang. Do population control policies induce more human capital investment? Twins, birth weight and China's "one-child" policy. *Review of Economic Studies*, 76(3):1149–1174, 2009.

Theordore W. Schultz. *The Economic Organization of Agriculture*. McGraw-Hill Book Company, Inc., 1953.

Michael Sposi. Evolving comparative advantage, sectoral linkages, and structural change. *Journal of Monetary Economics*, 103:75–87, 2019.

Holger Strulik. Contraception and development: A unified growth theory. *International Economic Review*, 58(2):561–584, 2017.

Trevor Tombe. The missing food problem: Trade, agriculture, and international productivity differences. *American Economic Journal: Macroeconomics*, 7(3):226–258, 2015.

United Nations. World population prospects 2024: Summary of results. Technical Report UN DESA/POP/2024/TR/NO. 9, United Nations Department of Economic and Social Affairs, Population Division, 2024.

Timothy Uy, Kei-Mu Yi, and Jing Zhang. Structural change in an open economy. *Journal of Monetary Economics*, 60(6):667–682, 2013.

Nico Voigtländer and Hans-Joachim Voth. The three horsemen of riches: Plague, war, and urbanization in early modern europe. *Review of Economic Studies*, 80(2):774–811, 2013.

Marianne H Wanamaker. Industrialization and fertility in the nineteenth century: Evidence from south carolina. *Journal of Economic History*, 72(1):168–196, 2012.

Gail A Wasserman, Xinhua Liu, Faruque Parvez, Habibul Ahsan, Diane Levy, Pam Factor-Litvak, Jennie Kline, Alexander van Geen, Vesna Slavkovich, Nancy J LoIacono, et al. Water manganese exposure and children's intellectual function in Araihazar, Bangladesh. *Environmental Health Perspectives*, 114(1):124–129, 2006.

Asger M Wingender. Structural transformation in the 20th century: Additional data documentation. Available online at https://drive.google.com/file/d/1yRdz9YYGpY2abz5b0Q$_v l9IngnlQyDRb/view$, 2014a.

Asger Moll Wingender. Structural transformation in the 20th century: A new database on agricultural employment around the world. *Available at SSRN 2533360*, 2014b.

Appendix

A Theoretical Appendix

In this section, we provide several extensions to our simple baseline model from Section 2.

A.1 Adding Intermediate Inputs

Assume the production function in agriculture is

$$Q_a = A_a Z_a^{\theta_z} L_a^{\theta_\ell} T_a^{1-\theta_z-\theta_\ell},$$

and in manufacturing, it is

$$Q_m = A_m Z_m^{\alpha} (L_m h)^{1-\alpha}, \tag{A.1}$$

where Z_a and Z_m are imported intermediate inputs used in each sector. The exogenous price of this input is p_z. One can think of the intermediate inputs as imported capital in the long-run (in which capital is fully adjustable) or as materials used in production.

The first order conditions imply that

$$\frac{w}{p_z} = \frac{\theta_\ell}{\theta_z}\frac{Z_a}{L_a} = \frac{1-\alpha}{\alpha}\frac{Z_m}{L_m}.$$

The wage is then

$$w = (p_m A_m)^{\frac{1}{1-\alpha}} (1-\alpha) \left(\frac{\alpha}{p_z}\right)^{\frac{\alpha}{1-\alpha}} h$$

and the agricultural employment share is

$$\frac{L_a^*}{L} = \left[\frac{(p_a A_a)^{\frac{1}{1-\theta_z}} \theta_\ell \theta_z^{\frac{\theta_z}{1-\theta_z}}}{p_z^{\frac{\theta_z}{1-\theta_z}} (p_m A_m)^{\frac{1}{1-\alpha}} (1-\alpha) \left(\frac{\alpha}{p_z}\right)^{\frac{\alpha}{1-\alpha}} h}\right]^{\frac{1-\theta_z}{1-\theta_\ell-\theta_z}} \frac{T}{L}.$$

As in the baseline model, $\frac{\partial L_a/L}{\partial L} < 0$ and $\frac{\partial L_a/L}{\partial h} < 0$.

A.2 Adding Intermediate Inputs and CES Functional Form

In Section A.1 we assumed that the elasticity of substitution between labor and intermediate inputs is equal to one. It may be more realistic, however, to allow for a substitution elasticity different than one, as suggested by Herrendorf et al. (2015) and Boppart et al. (2023).

Production of the manufacturing good is the same in Equation (A.1). Production of the agricultural good follows a hybrid Cobb-Douglas/Constant Elasticity of Substitution (CES) production process which requires land T_a, labor L_a, and imported intermediate inputs Z_a:

$$Q_a = A_a \left[\omega Z_a^{\frac{\epsilon-1}{\epsilon}} + (1-\omega) L_a^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\theta\epsilon}{\epsilon-1}} T_a^{1-\theta} \tag{A.2}$$

where Q_a is the quantity of agricultural goods produced, and A_a is Hicks-neutral agricultural productivity. $\epsilon > 0$ is the elasticity of substitution between intermediate inputs and labor, and the parameters ω and θ are between 0 and 1. ω governs the relative productivity of Z_a relative to L_a, while $1-\theta$ is the revenue share accruing to landowners.

The marginal product of labor in agriculture is

$$MPL_a = A_a(1-\omega)\theta L_a^{-\frac{1}{\epsilon}} \left[\cdot\right]^{\frac{\theta\epsilon}{\epsilon-1}-1} T_a^{1-\theta},$$

where $[\cdot]$ is the CES portion of equation (A.2). A key determinant of the wage is the quantity of the fixed factor, T_a, available. Given a fixed amount of land T_a, as the number of workers allocated to agriculture L_a increases, the returns to that labor decline.

In the manufacturing sector, the marginal product is

$$MPL_m = A_m(1-\alpha)\left(\frac{Z_m}{L_m}\right)^{\alpha} h^{1-\alpha},$$

where wages serve to pull workers in when human capital rises.

A.2.1 Equilibrium

Since we are considering a small open economy, prices of goods are exogenous and determined by world markets. Profit maximization implies that the value of marginal products across sectors equal the wage w:

$$p_a MPL_a = w = p_m MPL_m$$

which determines the equilibrium wage,

$$w^* = (1-\alpha)\left(p_m A_m\right)^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{p_z}\right)^{\frac{\alpha}{1-\alpha}} h, \tag{A.3}$$

which is rising in the price of manufacturing goods p_m, manufacturing productivity A_m, and human capital h. In contrast, wages are falling in the price of intermediate inputs p_z. Intuitively, due to the substitutability of workers with imported inputs, firms are able to maintain zero profits only when wages fall as the price of inputs rises.

The equilibrium wage plus land market clearing ($T_a = T$, where T is the aggregate endowment of land) determine the equilibrium share of labor working in agriculture:

$$\frac{L_a^*}{L} = \left(\Lambda \frac{\left[\left(\frac{\omega}{1-\omega}\right)^{\epsilon} \left(\frac{w^*}{p_z}\right)^{\epsilon-1} + 1 \right]^{\frac{\theta\epsilon}{\epsilon-1}-1}}{\left(\frac{\alpha}{1-\alpha}\frac{w^*}{p_z}\right)^{\alpha} h^{1-\alpha}} \right)^{\frac{1}{1-\theta}} \frac{T}{L}, \tag{A.4}$$

where $\Lambda \equiv \frac{(1-\omega)^{\frac{\theta\epsilon}{\epsilon-1}}\theta}{1-\alpha} \frac{p_a}{p_m} \frac{A_a}{A_m}$ is a collection of exogenous parameters.

The fraction of workers employed in the factory sector can be obtained using the labor market clearing constraint, $L = L_a + L_m$.

Furthermore, the equilibrium per-household use of intermediate inputs in agriculture is

$$\frac{Z_a^*}{L} = \left(\frac{\omega}{1-\omega}\frac{w^*}{p_z}\right)^{\epsilon} \frac{L_a^*}{L}. \tag{A.5}$$

A.2.2 Comparative Statics

We next assess the effect of the demographic transition on sectoral employment. As with our baseline model, we find contrasting effects of each channel on agricultural employment. The model generates two key empirical predictions:

(a) A relatively lower population L will result in an increased share of workers employed in the agricultural sector.

(b) The sign of the effect of a rise in average human capital h on the share of workers employed in the agricultural sector depends on parameter values, as detailed below.

In particular, we find that in the model $\frac{\partial L_a/L}{\partial h} < 0$ if and only if the below parameter restriction holds:

$$\frac{\left(\frac{\omega}{1-\omega}\right)^{\epsilon} \left(\frac{w^*}{p_z}\right)^{\epsilon-1}}{\left(\frac{\omega}{1-\omega}\right)^{\epsilon} \left(\frac{w^*}{p_z}\right)^{\epsilon-1} + 1} < \frac{1-\epsilon(1-\theta)}{p_z} \tag{A.6}$$

The term $\left(\frac{\omega}{1-\omega}\right)^{\epsilon}$ captures the productivity of Z relative to L in the agriculture sector and $(w^*/p_z)^{\epsilon-1}$ captures the corresponding relative cost of inputs. The product of these two terms, $\left(\frac{\omega}{1-\omega}\right)^{\epsilon} (w^*/p_z)^{\epsilon-1}$, is equal to 1 when agriculture is produced using a Cobb-Douglas production function. That is, when $\omega = 0.5$ and $\epsilon = 1$, as we assume for the manufacturing sector. Hence, the term on the left of inequality (A.6) indexes the difficulty of substituting between Z and L in agriculture relative to manufacturing and must be between 0 and 1.

On the right-hand side, the term $\epsilon(1-\theta)$ measures the ease of substituting between Z and L in agriculture, weighted by the importance of land $1-\theta$. This term equals 1 in manufacturing, in which $\epsilon = 1$ and the land cost share is 0. Hence the numerator $1-\epsilon(1-\theta)$ measures the difference between the weighted ease of substituting between Z and L between the manufacturing and agricultural sectors. The denominator p_z scales this difference by the cost of input Z.

Inequality (A.6) is most likely to hold (and hence $\frac{\partial L_a/L}{\partial h} < 0$) when a country is less developed: when manufacturing productivity and human capital are low, so long as the $\epsilon > 1$, as suggested by the estimates of Herrendorf et al. (2015) and Boppart et al. (2023). Hence, the net long-run effect of the demographic transition on industrialization is ambiguous for developing countries, and depends on the parameters which preferences and production, and hence the relative strength of the human capital versus population size effects.

For the most developed countries, on the other hand, the model suggests that both forces shift labor into the agricultural sector. This is because human capital increases essentially free-up labor to move into agriculture one labor is sufficiently productive.[25]

A.3 Partially Closed Economy

The effect of population on structural transformation necessarily depends on whether the economy is open or closed (Matsuyama 1992). Our baseline model assumes a fully open economy, but the predicted effect of population size on agricultural employment share would be reversed if the economy were fully closed, as the food problem dominates. In this section, consider the implications of nesting both closed and open economy cases by introducing trade costs.

No arbitrage implies that if sector x is exporting, then $P_x^W = P_x\tau$ otherwise, if sector x is importing, then $P_x^W = P_x/\tau$.

The price P_x is knowable with the following steps: (i) solve for the price P_x^{closed} when the economy is closed. (ii) compare P_x^{closed} to P_x^W to determine if m is exported or imported. (iii) set $P_x = P_x\tau$ if x is exported or $P_x = P_x/\tau$ if x is imported.

[25]Because developed countries are on the technological frontier, an endogenous growth model may be more appropriate however, which may instead pull workers into the innovative sector.

Hence, the equilibrium price of sector x's output is

$$P_x^* = \begin{cases} P_x^{cl} & \text{if } \tau P_x^W \geq P_x^{cl} \geq P_x^W/\tau \text{ (closed)} \\ \tau P_x^W & \text{if } \tau P_x^W < P_x^{cl} \text{ (importing)} \\ P_x^W/\tau & \text{if } P_x^W/\tau > P_x^{cl} \text{ (exporting)} \end{cases} \tag{A.7}$$

where P_x^W is the world price, P_x^{cl} is the prevailing local price given a closed economy, and τ is the iceberg trade cost.

If the agricultural sector is closed, consistent with Matsuyama (1992), the predicted effect of population size reverses. A larger population induces a higher agricultural employment share in order to feed the population. If the agricultural sector imports or exports, then consistent with our baseline model a greater population induces a lower agricultural employment share.

B Data Appendix

B.1 Matlab Health and Socioeconomic Survey

Our study relies on household-level and individual-level data collected through two waves of the Matlab Health and Socioeconomic Survey (MHSS1 and MHSS2). The first wave of the survey (MHSS1) collected in 1996 provides the sampling frame for our analysis. MHSS1 was a seven percent random sample survey of household compounds (i.e., baris) in the Matlab area. In each bari, two households were randomly selected for interview: a primary household selected randomly, and a secondary household selected purposively. Within a household, individuals (aged 6 or older) were randomly sampled for in depth interviews.

We begin by building a sample of households using the primary households that were randomly selected for interview in MHSS1. We select households where the household head was a respondent to Book 3 ("Adult Information") of the MHSS1 Household survey. From this set, we remove households where the household head could not be linked back to a treatment status or who could not be linked back to the Matlab area (i.e., the DSS) prior to the start of the MCH-FP in 1977. These criteria result in a set of 2,534 households. When measuring individual-level outcomes in MHSS1, we consider outcomes from Book 3 respondents from these households.

MHSS2 is a panel follow-up survey to the original MHSS1 Household survey that was collected between 2012 and 2014. The sample for MHSS2 includes all individuals who were from primary households in MHSS1 and were selected for personal interviews. The MHSS2 sample further includes the spouses of MHSS1 primary respondents, their descendants, and an additional sample of "pre-MHSS1" migrants who were individuals who had migrated out of the DSS from primary MHSSA households area prior to the collection of the survey. MHSS2 respondents were tracked throughout Bangladesh and intensive efforts were made to interview international migrants and difficult-to-track migrants when they returned to the study area to visit family. Migrants were intensively interviewed around Eid celebrations if they were visiting family in Matlab. Most data were collected in face-to-face interviews, so are not proxy reports. Fifteen percent of men in our sample, international migrants living abroad, were contacted using a phone survey.

We link outcomes measured in MHSS2 back to our sample of MHSS1 households either through the individuals from the MHSS1 households and their descendants, or based on the household-level outcomes in MHSS2 households where our sample members (and their descendants) reside. For that reason, an MHSS1 household may have sample members living in multiple MHSS2 households. Because of attrition, it is also the case that an MHSS1 household may not have had any respondents in the MHSS2 survey. Indeed, we are able to track outcomes in MHSS2 for 2,484 of the 2,534 MHSS1 household, just over 98 percent. For each outcome, we describe below how we aggregate both household-level and individual-level outcomes to the MHSS1 household-level.

Classifying Industry of Employment

Neither the MHSS1 nor the MHSS2 surveys asked respondents directly about their non-agricultural industry of employment. Therefore, we must classify industry using indirect measures. Moreover, because the survey questions differed between waves, we take slightly different approaches to industry classification for each survey round.

MHSS1. Employment information for MHSS1 come from three modules in the survey: (i) Book 2 Agricultural Employment (AE); (ii) Book 2 Non-Agricultural Employment (NAE); and (iii) Book 3 Employment (EMP). The household head was the respondent to the two modules from Book 2 and they provided information about household members' farm and off-farm employment. All work reported in the AE module was considered agricultural employment. We further classify agricultural and fishing occupations reported in NAE and EMP as agricultural employment. These occupations and their corresponding codes include: (1, 2) agriculturalist; (3) agricultural laborer; (24) fisherman; (65) husking, boiling, and drying paddy; (66) goat rearing; (67) duck or hen rearing; and (70) produce vegetables or fruits. We classify all other occupations as non-agricultural.

In each module (AE, NAE, and EMP) we observe the number of months that an individual spent working in their given occupation. To measure the amount of time an individual spends working in each sector, we sum the number of months an individual reports working in each sector across their different occupations. If that summation exceeds 12 months, we top code the amount of work in that sector at 12 months.

MHSS2. Employment information from MHSS2 come from two of the Book 3 Employment modules, Parts A and B. Part A of the Employment module (EMPA), collects information by activity type (e.g., salaried work, piece-rate work, work on the family farm, etc.) for work over the previous 12 months. From this module, we observe number of weeks worked by activity over the previous 12 months and the typical number of hours worked in that activity in a week, the product of which gives us our measure of annual hours worked in the activity.

Activities do not directly have an occupation attached to them. We assign these hours to a sector by merging the occupation code collected in Part B of the Employment module (EMPB) to the respective occupation. EMPB collects information on each individual's primary and secondary occupation and each are linked to an activity type. Because only two jobs are present in EMPB, some activities in EMPA are not assigned an occupation (i.e., they worked in an activity but it was not their primary/secondary occupation). Beyond occupation code, we use additional information from EMPB to help classify work.

We assign work into one of four sectors: manufacturing, agriculture, service, and construction.

We classify work into manufacturing using the following rules. First, we include all factory work. We determine factory work based on whether an individual works at a government or private factory mill (empb04). We further classify factory work based on occupation codes: garment factory worker (712); jute mill worker (713); food processing factory worker (714); and other factory machine operator (715). Finally, we rely on translated job titles and select occupation titles that include the words "factory" or "mill". In addition to factory work, we also classify crafts-making occupations as manufacturing, including the following occupations: sheet and structural metal supervisor, moulders, and welders (621); blacksmith or tool maker (622); handicraft worker (e.g. jewelry, fabrics, pottery, printing, hand embroidery) (630); food processing (e.g. baker, butcher, dried fish maker) (650); woodworking (e.g. treaters, cabinet makers, furniture maker) (651); garment and related trade workers (e.g. tailor, seamstress, machine embroidery, upholstery, tanning) (652); other craft workers (680); and mine worker or mineral processing (711).

To classify agricultural work, we rely on the activity types that work is reported by in EMPA, as well as occupation codes from EMPB. Two activities from EMPA are explicitly related to agriculture—work as an agricultural day laborer and work on a family farm. We further include work reported in other activities in EMPA if the corresponding occupation code from EMPB is related to agricultural work: farmer, own farm (511); farmer, sharecropper (512); raising cows, goats, or sheep (513); raising ducks or hens (514); fish farm or fish hatchery (515); fishing in river or sea (516); other agriculture or forestry production (517); and agricultural laborer (820). From these, we exclude any work that was classified as manufacturing because the occupation title included the words "mill" or "factory."

We classify a job in the service sector if the occupation corresponds to a purely service occupation, as well as other occupations not classified into the agriculture or manufacturing sector. We include occupation codes 100–442, which broadly represent work as managers (100s), professionals (200s), technicians and associate professionals (300s), and clerical support, sales workers and security (400s). Beyond these broad categories, we also include: skilled home finish or repair (612); machinery mechanics and repair (623); electrical and electronic appliance repair, maintenance and installation (640); traditional healer (660); traditional birth attendant (661); entry-level or non-degree healthcare worker (662); social worker (663); tutor (670); driver of car, van or motorcycle (730); driver of heavy equipment (731); driver of taxi, CNG, autorickshaw (732); domestic worker in home or office (811); caretaker, gardener, messenger, or doorman of home or office (812); rickshaw drive (813); boatman (814); street vendor or hawker (815); bearer or peon (816); food preparation assistant or kitchen helper (840); sweeper (860); refuse worker, sorter recycler, forager (870); and other daily laborer or elementary worker (890). We also include some records with occupation code 830 if the given occupation title was translated to be bus conductor, transport labor, tire business, transport worker, truck helper, and truck labor. Finally, any work that could not be classified with an occupation code (i.e., work reported in EMPA that did not have a corresponding job reported in EMPB) and was not in an agricultural activity was included in service.

The final sector we classify is the construction sector. Here we include work as: carpenter, skilled house builder, supervisor, house contractor, mason (611); construction or earth-work laborer, non-food for work (821); construction or earth-work laborer, food for work (822), and any remaining unclassified work as laborer in factory, mine, or transport (830). A relatively small share of work is in construction (about 7 percent among comparison households) so we do not report results for this sector.

Aggregating MHSS2 Outcomes to MHSS1 Households

Our MHSS2 sample includes individuals who resided in or descended from an MHSS1 household. Consequently, every MHSS2 respondent in our sample links back to a single MHSS1 household, making it relatively straightforward to aggregate individual-level outcomes to the

MHSS1 household level. When constructing measures of share of work time by sector, we first sum total hours worked and hours by sector to the MHSS1 household level. We then construct our sectoral share measures by dividing time spent working in a given sector by the total time spent working. When measuring binary outcomes at the individual level (e.g., whether an individual ever worked in a factory), we aggregate to the MHSS1 household level by averaging across respondents in the household.

MHSS2 respondents from a given MHSS1 household, however, reside in (potentially) multiple MHSS2 households, making it less straightforward to aggregate MHSS2 household-level outcomes to a single MHSS1 household. When constructing binary outcomes (e.g., does the household farm?), we aggregate to the MHSS1 household by asking whether any MHSS2 respondents from the household live in a household with that outcome (i.e., taking the maximum value across MHSS2 households with a sample member). When constructing continuous measures (e.g., acres of land owned by the household), we sum the amounts across the MHSS2 households, using each household's outcome only once regardless of the number of sample respondents residing in a given household.[26]

Accounting for Household-Level Attrition in MHSS2

The main results are weighted to account for household-level attrition between MHSS1 and MHSS2. Our analysis sample includes 2,534 households selected from the primary MHSS1 sample. We are able to track outcomes into MHSS2 for more than 98 percent of them. To account for this small amount of attrition, we construct inverse propensity weights that predict household-level attrition using the set of baseline characteristics reported in Table D.1 as well as their interaction with treatment assignment. Similarly, in our individual-level analysis we construct weights to account for attrition in MHSS2 among our individual panel sample following (Barham et al. 2023).

B.2 U.S. State-level Data Construction

This section summarizes the data construction decisions taken by Craig and Weiss (1998) to generate agricultural employment to population ratios for each U.S. state between 1800 and 1900.

States appear in the data over time as the U.S. expanded westward and the Census Bureau began covering them. Our interest is in computing the agricultural employment to

[26] In principle, individuals from two separate MHSS1 households could reside in the same MHSS2 household. In those cases, the household's outcome is used in constructing the outcome for each MHSS1 household. In practice, this was very rare, which makes sense given the low sampling rate in MHSS1.

population ratio over time. The denominator, the total population, is readily available from the U.S. Census.[27]

The numerator, the agricultural workforce, is trickier to compute and requires some assumptions and imputations. Craig and Weiss (1998) focus on rural agricultural employment;[28] we further restrict our focus to male workers, since unpaid work, which was disproportionately done by women, was substantially undermeasured by the Census (Goldin 1990; Ngai et al. 2024). Agricultural employment is measured for those age 10 and up.

The approach to imputing male agricultural employment differs between the antebellum and post-civil war periods. For censuses conducted between 1870 and 1900, agricultural work was imputed based on each respondent's occupation. For occupations with an ambiguous sector, specifically "laborers not otherwise specified," Craig and Weiss (1998) used the 1910 census's proportion of such workers by industry among workers living in rural areas. 1910 was the first census wave in which industry was asked of respondents. This approach contrasts with the IPUMS's construction of a consistent industry variable (`ind1950`) across census waves, in which they do not imput an industry for "non classifiable" workers.[29] As a robustness check, we show very similar results to our baseline in Figure D.4 when using the 1850 to 1900 full count censuses from IPUMS (Ruggles et al. 2024). We stick with the data of Craig and Weiss (1998) as our baseline to maximize comparability and consistency in data construction across census waves.

For censuses conducted between 1800 and 1860, we sum free and enslaved farm workforces. Craig and Weiss (1998) directly observe state-level male agricultural employment for those 16 and older in 1850 and 1860. They impute free male agricultural employment among those age 10–15 using both the fraction residing in rural areas as of 1860 and the fraction of rural residents employed in agriculture within the 10–15 age group. For enslaved people within the same age group, Craig and Weiss (1998) allocate a fraction of rural enslaved people age 10 and older to agriculture according to patterns observed in the 1820 and 1840 censuses, following Weiss (1992). Again, we emphasize that results are little changed when using the complete count census waves from 1850 onwards by Ruggles et al. (2024).

For the 1820 and 1840 waves, Weiss (1992) notes in his appendix several shortcomings in census tabulations. These include nonexhaustive industry coverage, the exclusion of some enslaved people, and seemingly arbitrary variation in demographic and industry coverage across states related to local census supervisors' discretion. This leads to the presence of

[27] See, for example, `https://www2.census.gov/library/publications/decennial/1850/1850a/1850a-02.pdf` for the state population between 1800 and 1850.

[28] This is comparable to the use of urbanization rates as a proxy for nonagricultural employment shares by Wingender (2014b).

[29] See `https://usa.ipums.org/usa-action/variables/IND1950#comparability_section`.

many outliers. Weiss corrects these outliers using the following procedure. First, he identifies counties within the same census year that exhibited reliable coverage, or looks to other census years when coverage was more reliable. In many cases, Weiss uses observations from these reliable counties/years to impute values for unreliable counties.

For census years 1800, 1810, and 1830, additional imputations were done by Weiss (1992). These relied primarily on the 1820 and 1840 waves, but, in some cases, also the 1860 census.

C Maternal and Child Health and Family Planning Program Details

In this appendix, we describe in greater detail the Matlab Maternal and Child Health and Family Planning program, or MCH-FP. Program interventions were phased in over time. Between 1977 and 1981, program services focused on family planning and maternal health through the provision of modern contraception, tetanus toxoid vaccinations for pregnant women, and iron folic acid tables for women in the last trimester of pregnancy (Bhatia et al. 1980). Take up of tetanus toxoid was low during this period at less than 30 percent of eligible women (Chen et al. 1983). Health workers provided a variety of family planning methods in the homes of the beneficiaries including condoms, oral pills, vaginal foam tablets, and injectables. In addition, beneficiaries were informed about fertility control services provided by the project in health clinics such as intrauterine device insertion, tubectomy, and menstrual regulation. During these visits the female health worker also provided counseling on contraception, nutrition, hygiene, and breastfeeding, and motivated women to continue using contraceptives. These services were supported by followup and referral systems to manage side effects and continued use of contraceptives (Phillips et al. 1982; Fauveau 1994).

Program implementation followed the planned timeline, and uptake was rapid as evidenced by the takeup of two key interventions: family planning and the measles vaccine (see Figure D.7). Prior to the program, the contraceptive prevalence rate (CPR) for married women 15–49 was low ($<$ 6 percent) in both the treatment and comparison areas. The CPR reached 30 percent in the treatment area in the first year, then rose steadily, reaching almost 50 percent by 1988. Because contraceptives were also provided by the government, the CPR increased in the comparison area, but not as quickly, and remained below 20 percent in 1988. By 1990, there was still a 20 percentage point difference in the CPR rate between the two areas. The measles vaccination rate rose to 60 percent in 1982 after it was introduced in half of the treatment area, and in 1985 when it was introduced in the other half as shown in Figure D.7. By 1988, coverage rates for children aged 12–23 months living in the treatment area were 93 percent for the vaccine against tuberculosis, 83 percent for all three doses of the vaccines against diptheria, pertussis, tetanus, and polio, 88 percent for measles, and 77 percent across all three major immunizations (icddr,b 2007). Government services did not regularly provide measles vaccination for children until around 1989, so the comparison area was an almost entirely unvaccinated population (Koenig et al. 1991). Nationally, measles vaccination for children under the age of five was less than 2 percent in 1986 (Khan 1998) and was below 40 percent in the comparison area in 1990 (Fauveau 1994).

Online Appendix References

Tania Barham, Randall Kuhn, and Patrick S Turner. No place like home: Long-run impacts of early child health and family planning on labor and migration outcomes. *Journal of Human Resources*, 2023.

Shushum Bhatia, W Henry Mosley, Abu SG Faruque, and Jotsnamoy Chakraborty. The Matlab family planning-health services project. *Studies in Family Planning*, 11(6):202–212, 1980.

David E Bloom, David Canning, Günther Fink, and Jocelyn E Finlay. Fertility, female labor force participation, and the demographic dividend. *Journal of Economic Growth*, 14:79–101, 2009.

Timo Boppart, Patrick Kiernan, Per Krusell, and Hannes Malmberg. The macroeconomics of intensive agriculture. Technical report, National Bureau of Economic Research, 2023.

Lincoln C Chen, Makhlisur Rahman, Stan D'Souza, J Chakraborty, and AM Sardar. Mortality impact of an MCH-FP program in Matlab, Bangladesh. *Studies in Family Planning*, pages 199–209, 1983.

Lee A Craig and Thomas Weiss. Rural agricultural workforce by county, 1800 to 1900. Technical report, University of Kansas, 1998. URL `https://eh.net/database/u-s-agricultural-workforce1800-1900/`.

Clément de Chaisemartin, Diego Ciccia, Xavier D'Haultfœuille, Felix Knau, Mélitine Malézieux, and Doulo Sow. Did_multiplegt_dyn: Stata module to estimate event-study difference-in-difference (did) estimators in designs with multiple groups and periods, with a potentially non-binary treatment that may increase or decrease multiple times. Technical report, Boston College Department of Economics, 2024.

Matthew J Delventhal, Jesús Fernández-Villaverde, and Nezih Guner. Demographic transitions across time and space. Technical report, National Bureau of Economic Research, 2021.

Vincent Fauveau. *Matlab: Women, Children and Health*. Dhaka; ICDDR, B, 1994.

Claudia Goldin. *Understanding the gender gap: An economic history of American women*. National Bureau of Economic Research, 1990.

Berthold Herrendorf, Christopher Herrington, and Akos Valentinyi. Sectoral technology and structural transformation. *American Economic Journal: Macroeconomics*, 7(4):104–133, 2015.

icddr,b. Health and demographic surveillance system - Matlab, 2007.

M Mahmud Khan. *Expanded Program on Immunization in Bangladesh: Cost, cost-effectiveness, and financing estimates*. Number 24. Partnerships for Health Reform, 1998. URL http://www.path.org/vaccineresources/files/Abt-PNACH278.pdf.

Michael A Koenig, Vincent Fauveau, and Bogdan Wojtyniak. Mortality reductions from health interventions: The case of immunization in Bangladesh. *Population and Development Review*, pages 87–104, 1991.

Joanna N Lahey. Birthing a nation: The effect of fertility control access on the nineteenth-century demographic transition. *Journal of Economic History*, 74(2):482–508, 2014.

Joanna N Lahey and Marianne H Wanamaker. Effects of restrictive abortion legislation on cohort mortality evidence from 19th century law variation. *Journal of Public Economics*, 243:105329, 2025.

Kiminori Matsuyama. Agricultural productivity, comparative advantage, and economic growth. *Journal of Economic Theory*, 58(2):317–334, 1992.

L Rachel Ngai, Claudia Olivetti, and Barbara Petrongolo. Gendered change: 150 years of transformation in US hours. Technical report, National Bureau of Economic Research, 2024.

James F. Phillips, Wayne S. Stinson, Shushum Bhatia, Makhlisur Rahman, and Jyotsnamoy Chakraborty. The demographic impact of the family planning–health services project in Matlab, Bangladesh. *Studies in Family Planning*, pages 131–140, 1982.

Steven Ruggles, Matt A. Nelson, Matthew Sobek, Catherine A. Fitch, Ronald Goeken, J. David Hacker, Evan Roberts, and J. Robert Warren. Ipums ancestry full count data: Version 4.0 [dataset], 2024. URL https://doi.org/10.18128/D014.V4.0.

United Nations. Classification of individual consumption according to purpose (COICOP). Department of economic and social affairs, statistical papers series m no. 99, 2018.

Thomas Weiss. US labor force estimates and economic growth, 1800-1860. In Robert E. Gallman and John Joseph Wallis, editors, *American Economic Growth and Standards of Living before the Civil War*, pages 19–78. University of Chicago Press, 1992.

Asger Moll Wingender. Structural transformation in the 20th century: A new database on agricultural employment around the world. *Available at SSRN 2533360*, 2014.

D Additional Tables and Figures

Table D.1: Baseline Balance

	Treatment Area		Comparison Area		Difference in Means		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mean	SD	Mean	SD	Diff.	T-stat	Diff./SD
Land size 1982 (decimals)	11.68	(15.96)	11.06	(16.19)	-0.62	-0.72	-0.03
Bari size	8.06	(5.50)	8.87	(5.99)	0.81	1.75	0.08
Family size	6.87	(2.95)	7.01	(2.94)	0.15	1.14	0.04
Wall tin or tin mix (=1)	0.314	(0.460)	0.317	(0.462)	0.003	0.13	0.01
Tin roof (=1)	0.833	(0.370)	0.828	(0.375)	-0.005	-0.26	-0.01
Number of boats	0.672	(0.623)	0.667	(0.630)	-0.006	-0.13	-0.01
Owns a lamp (=1)	0.613	(0.484)	0.652	(0.473)	0.040	1.08	0.07
Owns a watch (=1)	0.149	(0.354)	0.160	(0.364)	0.011	0.58	0.03
Owns a radio (=1)	0.080	(0.269)	0.081	(0.271)	0.001	0.10	0.00
Number of rooms (per capita)	0.206	(0.097)	0.212	(0.102)	0.007	1.49	0.06
Number of cows	1.29	(1.73)	1.45	(1.70)	0.16	1.81	0.08
Latrine (=1)	0.864	(0.341)	0.821	(0.381)	-0.043	-1.62	-0.06
Drinking water, tubewell (=1)	0.163	(0.367)	0.322	(0.464)	0.159	4.14	0.20
Drinking water, tank (=1)	0.321	(0.464)	0.394	(0.485)	0.073	1.40	0.05
HH head < 2 years education	0.610	(0.485)	0.564	(0.493)	-0.046	-1.84	-0.07
HH head works in agriculture (=1)	0.592	(0.489)	0.596	(0.487)	0.004	0.15	0.01
HH head works in fishing (=1)	0.063	(0.241)	0.055	(0.227)	-0.008	-0.49	-0.02
HH head works in business (=1)	0.096	(0.293)	0.125	(0.329)	0.029	1.40	0.07
HH head age	46.24	(13.38)	47.17	(13.72)	0.93	1.76	0.07
HH head spouse < 2 years education	0.844	(0.334)	0.806	(0.366)	-0.038	-2.02	-0.09
HH head spouse's age	36.04	(10.29)	36.65	(10.81)	0.62	1.32	0.06
1996 HH head Muslim	0.959	(0.199)	0.839	(0.367)	-0.119	-3.47	-0.34

Notes: The sample includes MHSS1 households where the household head could be traced back to the DSS area before 1977 and that had at least one household member or descendant who appeared in the MHSS2 survey. Unless otherwise noted, household characteristics come from the 1974 census. MHSS1 household baseline (1974) characteristics are traced back from the MHSS1 head. Standard deviations (SD) are clustered at the treatment village level. There are 1,176 treatment area households and 1,308 comparison area households. Standard deviations used in Column (7) come from comparison area households.

Table D.2: ITT Effects of MCH-FP on Farming and Land Ownership

	MHSS1 (1996)		MHSS2 (2012-2014)	
	(1) =1 if household farms	(2) Acres owned	(3) =1 if household farms	(4) Acres owned
Treatment	0.033	-0.044	0.040**	0.017
	(0.028)	(0.108)	(0.017)	(0.097)
% chg. rel. to mean	4.9	-2.7	5.0	1.3
Mean	0.68	1.61	0.80	1.33
Baseline controls	Y	Y	Y	Y
Observations	2525	2525	2484	2482

Notes: The table presents estimates of equation (5) for outcomes aggregated to the MHSS1 household-level and measured in 1996 (columns 1 and 2) and 2014 (columns 3 and 4). Variable means refer to the comparison area. Standard errors are clustered by the 1996 household head's pre-program village. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table D.3: ITT Effects of MCH-FP on Long-term Entrepreneurship and Employer Characteristics: Household-Level

	Entrepreneurship by Sector					
	(1)	(2)	(3)	(4)	(5)	(6)
	Agriculture	Manufacturing	Services	Ever worked in factory	Currently works in factory	Works at employer with > 100 employees
Treatment	0.04***	0.00	0.01	-0.02**	-0.02***	-0.02**
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
% chg. rel. to mean	19.9	5.4	3.6	-14.4	-22.6	-20.5
Mean	0.22	0.02	0.14	0.15	0.08	0.08
Baseline controls	Y	Y	Y	Y	Y	Y
Observations	2484	2484	2484	2484	2484	2484

Notes: The table presents estimates of the effect of the MCH-FP on 2014 outcomes aggregated to the MHSS1 household level. Each dependent variable is the share of household members exhibiting the described behavior. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table D.4: ITT Effects of MCH-FP on Long-term Work Hour Shares by Sector and Urbanicity: Household-Level

	(1) Urban Agriculture	(2) Urban Manufacturing	(3) Urban Services	(4) Rural Agriculture	(5) Rural Manufacturing	(6) Rural Services
Treatment	0.008	-0.028***	-0.008	0.031**	0.006	-0.002
	(0.005)	(0.010)	(0.020)	(0.014)	(0.009)	(0.017)
% chg. rel. to mean	205.6	-18.4	-3.3	15.4	12.7	-0.7
Mean	0.00	0.15	0.24	0.20	0.05	0.24
Baseline controls	Y	Y	Y	Y	Y	Y
Embankment control	Y	Y	Y	Y	Y	Y
Observations	2488	2488	2488	2488	2488	2488

Notes: The table presents estimates of equation 5 for outcomes at the MHSS1 household-level. Variable means refer to the comparison group. Standard errors are clustered by the 1996 household head's pre-program village. The dependent variable is the share of hours worked within the household in different sectors and in different locations. See Appendix B.1 for more details on how we classify workers into sectors. Due to changes between survey waves, sectors are constructed differently in the MHSS1 and MHSS2, and therefore are not directly comparable. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table D.5: ITT Effects of MCH-FP on Work Time Shares by Sector: Household-Level, Robustness

	MHSS1 (1996)		MHSS2 (2012–2014)			
	(1) Agriculture Share	(2) Non-Agriculture Share	(3) Agriculture Share	(4) Manufacturing Share	(5) Services Share	(6) Annual Hours Per Person
Panel A: Full Sample						
Treatment	0.007	0.004	0.041***	-0.032**	-0.013	-27.083
	(0.021)	(0.021)	(0.014)	(0.014)	(0.018)	(35.457)
% chg. rel. to mean	1.1	1.2	19.9	-15.8	-2.8	-1.9
Mean	0.68	0.36	0.21	0.20	0.48	1445.47
Observations	2534	2534	2484	2484	2484	2484
Panel B: Within 3km of Treatment Border						
Treatment	-0.009	0.010	0.029*	-0.007	-0.013	-5.758
	(0.027)	(0.027)	(0.017)	(0.017)	(0.023)	(40.947)
% chg. rel. to mean	-1.2	3.0	13.4	-3.8	-2.8	-0.4
Mean	0.71	0.34	0.22	0.18	0.48	1425.30
Observations	1718	1718	1686	1686	1686	1686
Panel C: Only Muslim Households						
Treatment	0.003	0.009	0.035**	-0.032**	-0.007	-27.852
	(0.022)	(0.022)	(0.015)	(0.015)	(0.018)	(36.094)
% chg. rel. to mean	0.5	2.7	16.7	-16.1	-1.4	-1.9
Mean	0.68	0.35	0.21	0.20	0.48	1440.58
Observations	2286	2286	2241	2241	2241	2241
Panel D: Exclude Main City						
Treatment	0.018	-0.003	0.057***	-0.041***	-0.014	-60.979
	(0.023)	(0.023)	(0.014)	(0.015)	(0.020)	(39.354)
% chg. rel. to mean	2.6	-0.9	27.1	-19.7	-3.1	-4.2
Mean	0.68	0.35	0.21	0.21	0.47	1446.75
Observations	2064	2064	2020	2020	2020	2020

Notes: The table presents estimates of equation 5 for outcomes at the MHSS1 household-level. Variable means refer to the comparison group. Standard errors are clustered by the 1996 household head's pre-program village. Columns (1) and (2) measure outcomes in the 1996 MHSS1, while Columns (3) through (5) measure outcomes in the 2012–2015 MHSS2. MHSS1 ourcomes are the share of working months in the year in which household members could work allocated to each sector. MHSS2 outcomes are the share of hours worked by sector within the household. Panel A uses the full sample of households. Panels B and C restrict the sample to households from villages within 3km of the treatment border and Muslim households, respectively. Panel D excludes households whose pre-program village is within the Matlab town boundary. See Appendix B.1 for more details on how we classify workers into sectors. Due to changes between survey waves, sectors are constructed differently in the MHSS1 and MHSS2, and therefore are not directly comparable. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table D.6: ITT Effects of MCH-FP on Household Size and Composition

	(1) Number of Men Age 24–34	(2) Number of Women Age 24–34
Treatment	-0.16***	-0.10***
	(0.04)	(0.04)
% chg. rel. to mean	-16.2	-11.4
Mean	0.98	0.90
Baseline controls	Y	Y
Observations	2484	2484

Notes: The table presents estimates of the effect of the MCH-FP on 2014 outcomes at the MHSS1 household-level. Variable means refer to the comparison group. Standard errors are clustered by pre-program village. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table D.7: ITT Effects of MCH-FP on Long-term Work Hour Shares by Sector: Individual-Level, Women

	Share hours by sector				
	(1)	(2)	(3)	(4)	(5)
	Agriculture	Manufacturing	Services	Non-Market	Hours worked
Treatment × Born 1982–1988	0.05***	0.01	-0.01	-0.05*	46.22
	(0.02)	(0.02)	(0.02)	(0.03)	(58.65)
Treatment × Born 1977–1981	-0.03	-0.02	0.03	0.01	-90.23
	(0.03)	(0.02)	(0.02)	(0.04)	(83.72)
Treatment × Born Pre-1977	-0.00	-0.00	0.01	-0.00	-4.31
	(0.02)	(0.01)	(0.01)	(0.02)	(29.08)
% chg. (1982–88)	40.8	6.7	-8.0	-7.8	10.9
% chg. (1977–81)	-12.5	-16.4	44.7	2.3	-17.5
% chg. (Pre-1977)	-0.6	-8.8	23.2	-0.7	-1.1
Comparison mean (1982–88)	0.12	0.12	0.08	0.67	423.77
Comparison mean (1977–81)	0.21	0.11	0.07	0.61	514.93
Comparison mean (Pre-1977)	0.36	0.03	0.05	0.56	392.90
Observations	4628	4628	4628	4628	4628

Notes: The table presents estimates of the effect of the MCH-FP on 2014 outcomes for women at the individual level. Means by age group refer to the comparison area. Standard errors are clustered by pre-program village. Regressions are weighted to adjust for attrition between the MHSS1 and MHSS2 surveys. All variables control for the baseline controls listed in Table D.1 as well as erosion exposure. The dependent variable in columns (1) through (3) is the fraction of total hours worked by sector. See Appendix B.1 for more details on how we classify workers into sectors. Employment shares do not sum to 1 for two reasons. First, we do not report results for two small sectors, construction and mining. Second, a small set of respondents do not work and are coded as spending 0 percent of their time working in each of the given sectors. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table D.8: ITT Effects of MCH-FP on Revenue and Profits per Acre

	Revenue per acre		Profit per acre	
	(1) Min. Price	(2) Max. Price	(3) Min. Price	(4) Max. Price
Treatment	34.604	28.261	18.641	12.298
	(37.612)	(47.956)	(29.487)	(40.644)
% chg. rel. to mean	10.1	5.4	11.8	3.7
Mean	341.02	519.65	157.64	336.28
Baseline controls	Y	Y	Y	Y
Observations	2003	2003	2003	2003

Notes: The table presents estimates of the effect of the MCH-FP on 2014 outcomes at the MHSS1 household-level. Standard errors are clustered by pre-program village. Revenues are constructed for each crop and are equal to the total amount of the crop harvested (in kilograms) multiplied by the prevailing national price (per kilogram). Prices are derived from the national Bangladeshi statistical yearbooks 2012–2014. Minimum (maximum) prices are the minimum (maximum) price listed in the yearbook for a given year within a crop type (e.g., Paddy Aman) among all varieties of that crop type (e.g., coarse or fine). Profits are equal to revenues net of cost of inputs (e.g., seeds, fertilizers, pesticides, irrigation, tilling, and labor for cultivation). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table D.9: ITT Effects of Consumption Shares by Sector

	(1) Agriculture	(2) Manufacturing	(3) Services
Treatment	-0.01	-0.00	0.01*
	(0.01)	(0.00)	(0.01)
% chg. rel. to mean	-2.6	-2.5	5.8
Mean	0.52	0.19	0.25
Baseline controls	Y	Y	Y
Observations	2013	2013	2013

Notes: The table presents estimates of the effect of the MCH-FP on 2014 consumption outcomes aggregated to the MHSS1 household-level. Consumption within MHSS2 households is summed within the MHSS1 household. The sample is restricted to MHSS1 households where MHSS2 consumption was observed within at least one household. Consumption goods classified into sectors based on United Nations (2018). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table D.10: Mincer Regressions, Returns to Experience and Education by Sector

	(1) Agriculture	(2) Manufacturing	(3) Services
Years of education	0.025**	0.047***	0.062***
	(0.010)	(0.008)	(0.004)
Age	0.019	0.129***	0.057***
	(0.024)	(0.023)	(0.015)
Age squared	-0.000	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)
Average wage (Taka)	46	58	91
Average years of education	3.6	6.7	7.0
Average age	46.9	36.3	39.9
Observations	1129	650	2465

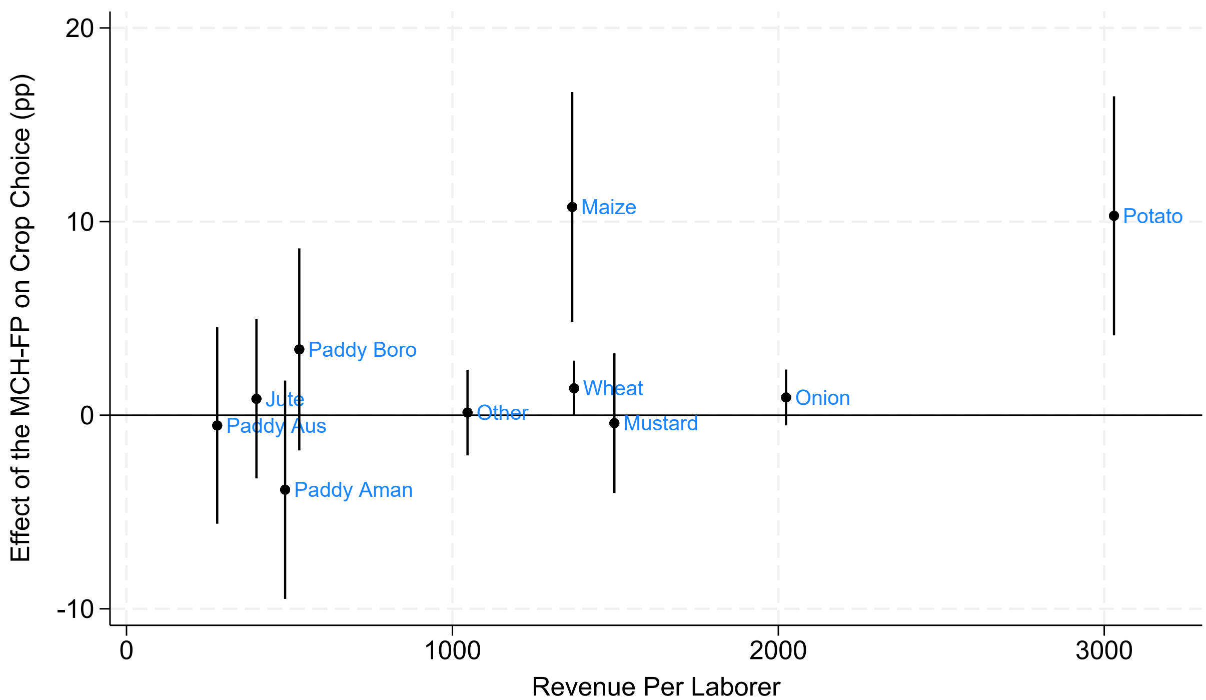
Notes: The table presents estimates from a Mincer wage regression by sector. The dependent variable—log hourly wage—is calculated based on earnings and hours worked in a sector. The sample includes MHSS2 respondents who are MHSS1 household members or their descendants, and is restricted to men born between 1947 and 1988. Heteroskedasticity-robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table D.11: ITT Effects of MCH-FP on Years of Education

	All Adults			Adults Born 1982–1988		
	(1) Pooled	(2) Men	(3) Women	(4) Pooled	(5) Men	(6) Women
Treatment	-0.002	0.049	-0.011	0.406**	0.695**	0.147
	(0.132)	(0.158)	(0.134)	(0.200)	(0.279)	(0.205)
% chg. rel. to mean	-0.0	0.8	-0.2	5.7	9.8	2.0
Mean	5.51	6.06	4.79	7.18	7.08	7.20
Baseline controls	Y	Y	Y	Y	Y	Y
Observations	2483	2358	2373	1463	935	946

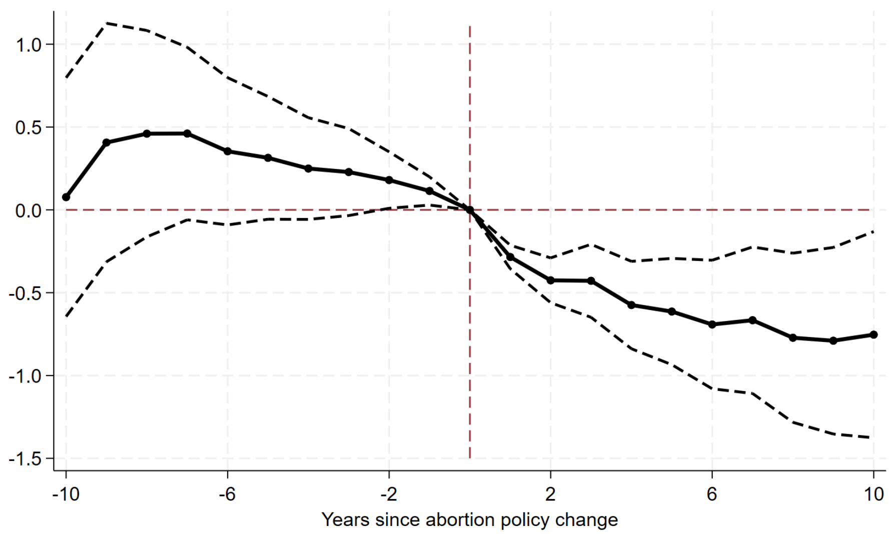
Notes: The table presents estimates of the effect of the MCH-FP on 2014 outcomes at the MHSS1 household-level. Variable means refer to the comparison group. Standard errors are clustered by pre-program village. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure D.1: ITT Effects of MCH-FP on Crop Choice and Average Crop Productivity



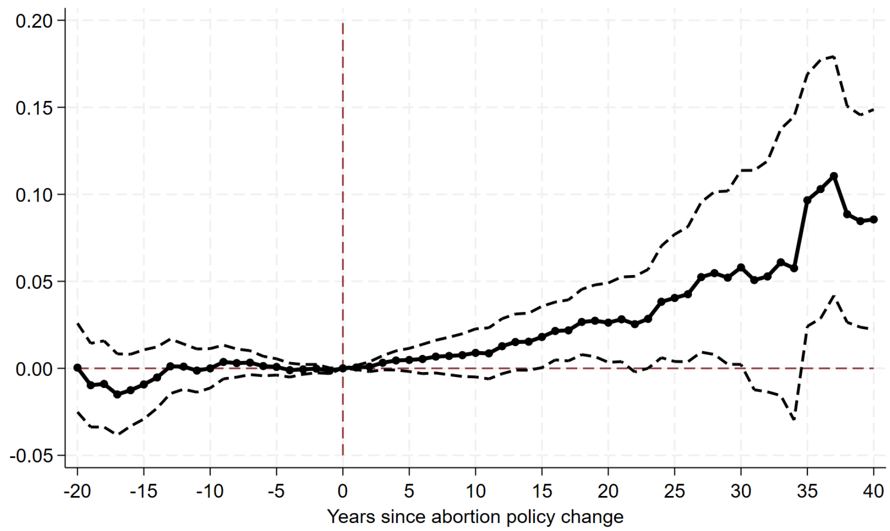
Notes: The figure reports estimates of equation 5. The vertical axis reports the ITT effect on whether the household grew the given crop. The horizontal axis reports the average revenue per unit of labor when producing the crop, which comes from XXX. Vertical bars represent the 95% confidence intervals.

Figure D.2: Effect of Abortion Policy Changes on Crude Birth Rate



Notes: The figure shows event study coefficient estimates for the effect of abortion policy changes on the crude birth rate. 95% confidence intervals depicted with standard errors clustered at the country level. Annual data on crude birth rate come from the World Bank Development Indicators as compiled by Delventhal et al. (2021). Abortion policy change database compiled by Bloom et al. (2009). Estimated using the Stata command `did_multiplegt_dyn` by de Chaisemartin et al. (2024).

Figure D.3: Effect of Abortion Policy Changes on Agricultural Employment Share Using Indicator of Free Abortion

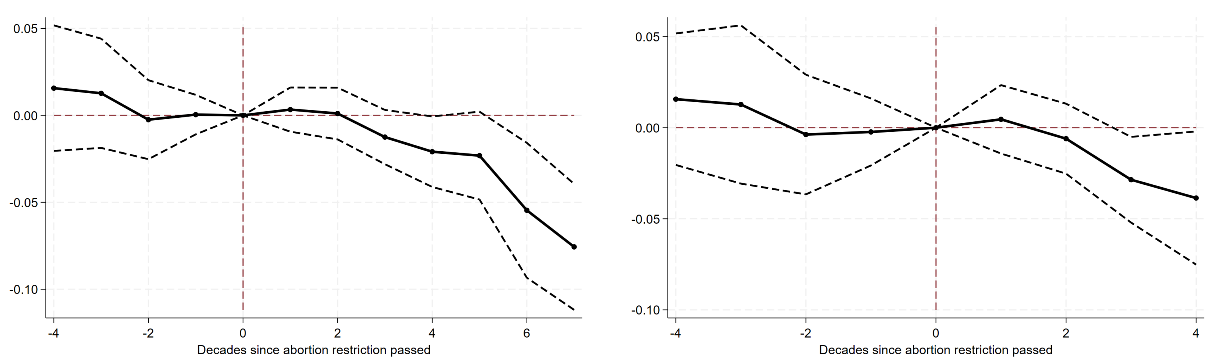


Notes: The figure shows event study coefficient estimates for the effect of abortion policy changes on the agricultural employment share, using an binary indicator of abortion policy which is 1 when the abortion index if 5 and zero otherwise. 95% confidence intervals depicted with standard errors clustered at the country level. Data on country-level agricultural employment shares 1960–2020 comes from Wingender (2014b). Abortion policy change database compiled by Bloom et al. (2009). Estimated using the Stata command `did_multiplegt_dyn` by de Chaisemartin et al. (2024).

Figure D.4: Effect of Abortion Restrictions on Agricultural Employment Share, U.S. States, Full Count Census 1850–1900

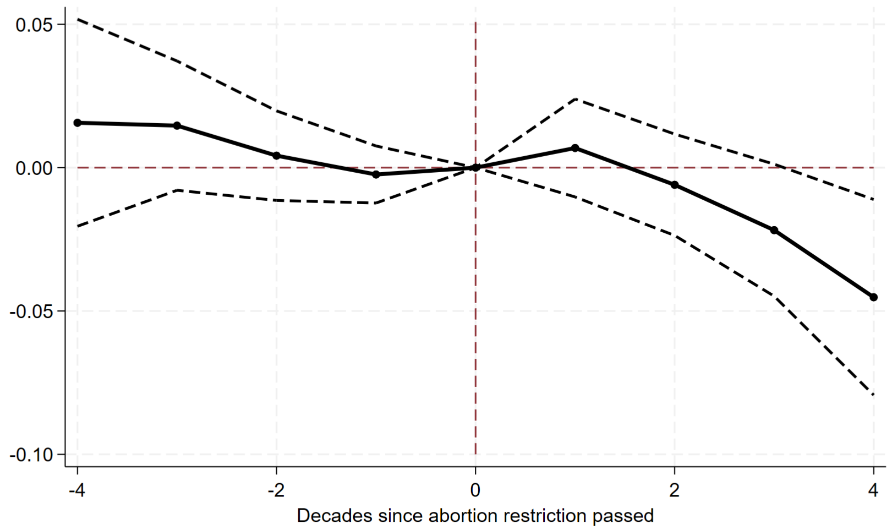
(a) all abortion policies

(b) post-1840 abortion policies



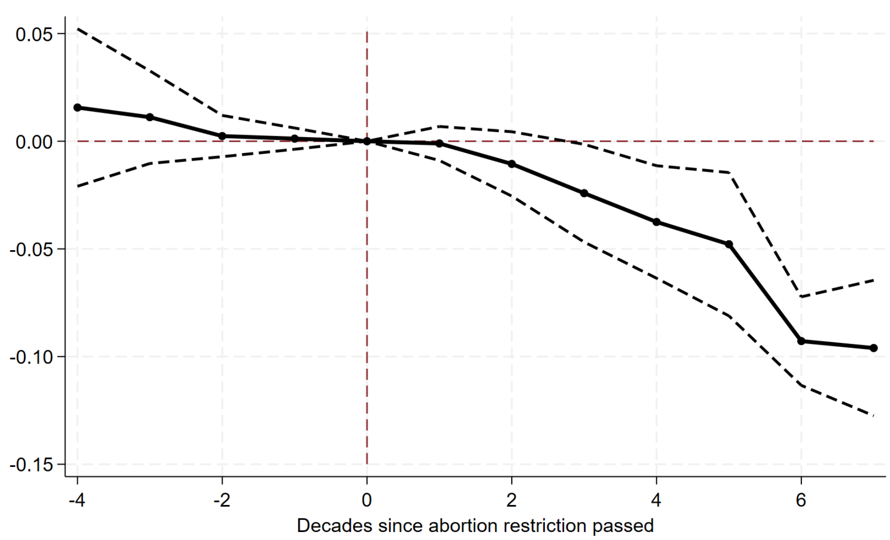
Notes: Data on state-level agricultural employment shares 1800-1840 comes from Craig and Weiss (1998). Agricultural employment shares for 1850–1900 computed from Ruggles et al. (2024). Timing of abortion restriction laws come from Lahey (2014) and Lahey and Wanamaker (2025). 95% confidence intervals depicted with standard errors clustered at the state level. Estimated using the Stata command `did_multiplegt_dyn` by de Chaisemartin et al. (2024).

Figure D.5: Effect of Abortion Restrictions (excluding those passed before 1840) on Agricultural Employment Share, U.S. States



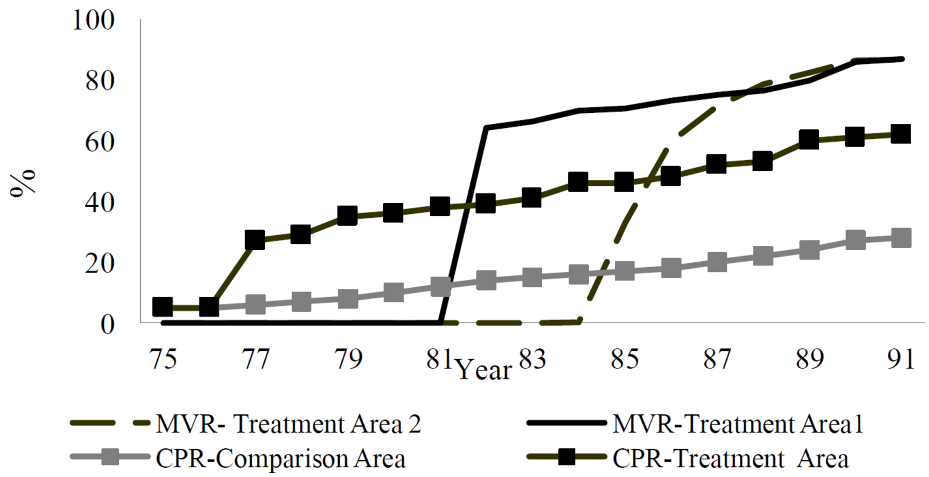
Notes: Data on state-level agricultural employment shares 1800-1900 comes from Craig and Weiss (1998). Timing of abortion restriction laws come from Lahey (2014) and Lahey and Wanamaker (2025). 95% confidence intervals depicted with standard errors clustered at the state level. Estimated using the Stata command `did_multiplegt_dyn` by de Chaisemartin et al. (2024).

Figure D.6: Effect of Abortion Restrictions on Agricultural Employment Share, U.S. States Observed in 1800 Only



Notes: Data on state-level agricultural employment shares 1800-1900 comes from Craig and Weiss (1998). Timing of abortion restriction laws come from Lahey (2014) and Lahey and Wanamaker (2025). 95% confidence intervals depicted with standard errors clustered at the state level, computed via 1,000 bootstrap repetitions. Estimated using the Stata command `did_multiplegt_dyn` by de Chaisemartin et al. (2024).

Figure D.7: Trends in contraceptive prevalence rate (CPR) and measles vaccination rates (MVR) for children 12-59 months by calendar year



Source: Replicated from Figure 2 in Barham et al. (2023).