Quarter of Birth, Gender Inequality, and Economic Development

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Abstract

This paper discovers that people born in the fourth quarter tend to have better lifecycle outcomes for 1930-1990 cohorts in China, and this birth quarter effect (BQE) is larger for females than males. To explain this finding, we hypothesize that seasonality in agricultural production, combined with son preference, leads to a gender gap in BQEs on child neonatal investment, and subsequently, on lifecycle outcomes. Exploiting seasonal agricultural production patterns and spatial variations in crop structures across provinces in China, we find individuals born in seasons with more abundant household resources for neonatal investment tend to have better lifecycle outcomes. In addition, we leverage weather shocks as a natural experiment for agricultural production and find that higher agricultural output in the previous year reduces the gender gap in BQEs in a given year of birth. Exploring China's economic reform in 1979 as a quasi-experiment, we further find that the effect of previous-year agricultural output is mitigated by economic development. Finally, we find a gender gap in BQEs on child neonatal investment, which is proxied by infant breastfeeding. Our findings demonstrate that economic development lessens the effect of poverty on gender inequality.

Keywords: Birth quarter effect; economic development; gender inequality; neonatal investment; son preference
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1 Introduction

Compared with women in developed countries, women in less developed countries fare worse relative to men on a variety of lifecycle outcomes, such as educational attainment, health, and employment (De la Croix and Vander Donckt, 2010; Doepke and Tertilt, 2019; Duflo, 2012; Jayachandran, 2015; Rosenzweig and Zhang, 2013). The gender gap in lifecycle outcomes opens early in life (Heckman, 2007). This paper studies a new channel through which economic development promotes gender equality through reducing the gender disparity in neonatal investment by combining two facts. First, agricultural production varies across seasons, which results in seasonal variations in household resources in traditional agricultural societies with liquidity constraints (Behrman et al., 1997; Fink et al., 2020). Second, when household resource constraints become more stringent, parents are more likely to allocate fewer resources to girls than boys for neonatal investment, especially in societies with preference for boys, and the effect of neonatal investment persists over the lifecycle (Carneiro et al., 2015, 2021a,b; Cunha et al., 2010; Heckman, 2007). Combining these facts, the interaction between gender preference and seasonal variations in household resources results in gender inequality in traditional agricultural societies. With economic development, household resources depend less on agricultural production, and household resources in lean seasons become less constrained. Consequently, the seasonal variation in gender inequality—the greater gender inequality for children born in seasons with fewer resources for neonatal investment—shrinks, as does overall gender inequality.

Such a channel is suggested by Figure 1, which presents three new observations that motivate our study.[1] First, people born in the fourth quarter (Q4) have the highest educational attainment in China. Second, the difference in education across birth quarters is larger for females than males. Third, the difference decreases steadily over time, except for two periods: It spiked during the Great Famine (1959-1962) and decreased abruptly after the economic reform in 1979. To the best of our knowledge, this is the first study to discover that the difference in education across quarters of birth (QOBs) differs by gender.

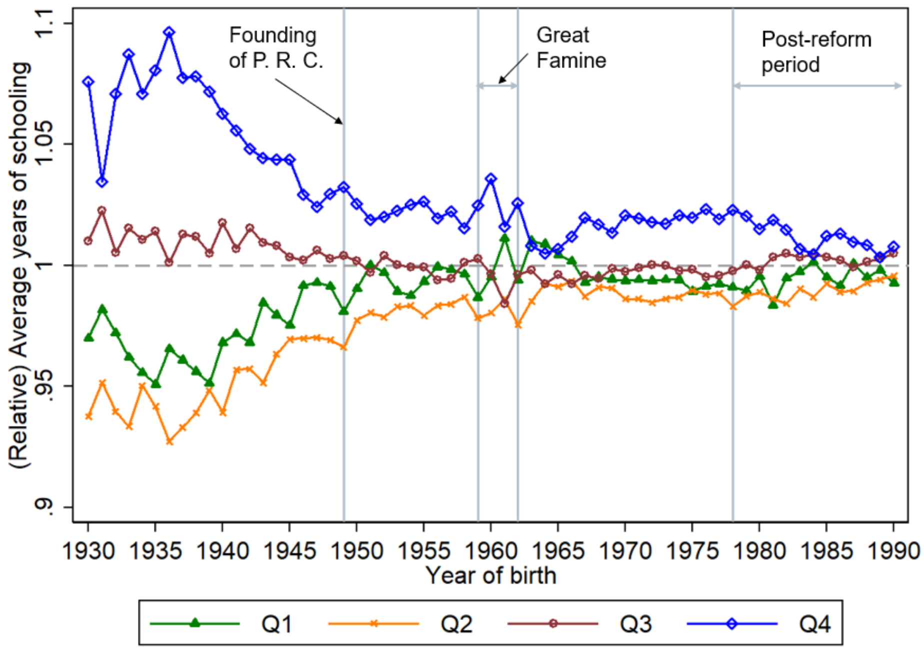
In this paper, we identify the gender difference in the birth quarters effects (BQEs) on lifecycle outcomes, investigate the mechanism, and discuss the implications of our results for early-life conditions, economic development, and gender equality in general.

Using data from five waves of Chinese population censuses or mini-censuses and the China Education Panel Survey (CEPS), we first identify the gender difference in BQEs, providing robust evidence that BQEs on lifecycle outcomes—including educational and labor market outcomes—differ by gender. The identification assumption for estimating the *gender gap* in BQEs is weaker than

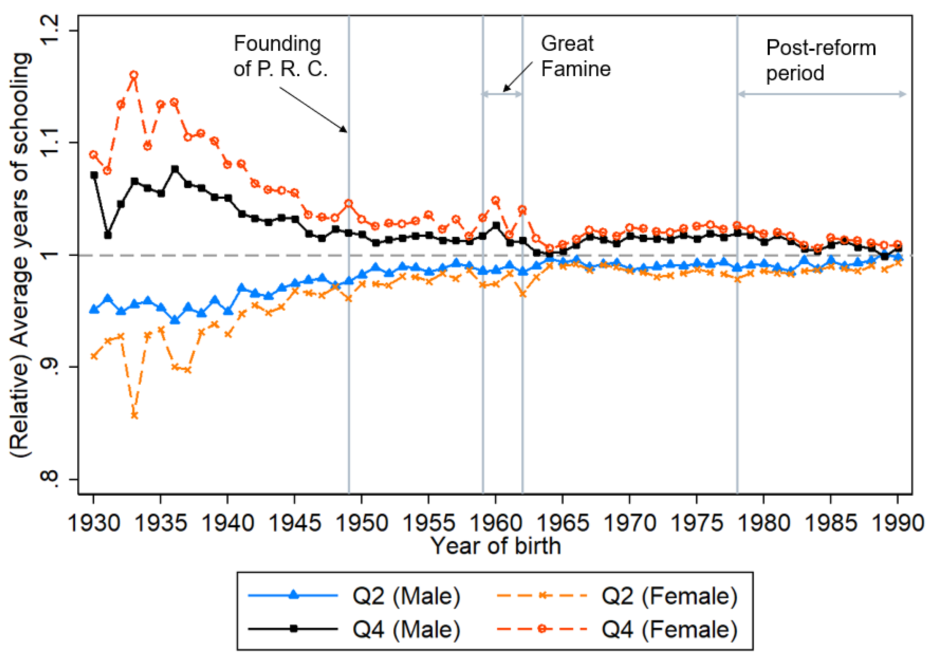
[1] The figure depicts schooling years across quarters of birth (QOBs) for cohorts born during 1930-1990 based on Chinese population censuses 1990, 2000, and 2010 and mini-censuses 2005 and 2015. We describe data sources and define the sample in Section 2.

Figure 1: Average Schooling Years by Quarter and Year of Birth

(a) Whole Sample



(b) Subsamples by Gender



Note: Data sources: Censuses 1990, 2000, and 2010 and mini-censuses 2005 and 2015. The sample includes individuals born during 1930-1990 and aged 25-60 in the census year. Figure (a) presents the quarter-by-cohort average schooling years relative to the cohort average schooling years. Figure (b) presents the quarter-by-cohort average schooling years by gender relative to the cohort average schooling years in the same gender subsample. Q1, Q2, Q3, and Q4 indicate people born in the first, second, third, and fourth quarter, respectively.

that for BQEs. In particular, our identification does not require the absence of gender selection on unobservables, as long as such selection does not systematically vary between QOBs. This is equivalent to saying, we do not require the absence of selection of QOBs on unobservables, as long as such selection does not systematically vary between genders. We test and validate the assumption using census data on newborns, as well as a nationally representative household survey containing information on maternal gender preferences.

Our estimates show that compared with people born in Q2, schooling years increase by 0.27 for females and 0.20 for males born in Q4 for 1930-1990 birth cohorts.[2] This indicates that the gender gap in schooling years shrinks by 0.07 in Q4, corresponding to a 5% decrease in the sample's average gender gap. This pattern of gender differences in such Q4 effects remains when we examine other lifecycle outcomes. Our baseline estimates of gender differences in BQEs are robust to considering sample attrition due to potential mortality selection, excluding cohorts born in some special time periods, and controlling for the seasonality in maternal characteristics.

Having obtained robust evidence on estimated BQEs and their gender differences, we then explore the mechanism. We conjecture that the estimated BQEs are associated with seasonality in agricultural production, where most food crops are sown between March and June and harvested between September and November. Because of liquidity constraints and migration restrictions, seasonality in agricultural production translates into seasonal variations in household resources. Based on agricultural statistics and the crop calendar in China, our calculation reveals that household resources—in terms of both food and parental childcare time—are most abundant for children born in Q4 during their neonatal period (the four months during and after birth). Since household investment in the neonatal period is critical for a child's lifecycle outcomes,[3] seasonality in agricultural production may lead to BQEs on lifecycle outcomes.

To explain the gender-differentiated BQEs, we build a model which incorporates seasonal variations in household resources and son preference (Ebenstein, 2010; Jayachandran and Pande, 2017; Qian, 2008). Because of son preference, investment in girls is more sensitive to household resources than boys. Thus, the gap in neonatal investment between girls born in an abundant and a lean season is larger than the corresponding gap between boys. The model further predicts that economic development, reflected by both more household resources and a smaller gap in household resources between seasons, reduces the gender gap in BQEs on child neonatal investment. This explains the observed time pattern in the gendered BQEs in Figure 1.

We conduct five analyses to investigate our hypothesized mechanism. The first analysis is at the individual level, whereby we regress individual adult outcomes on the level of household resource

[2]The sizes of the estimates are comparable to those in the literature. For example, Duflo (2001) finds that schooling years increase by 0.12 to 0.19 when one more primary school was built per 1,000 children in Indonesia.

[3]See, for example, Cunha et al. (2010); Heckman et al. (2013); Carneiro et al. (2015); Lucas et al. (1998); Singhal et al. (2001); and Wiedmeier et al. (2011).

abundance during the neonatal period—which is calculated based on the crop calendar in China—by gender. In particular, we exploit spatial variations in agricultural seasonality by exploiting differential crop structures across provinces in China, which allows us to construct province-by-quarter (or month)-level measures of neonatal household resource abundance. We find that, individuals born in seasons with more resources for neonatal investment—in terms of both higher food abundance and lower agricultural work intensity—tend to have better education and labor market outcomes, and this effect is significantly larger for females than males. This result is consistent with our hypothesis on the gender-differentiated effects of seasonality in household resources for neonatal investment.

While the above analysis suggests the role of agricultural seasonality in shaping BQEs by gender, it is possible that the results are driven by unobserved factors that may vary across seasons and provinces and correlate with measures of seasonal resource abundance constructed based on the crop calendar. To alleviate this concern, in the next three analyses, we exploit the cross-year variation in the seasonality in household resource abundance induced by agricultural output. In the second analysis, we calculate differences in schooling years between those born in Q4 and Q1 (Q4-Q1 difference) by province, birth year, and gender, using the census data. We then regress the Q4-Q1 difference on grain production in the previous year separately for females and males at the province-by-cohort level with province and year fixed effects controlled for.[4] The mechanism of agricultural seasonality predicts that higher previous-year agricultural output reduces the Q4-Q1 difference. The estimated coefficient is negative for both females and males, but the coefficient size is larger for females and the estimate is only statistically significant for females.

Considering the potential endogeneity whereby agricultural output may correlate with unobserved time-variant cross-province heterogeneities—and the latter may also correlate with household investment in children, in the third analysis, we use records from 819 weather stations to construct a measure of thermal agricultural productivity (TAP) at the county level.[5] Within-county variations in temperatures serve as a natural experiment for agricultural output. We recalculate the Q4-Q1 difference by county, birth year, and gender. We regress the Q4-Q1 difference on the TAP in the previous year separately for females and males at the county-by-cohort level, conditional on county and year fixed effects. We find that a positive shock to previous-year TAP significantly reduces the Q4-Q1 difference only for females in rural areas. In addition, very similar results hold if we use alternative ways of constructing TAP measures, exclude county-cohort observations with

[4] We focus on the Q4-Q1 difference because agricultural production in year $t-1$ affects children born in Q1 the most and those born in Q4 the least in year t in terms of household resources during a child's neonatal period, based on the seasonal pattern of agricultural production in China. Thus, higher agricultural output in year $t-1$ reduces seasonal variations in household resources for child neonatal investment in year t.

[5] We follow the agronomic literature to define thermal agricultural productivity based on weather records. The formal definition is presented in Section 5.5.

few individuals in the microdata, exclude some special provinces, and use Q2 as the reference group. We also carefully examine the issue of potential mortality selection and find it less likely to induce estimation biases in our results.

In the fourth analysis, we test the mechanism about economic development by examining the moderating role of economic development in the effect of previous-year TAP on the gender gap in BQEs. Chinese rural economic reform in 1979 provides us with a unique opportunity to directly study the effect of economic development. The quasi-experimental reform induced a substantial increase in agricultural productivity and enhanced households' ability to smooth consumption across seasons. We find that this market-oriented reform mitigates the effect of TAP on the gender gap in BQEs, which suggests the role of economic development in promoting gender equality in intrahousehold child investment. In addition, the estimated effect of the economic reform is less likely to be confounded by contemporaneous historical events, such as the implementation of the one-child policy and education expansions.

In the final analysis, we estimate the BQE on infant breastfeeding—a proxy for intrahousehold neonatal investment—based on China Health and Nutrition Survey (CHNS) data. We find that infants born in Q4 are more likely to be breastfed than those born in other quarters, and this Q4 effect is larger and only statistically significant for females, especially in households with tighter resource constraints. This result is consistent with our proposed mechanism, whereby the quarter of birth (QOB) affects lifecycle outcomes through intrahousehold neonatal investment. Reassuringly, similar results hold if we examine the alternative outcome variable related to the length of breastfeeding or use different methods to define the subsample of households with tight resource constraints.

In sum, the above analyses provide support for the mechanism whereby the gender gap in BQEs is driven by seasonality in agricultural production and son preference through the channel of child neonatal investment, and suggest the role of relaxing household resource constraints in promoting gender equality. We also carefully examine alternative explanations for our results, including school starting age and seasonal disease patterns. We conclude that our baseline findings on the BQE and its gender difference are less likely to be primarily driven by these alternative mechanisms.

1.1 Related Literature

Our paper is related to the literature on economic development and gender inequality (Duflo, 2012). A fundamental channel through which economic development promotes gender equality is by relaxing the grip of poverty. Prominent studies in the literature document gender bias in the intrahousehold allocation of nutrition and other resources, particularly when a household faces a tight resource constraint (Aurino, 2017; Barcellos et al., 2014; Behrman, 1988; Björkman-Nyqvist, 2013; Jayachandran and Kuziemko, 2011; Maccini and Yang, 2009; Rose, 1999, 2000).[6] For example, Rose (1999) finds that the mortality rate increases more for girls than boys when districts experience drought in India. The literature thus suggests that economic development, even without specifically targeting women, reduces the vulnerability of the poor to crises induced by variations in socioeconomic conditions and, consequently, disproportionately improves women's well-being. Despite the extensive research, Duflo (2012) highlight the limited evidence on such a gender-heterogeneous impact of economic development under *normal circumstances*,[7] from which we can derive more relevant implications for development policies in general.[8]

We contribute to this line of research in two important respects. First, we discover a new and general source of variations in socioeconomic conditions that drive gender inequality: the seasonal variation in agricultural production, which is inherent in traditional agricultural societies. This variation induces seasonal variations in the food abundance and the amount of time out of agricultural work across seasons, which in turn induces seasonality in gender inequality through the channel of child neonatal investment. This source of gender inequality is general, since it is prevalent in traditional agricultural societies. For example, we robustly document a persistent gender gap in the differences in schooling years between birth quarters for people born in the world's most populous society, China, over 60 years.

Second, this paper presents novel evidence that more abundant household resources promote gender equality in neonatal investment and lifecycle outcomes under normal circumstances. To this end, we conduct a rich set of mechanism analyses to connect seasonality in agricultural production to gender inequality in neonatal investment, and then to gender inequality in adult outcomes. We further use the economic reform in China as a quasi-experiment to explore how economic development mitigates the effect of shocks to agricultural production on gender inequality. To the best of our knowledge, we are the first to directly examine the moderating role of economic development in lessening the effect of poverty on gender inequality.

Our paper also enriches the literature on children's birth timing within a year and their lifecycle

[6] In China, gender disparities in intrahousehold education investment due to son preferences have also been documented in the literature (Hu et al., 2022; Wang, 2005). Relatedly, Kaushal and Muchomba (2018) find differences in time allocations among Asian immigrant families in the US due to son preference.

[7] Based on cash transfer programs (CTP), experimental evidence on the effect of household resources on gender inequality in human capital investment is mixed. For example, Akresh et al. (2013) find that an unconditional CTP increase school participation more for boys than girls in rural Burkina Faso; Benhassine et al. (2015) find that an unconditional CTP for education positively affect females' relative schooling outcomes for some measures but not for other measures in Morocco; Barrera-Osorio et al. (2011) find that a conditional CTP in Columbia enhances boys' relative school attendance and enrollment rates.

[8] Duflo (2012) concludes that "even in the countries where the preference for boys is strongest, the evidence that girls systematically receive less care than boys under normal circumstances is not as clear-cut as one might guess." The reason might be that, as suggested in Deaton (1997), it is difficult to find general variations in household resources under normal circumstances, which would generate detectable gender differences in intrahousehold investment.

outcomes. It has been well documented that the month of birth is associated with various lifecycle outcomes around the world, such as birthweights (Currie and Schwandt, 2013), health (Doblhammer and Vaupel, 2001; Doblhammer and Fritze, 2015; Lokshin and Radyakin, 2012; Sohn, 2016), as well as education and labor market outcomes (Angrist and Krueger, 1991; Card, 1999).[9] For example, Currie and Schwandt (2013) conduct a within-mother analysis and find that babies conceived in May have the lowest gestation length; they also find that conditional on gestation length, birthweight is the highest for summer conceptions. Lokshin and Radyakin (2012) find that in India, children born in monsoon months have lower anthropometric scores than those born during fall and winter months. Moreover, prior studies propose explanations for birth season effects in multiple respects, such as seasonal disease patterns (Currie and Schwandt, 2013; Lokshin and Radyakin, 2012), food availability and nutrition (Doblhammer and Vaupel, 2001), and school starting age (Angrist and Krueger, 1991).

Compared with this literature, we are the first to document a Q4 premium—higher educational attainment for people born in Q4 than in other quarters—in China over 60 years. Further, we are the first to find significant gender gaps in the differences across birth months in education. Last and most importantly, this is also the first study to provide causal evidence on the mechanism of seasonality in agricultural production underlying the gender-differentiated QOB effects and examine the role of economic development in closing the gender gap in such effects.

Our paper also relates to the literature on prenatal and neonatal investment and child lifecycle outcomes (Adhvaryu et al., 2019; Almond and Currie, 2011; Carneiro et al., 2015, 2021b; García et al., 2020; Heckman et al., 2013; Rivera et al., 2004). For example, Carneiro et al. (2015) use a quasi-experimental change in maternity leave entitlements in Norway and find that an increase in maternal time spent with children during the neonatal period has positive effects on children's education and labor market outcomes in the long run. We complement this line of research by enriching the evidence on the gender gap in early-life investment in developing countries and highlighting the role of agricultural seasonality and associated seasonal variations in household resources—in terms of nutrition and parental time for childcare—in affecting gender inequality in lifecycle outcomes through the channel of early-life investment.

Finally, our paper adds to the literature on seasonality in agricultural production, which has been well documented to be associated with seasonal variations in household income, consumption, and liquidity constraints in developing countries (Behrman et al., 1997; Fink et al., 2020; Kaminski et al., 2014; Montero and Yang, 2022; Pitt and Khandker, 2002). For example, Fink et al. (2020) find that households face tighter liquidity constraints during lean seasons based on

[9] Angrist and Krueger (1991) find that people born in Q4 tend to have higher education and income in the US due to the school starting age difference induced by compulsory schooling. This finding as well as the method of using QOB as an instrumental variable are challenged by subsequent studies (Bound and Jaeger, 1996; Buckles and Hungerman, 2013). We examine the potential school starting age mechanism in Section 6.1.

experimental evidence from a subsidized loan program in Zambia. Our paper complements this literature by exploiting the seasonality in agricultural production as a natural variation in household resources, associating it with gender inequality in neonatal investment and lifecycle outcomes, and deriving implications for the role of reducing poverty in promoting gender equality in general.

2 Data and Variables

2.1 Data Sources

Our data are drawn from six sources: (1) Chinese population censuses; (2) the China Education Panel Survey (CEPS); (3) various statistical yearbooks; (4) the China Meteorological Administration, for daily weather records; and (5) the China Health and Nutrition Survey (CHNS); (6) the China Family Panel Studies (CFPS). We use censuses to estimate gender differences in BQEs on adult educational attainment and labor market outcomes at the national level; we supplement this analysis by using the CEPS to estimate the gendered BQEs on cognitive skills and academic performance for junior high school students. We then generate socioeconomic variables from the yearbooks at the province level and correlate these variables with BQE estimates and their gender differences. We use weather records to generate thermal agricultural productivity and estimate its effect on the gender gap in BQEs at the county level. Finally, we use CHNS data to study BQEs on infant breastfeeding. In addition, CFPS data are used for providing supportive evidence for our identification assumption and mechanism analysis.

Censuses We use a 1% random sample of censuses 1990 and 2000; 0.35% of census 2010; 20% of mini-census 2005; and 15% of mini-census 2015.[10] The data, which are collected and maintained by the National Bureau of Statistics of China, are nationally representative. A unique feature of Chinese censuses is that the date of birth is precisely recorded and cross-checked with administrative records. This minimizes measurement error, if any, associated with the birth quarter variable, which is the main independent variable in our analysis. For outcome variables, individuals' educational attainment is recorded across all censuses; labor market outcomes—including monthly income, the employment sector, and insurance coverage—are only recorded in mini-census 2005. In addition, the fertility history of married women aged 15 to 50 is recorded in all censuses. Finally, the censuses record demographic information such as gender, ethnicity, birthplace, residence, migration status, and hukou status.[11]

[10]Since 1990, China has conducted a census every 10 years and an inter-census population survey (also called a "mini-census") at the midpoint year between two censuses, with a sampling fraction of 1%.

[11]Hukou is a household registration system in China. Based on their registered place of residence, each Chinese citizen holds either a rural or urban hukou. A person's hukou is assigned according to their parents' registration;

China Education Panel Survey We use the CEPS data to examine adolescent cognitive skills and academic performance, which complements the analysis based on censuses. Conducted by the National Survey Research Center at Renmin University of China, the CEPS (in academic year 2013-2014) contains a school-based, nationally representative sample of approximately 20,000 junior high students (in grades 7 and 9) from 438 classes in 112 schools in 28 county-level units in China. The CEPS provides an internationally standard cognitive test score and collects administrative transcript records for math, Chinese, and English scores on the most recent midterm or final exam. It also contains rich information on parental investment in children.[12]

Statistical Yearbooks We collect data at the province level from multiple yearbooks: *China Agricultural Yearbook (1980)*; *China Compendium of Statistics 1949-2008*; *China Population Statistics Yearbook (1981, 1987, 1990)*; and *China Health Statistics Yearbook (2003)*.

Weather Records We collect data from the China Meteorological Administration for daily instrumental temperature records at 819 stations between 1956 and 1990.

China Health and Nutrition Survey The CHNS uses a multistage, random cluster method to draw a sample of about 7,200 households that contains more than 30,000 individuals in 15 provinces.[13] The survey collects rich information on household socioeconomic status, nutrition, and health status. It provides the only microdata in China with information on breastfeeding, which we use as a proxy for child neonatal investment.

China Family Panel Studies The CFPS is a nationally representative survey administered by the Institute of Social Science Survey at Peking University, covering 25 out of 31 provinces in mainland China. We utilize the 2010 and 2014 waves of the survey. This survey includes information on individuals' gender attitudes, which we use to examine our identification assumption in Section 3.4. Moreover, the survey data contain rich information on monthly household consumption, particularly food consumption, allowing us to examine seasonal liquidity constraints faced by households, as discussed in Section 5.1.

hukou status (i.e., rural or urban) may affect a person's eligibility for social benefits provided by the government (Zhang, 2021; Zhao, 1999).

[12]Appendix B provides more details on the CEPS data and the CEPS sample used in our empirical analysis.

[13]The CHNS is conducted by the Carolina Population Center at the University of North Carolina at Chapel Hill and the National Institute for Nutrition and Health (formerly the National Institute of Nutrition and Food Safety) at the Chinese Center for Disease Control and Prevention. It contains 10 waves to date (1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011, and 2015).

2.2 Analytic Samples

Our primary analyses are conducted at the individual, province, and county levels. For our analyses at the individual level based on censuses, we use three samples: an adult sample from pooled censuses, an adult sample from mini-census 2005, and a newborn sample from pooled censuses. The samples used for analyses at the province and county levels are defined in Section 5. We define samples from the CFPS and CHNS data when we reach specific analyses using these data sources.

Adult Sample from Pooled Censuses We pool the five (mini-)censuses to study BQEs on education. We restrict the sample to adults older than 25, since those younger than 25 might have not completed their schooling. We further exclude people aged above 60 to mitigate sample selection arising from mortality. The sample includes 1930-1990 birth cohorts, which contains 15,943,878 individuals, of whom 8,127,660 (51%) are male and 7,816,218 (49%) are female.

Adult Sample from Mini-census 2005 We use mini-census 2005 to examine BQEs on labor market outcomes. We restrict the sample to individuals aged between 25 and 60 who were employed at the survey time. The sample contains 1,123,988 individuals, of whom 615,444 (55%) are male and 508,544 (45%) are female.

Newborn Sample from Pooled Censuses We use the newborn sample from the pooled censuses to check the gender difference in correlations between birth quarters and parental characteristics. Across the five (mini-)censuses, all females aged 15 to 50 report whether they gave birth during the past 12 months. Census 1990 does not contain information on the birth month for newborns, so it is not included in the newborn sample. The newborn sample includes newborns' gender and birth month, as well as maternal information such as education, age, hukou, migration status, and birth history. The sample contains 204,205 newborns, of whom 54.3% are male.

2.3 Variables

We now describe the main variables based on the census data used for our analyses at the individual level. Table 1 presents summary statistics by gender. Variables in the CEPS data are defined in Appendix B. Variables used for analyses at the county level are defined and described in Section 5.

Education We use three variables to measure educational attainment: schooling years and two indicators for junior high school completion and senior high school completion. The three variables are consistently defined across the five (mini-)censuses. Table 1, Panel A shows that the average schooling years are 6.78 for women and 8.15 for men. Both junior and senior high school completion rates are higher for males than females.

Table 1: Summary Statistics of Main Variables

	Female sample			Male sample		
	N	Mean	Std. dev.	N	Mean	Std. dev.
Panel A: Pooled census data of 1990, 2000, 2005, 2010 and 2015						
Schooling years	7,816,218	6.78	4.30	8,127,660	8.15	3.79
Junior high school completion (Yes=1)	7,816,218	0.48	0.50	8,127,660	0.63	0.48
Senior high school completion (Yes=1)	7,816,218	0.16	0.37	8,127,660	0.22	0.41
Panel B: Mini-census data of 2005						
Monthly income (RMB Yuan)	508,544	510.89	661.26	615,444	775.24	1,009.91
Working in the public sector (Yes=1)	508,544	0.13	0.33	615,444	0.17	0.37
Unemployment insurance (Yes=1)	508,544	0.11	0.31	615,444	0.13	0.34

Note: The table presents summary statistics for the pooled census sample (Panel A) and mini-census 2005 sample (Panel B).

Labor Market Outcomes We have three measures of labor market outcomes. The first is monthly labor market earnings; we use its logarithm in the regression analysis. The second is a dummy variable to indicate whether the individual is employed in the public sector (e.g., government, state-owned enterprises, or public institutions). In China, working in the public sector signifies a higher social class and is considered to signal being more talented and having more resources (Bai et al., 2021; Meng, 2012). The third variable is a dummy variable that indicates whether an individual has unemployment insurance provided by the current employer. Unemployment insurance can be part of a benefits package, which signals stable employment and good working conditions.[14] These three variables are contained only in the mini-census 2005. Compared with males, females have lower monthly earnings and are less likely to work in the public sector or have unemployment insurance (Table 1, Panel B).

3 Econometric Model and Identification Assumption

In this section, we present our econometric model and discuss the assumption needed for identifying the gender difference in birth quarter effects (BQEs). Overall, we highlight that our identification does not require the absence of gender selection on unobservables, as long as such selection does not systematically vary between birth quarters. This is equivalent to saying that we do not require the absence of selection of birth quarters on unobservables, as long as such selection does not systematically vary between genders. We then provide evidence in support of our identifying assumption using a sample of newborns from the censuses.

[14]The enrollment rate for unemployment insurance is low in China: 11% and 13% for females and males, respectively, as shown in Table 1, Panel B. The rate is higher for employees in the public sector than in the private sector. Rural-to-urban migrant workers usually do not enroll.

3.1 Regression Specification

To identify the gender difference in the BQEs on individuals' lifecycle outcomes, we first estimate the difference in outcomes between QOBs within each gender separately, and then examine how this gender-specific between-QOB difference varies between females and males. We estimate the following equation for females and males ($G \in \{f, m\}$) separately:

$$Y_{icp} = \beta^G \times QOB_{icp} + \gamma^G \times X_{icp} + \lambda_c^G + \mu_p^G + \varepsilon_{icp}^G, \tag{1}$$

where subscripts i, c, and p denote individuals, cohorts (years of birth), and birthplaces (provinces), respectively. The dependent variable, Y_{icp}, denotes education or labor market outcomes. QOB_{icp} is the vector of indicators for quarters of birth (QOBs), with the indicator for the first quarter (Q1) omitted. X_{icp} represents a vector of control variables, such as ethnicity and hukou status. λ_c^G and μ_p^G stand for gender-specific birth year and birthplace fixed effects, respectively. ε_{icp}^G is the error term. We cluster standard errors at the birthplace-by-birthyear level.

Our goal is to identify $\beta^f - \beta^m$, where β^f (β^m) captures the between-QOB difference in outcomes for females (males). In other words, we aim to identify the gender difference in BQEs on individuals' outcomes.

3.2 Identification Assumption

We now explicitly present conditions required for the consistent estimate of $\beta^f - \beta^m$. We formally derive the conditions using the omitted variable bias (OVB) formula. For the convenience of mathematical derivation and illustration, and without loss of generosity, we streamline notation by simplifying the vector QOB_{icp} to a dummy variable, $Q4_{icp}$, and omitting control variables and fixed effects.[15] The simplified regression formula is as follows:

$$Y_{icp} = \alpha^G + \beta^G Q4_{icp} + \upsilon_{icp}^G. \tag{2}$$

Note that the error term in Eq. (2) can be expressed as the sum of two parts, i.e.,

$$\upsilon_{icp}^G = \delta^G \xi_{icp}^G + e_{icp}^G,$$

where e_{icp}^G is a random noise and ξ_{icp}^G is unobserved household heterogeneity (e.g., parental preferences for child quality) that might correlate with $Q4_{icp}$. Potential inconsistency in the estimate

[15] That is, throughout our derivation, we omit other QOB dummies ($Q2_{icp}$ and $Q3_{icp}$) by assuming that our estimation sample includes only children born in two quarters, Q1 and Q4. Moreover, under the simplification of omitting control variables and fixed effects, namely, X_{icp}, λ_c^G, and μ_p^G, we consider the dependent variables as residuals after regressing them on these covariates and fixed effects.

of β^G arises from the correlation between ξ^G_{icp} and $Q4_{icp}$. Using the OVB formula, the consistency of $\hat{\beta}^f - \hat{\beta}^m$ in Eq. (2) requires[16]

$$\delta^f \frac{\text{Cov}\left(Q4_{icp}, \xi^f_{icp}\right)}{\text{Var}^f\left(Q4_{icp}\right)} = \delta^m \frac{\text{Cov}\left(Q4_{icp}, \xi^m_{icp}\right)}{\text{Var}^m\left(Q4_{icp}\right)}. \tag{3}$$

The following three conditions are *sufficient* for Eq. (3) to hold:

(i) $\mathbb{E}^f\left(Q4_{icp}\right) = \mathbb{E}^m\left(Q4_{icp}\right)$, which indicates $\text{Var}^f\left(Q4_{icp}\right) = \text{Var}^m\left(Q4_{icp}\right)$, as $Q4_{icp}$ is a dummy variable.

(ii) $\text{Cov}\left(Q4_{icp}, \xi^f_{icp}\right) = \text{Cov}\left(Q4_{icp}, \xi^m_{icp}\right)$.

(iii) $\delta^f = \delta^m$.

Thus, our identification assumption is the combination of the three conditions, (i), (ii), and (iii).

To further facilitate our subsequent interpretations and empirical analysis, we re-state our identification assumption in the following way. We claim that the combination of conditions (i) and (ii) above is identical to the combination of the following two conditions:

(i') $\mathbb{E}^{Q1}\left(female_{icp}\right) = \mathbb{E}^{Q4}\left(female_{icp}\right)$.

(ii') $\text{Cov}\left(female_{icp}, \xi^{Q1}_{icp}\right) = \text{Cov}\left(female_{icp}, \xi^{Q4}_{icp}\right)$.

Here $female_{icp}$ is the indicator for females, and ξ^Q_{icp} is unobserved parental preferences for those born in quarter Q. Mathematically, we can show that conditions (i) and (ii) hold *if and only if* conditions (i') and (ii') hold, with the proof presented in Appendix C.1. Therefore, if we provide empirical support for (i') and (ii'), then conditions (i) and (ii) will also get supported, and *vice versa*. Thus, our identification can also be expressed as the combination of the three conditions, (i'), (ii'), and (iii). Note that either $\text{Cov}\left(Q4_{icp}, \xi^G_{icp}\right) \neq 0$ or $\text{Cov}\left(female_{icp}, \xi^Q_{icp}\right) \neq 0$ does not violate our identification assumption.

3.3 Economic Interpretation of the Identification Assumption

We now present interpretations of the economic intuition behind our identification assumption according to the conditions listed above. Due to the equivalence between "(i) & (ii)" and "(i') & (ii')," we focus on the interpretation of conditions (i'), (ii'), and (iii).

First, the sex ratio is balanced between quarters of birth (QOBs). Condition (i'), $\mathbb{E}^{Q1}\left(female_{icp}\right) = \mathbb{E}^{Q4}\left(female_{icp}\right)$, indicates that the proportion of females born in Q1 is equal to the counterpart in Q4. This gives the between-QOB balance of sex ratios.

Second, the covariance between child gender and unobserved parental preferences is balanced between QOBs. Condition (ii'), $\text{Cov}\left(female_{icp}, \xi^{Q1}_{icp}\right) = \text{Cov}\left(female_{icp}, \xi^{Q4}_{icp}\right)$, indicates that

[16]Using the OVB formula, in Eq. (2), the estimates $\hat{\beta}^G$ ($G \in \{f, m\}$) are $\text{plim}\left(\hat{\beta}^G\right) = \beta^G + \delta^G \frac{\text{Cov}\left(Q4_{icp}, \xi^G_{icp}\right)}{\text{Var}^G\left(Q4_{icp}\right)}$.

the covariance between child gender and unobserved parental preferences among children born in Q1 is equal to that among children born in Q4. Notably, our assumption does *not* require $\text{Cov}\left(female_{icp}, \xi^{Q}_{icp}\right)$ for a given Q to be zero. That is, child gender can be selected.[17] We only assume that the magnitude of such gender selection is similar between children born in different quarters. Similarly, the equivalent condition (ii), $\text{Cov}\left(Q4_{icp}, \xi^{f}_{icp}\right) = \text{Cov}\left(Q4_{icp}, \xi^{m}_{icp}\right)$, indicates that the covariance between QOBs and unobserved parental preferences among females is equal to the counterpart among males. That is, QOBs can be selected, and we only assume that such selection on QOBs is balanced between genders.

Finally, condition (iii), $\delta^{f} = \delta^{m}$, indicates that the effect of unobserved parental preferences on child outcomes is similar between females and males.

3.4 Empirical Evidence for the Validity of the Identification Assumption

We now provide empirical evidence to support the validity of our identification assumption. We present empirical analyses with respect to the three conditions, (i'), (ii'), and (iii), respectively, due to the equivalence between "(i') & (ii')" and "(i) & (ii)", as established in Section 3.2.

First, condition (i') indicates that the sex ratio does not differ significantly between QOBs. As both child gender and QOBs are observable in the sample of newborns, we can directly test this condition. Table 2 presents regression results with child gender as the dependent variable and QOB dummies as key explanatory variables. Column (1) reports results for the pooled census sample, and Columns (2) – (5) for (mini-)census 2000, 2005, 2010, and 2015, respectively. The sizes of the estimates are small. F-tests show that the three QOB coefficients are jointly statistically insignificant across all columns. This result indicates that child gender is balanced across birth quarters, thus lending support for condition (i'). Moreover, this result is consistent with that of Currie and Schwandt (2013), who find no correlation between child gender and the season of birth in the US.

Second, we provide support for condition (ii') that potential maternal gender selection is balanced across QOBs. Since ξ^{Q}_{icp} is unobservable, we cannot test condition (ii') directly. We use observable maternal characteristics of newborns, as denoted by $maternal^{Q}_{icp}$, to proxy for ξ^{Q}_{icp}, and to examine this condition. As these variables tend to correlate with unobserved parental preferences, if $\text{Cov}\left(female_{icp}, maternal^{Q}_{icp}\right)$ does not differ between QOBs (Q), then this suggests that $\text{Cov}\left(female_{icp}, \xi^{Q}_{icp}\right)$ is less likely to differ between QOBs, as represented by condition (ii').

[17] In addition to parental gender preferences, according to the Trivers-Willard (TW) hypothesis, natural selection and evolution can also induce correlation between child gender and parental characteristics, whereby parents in good (poor) condition would have more sons (daughters) (Almond and Edlund, 2007; Trivers and Willard, 1973). Note that this does not violate our identification assumption, as long as such correlation is of similar magnitudes between child QOBs, for which we provide evidence later in Section 3.4.

Table 2: Balance Test: Gender of Newborns by Quarter of Birth

Dependent variable	Gender of newborns (male=1)				
	Pooled censuses	Census year			
		2000	2005	2010	2015
	(1)	(2)	(3)	(4)	(5)
Q2	-0.001	-0.001	0.004	-0.008	0.008
	(0.003)	(0.004)	(0.009)	(0.006)	(0.011)
Q3	-0.005*	-0.005	-0.009	0.001	-0.018
	(0.003)	(0.004)	(0.011)	(0.007)	(0.012)
Q4	-0.003	-0.003	0.000	-0.001	-0.014
	(0.003)	(0.004)	(0.011)	(0.008)	(0.010)
p-value in F-test for joint significance	*0.326*	*0.494*	*0.545*	*0.260*	*0.272*
Outcome mean	0.543	0.545	0.536	0.545	0.536
Census year FE	Yes				
Province FE	Yes	Yes	Yes	Yes	Yes
Observations	204,205	118,155	25,830	43,731	16,489
R-squared	0.001	0.002	0.002	0.001	0.003

Note: Data are from population censuses of 2000 and 2010 and mini-censuses of 2005 and 2015. Each observation is a newborn during the year before the time of survey. The dependent variable is a dummy that takes 1 if the newborn is male. Standard errors in parentheses are clustered at the province-by-census-year level in Column (1) and province level in Columns (2) – (5). The table reports the p-values from each regression of the F-test for the joint significance of Q2, Q3, and Q4. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

To this end, we regress maternal characteristics—schooling years, age, hukou (urban versus rural), migration, number of previous births, and a dummy for previous male births—on the female dummy, QOB dummies, and their interactions. Table 3 presents the estimates. We find the coefficient on the female dummy to be statistically significant in most regressions, which indicates that there is gender selection based on maternal characteristics among children born in Q1. However, as discussed above, this does *not* violate our identification assumption. In terms of the coefficients on the interaction terms between the female dummy and the QOB dummies, we find almost none of these coefficients on the interaction terms are statically significant at the 10% level, with one exception, and F-test results show that the three coefficients on the interaction terms are jointly statistically insignificant across all columns.[18]

[18]Another way to interpret the results in Table 3 is from the perspective of condition (ii), which is equivalent to condition (ii'). Specifically, the coefficients on the QOB dummies capture the differences in maternal characteristics across QOBs for male newborns. We find significant estimates of these coefficients, which indicate significant selection on QOBs based on maternal characteristics among boys. However, as we have discussed, this does *not* violate our identification assumption. The coefficients on the interaction terms between female and QOB dummies are small and statistically insignificant, which suggests the correlation between QOBs and maternal characteristics does not differ significantly between genders, which then serves as suggestive evidence for the validity of condition (ii).

Table 3: Maternal Characteristics and Birth Quarter of Newborns by Gender

Dependent variable	Schooling years (1)	Age (2)	Urban (Yes=1) (3)	Migrant (Yes=1) (4)	Number of births before (5)	Male births before (Yes=1) (6)
Female	0.058*	-0.252***	0.007*	0.000	-0.086***	0.032***
	(0.030)	(0.063)	(0.004)	(0.002)	(0.009)	(0.004)
Q2	0.126***	-0.168**	0.015***	0.008***	0.010	-0.004
	(0.029)	(0.069)	(0.004)	(0.003)	(0.007)	(0.003)
Q3	0.226***	-0.595***	0.020***	0.002	-0.046***	-0.014***
	(0.036)	(0.058)	(0.004)	(0.003)	(0.007)	(0.004)
Q4	-0.059**	-0.264***	-0.019***	-0.012***	-0.024***	-0.009**
	(0.030)	(0.072)	(0.004)	(0.003)	(0.007)	(0.004)
Q2 $\times$ female	-0.011	0.012	0.006	-0.002	-0.006	0.003
	(0.033)	(0.079)	(0.004)	(0.004)	(0.008)	(0.005)
Q3 $\times$ female	0.030	0.018	0.007	0.003	0.005	-0.009*
	(0.042)	(0.069)	(0.005)	(0.004)	(0.007)	(0.005)
Q4 $\times$ female	0.016	-0.026	0.001	0.003	0.002	0.000
	(0.032)	(0.067)	(0.005)	(0.003)	(0.007)	(0.004)
p-value in F-test for joint significance	*0.733*	*0.868*	*0.238*	*0.386*	*0.571*	*0.153*
Outcome mean	8.555	26.983	0.203	0.122	0.412	0.152
Census year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	204,205	204,205	187,094	203,525	204,205	204,205
R-squared	0.174	0.042	0.046	0.112	0.056	0.044

Note: Data are from population censuses of 2000 and 2010 and mini-censuses of 2005 and 2015. Each observation is a newborn during the year before the time of survey. Dependent variables are the characteristics of the newborns' mothers aged 15 to 50. The urban dummy is not reported in the 2015 mini-census data. The migrant dummy takes 1 if one's county of residence is different from the county of hukou registration. Standard errors in parentheses are clustered at the province-by-census-year level. The table reports p-values from each regression of the F-test for the joint significance of Q2 $\times$ female, Q3 $\times$ female and Q4 $\times$ female. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

In addition to the aforementioned observable maternal characteristics recorded in the census data, we corroborate our argument using measures of maternal son preference and gender attitudes from household survey data. Specifically, we derive a sample of mothers with children younger than 15 years from the China Family Panel Studies dataset (the 2014 wave), which contains mothers' answers to five questions regarding son preferences and gender attitudes.[19] We use these

[19] In the 2014 wave of the CFPS, individuals are asked whether they agree with the following five statements, on a Likert scale from 1 (totally disagree) to 5 (totally agree): (1) "In order to continue the family lineage, women should give birth to at least one boy;" (2) "Men should focus on career, while women should focus on family;" (3) "Marrying well is more important for women than doing well;" (4) "Women should have at least one child;" (5) "Men should do

answers as dependent variables in regressions of the same specification as those in Table 3. The results are reported in Appendix Table A1. We do not detect significant difference in maternal son preferences and gender attitudes between children born in different quarters, nor do potential correlations between child gender and maternal preferences (which could suggest gender selection based on son preference) significantly vary across child QOBs.[20] This finding further lends support to the empirical validity of condition (ii').

Finally, condition (iii) implies that our estimates of the gender gap in BQEs might be biased if the correlations between unobserved parental characteristics and child outcomes differ by gender. Using the omitted variable bias formula, we show that such a bias arising from the difference between δ^f and δ^m, if any, is quantitatively negligible, as discussed in detail in Appendix C.2.

4 Estimates of the Gender Difference in Birth Quarter Effects

In this section, we present the estimates of the gender differences in birth quarter effects (BQEs) on educational and labor market outcomes at the individual level. We also discuss robustness of the results and show heterogeneity in the estimated BQEs and their gender difference across provinces in China.

4.1 Baseline Results

Educational Outcomes Table 4 reports BQE estimates on educational attainment based on the pooled census sample. We use three dependent variables: schooling years (Columns (1) - (2)), an indicator for junior high school completion (Columns (3) - (4)), and an indicator for senior high school completion (Columns (5) - (6)). We separately estimate Eq. (1) for females and males, with Columns (1), (3), and (5) for females and Columns (2), (4), and (6) for males. Standard errors are clustered at the province-by-birthyear level.

We have two findings. First, the BQE estimates are statistically significant. In particular, people born in the fourth quarter (Q4) have the highest level of educational attainment. Across all columns, coefficients on Q2 are negative and those on Q3 and Q4 are positive, with people born in Q1 as the reference group. All estimated coefficients are statistically significant at the 1% level. The magnitudes of the coefficients on Q4 are much larger than those on Q2 and Q3 in absolute

half of the housework." The first question serves as a direct measure of one's son preference, and the last four questions capture one's attitudes toward traditional gender norms, which answers are significantly correlated with the answer to the first question. We exclude observations in which a mother gives birth to a child at age lower than 15 or higher than 50. Our sample contains 6,406 mothers matched with a child younger than 15 years.

[20] In Column (1) of Appendix Table A1, we find that mothers of girls have significantly lower level of preference for a son. This is consistent with potential gender selection based on maternal gender preferences.

Table 4: Birth Quarter Effects on Educational Attainment by Gender

Dependent variable	Schooling years		Junior high school completion (Yes=1)		Senior high school completion (Yes=1)	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Q2	-0.045***	-0.035***	-0.004***	-0.004***	-0.004***	-0.003***
	(0.005)	(0.004)	(0.001)	(0.000)	(0.001)	(0.001)
Q3	0.050***	0.056***	0.006***	0.005***	0.002***	0.004***
	(0.006)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)
Q4	0.221***	0.165***	0.022***	0.015***	0.016***	0.014***
	(0.007)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)
p-value for Q2, Q3, and Q4 coefficient equality between gender subsamples	*0.000*		*0.000*		*0.000*	
Outcome mean	6.780	8.150	0.484	0.631	0.161	0.221
Han ethnicity (Yes=1)	Yes	Yes	Yes	Yes	Yes	Yes
Birth province FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth year FE	Yes	Yes	Yes	Yes	Yes	Yes
Census year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,816,218	8,127,660	7,816,218	8,127,660	7,816,218	8,127,660
R-squared	0.319	0.210	0.251	0.200	0.090	0.066

Note: Data are from censuses 1990, 2000, and 2010 and mini-censuses 2005 and 2015, and the sample includes individuals aged from 25 to 60. Standard errors in parentheses are clustered at the province-by-birthyear level. For each dependent variable, we report the *p*-value from the Wald test for the equality of the Q2, Q3, and Q4 coefficients in the two gender subsamples. ***, ** and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

value.[21]

Second, the estimated Q4 effect is larger for females than males across the three measures of educational attainment. For example, the estimates show that the difference in average schooling years is 0.17 between males born in Q4 and Q1, and this difference increases to 0.22 for females. Following Buckles and Hungerman (2013), we perform a Wald test with the null hypothesis that the coefficients on birth quarters (Q2, Q3, and Q4) do not differ between females and males, and we report the *p*-value for each dependent variable. The null hypothesis is rejected with a *p*-value lower than 0.001 for each of the three educational outcomes.[22]

[21] The census data only contain people's hukou status (rural or urban) at the survey time, which might be different from their hukou status at birth. Under the hukou system in China, people can change their hukou status from rural to urban by passing the entrance exam for tertiary education. The current hukou status is thus an endogenous choice and affected by schooling decisions. Therefore, it is undesirable to conduct the subsample analysis based on people's current hukou status.

[22] In the Wald test for the equality of coefficients on Q4, we also find significant differences in the Q4 coefficient estimates between females and males with a *p*-value lower than 0.001 for each of the three dependent variables.

The estimates in Table 4 are economically significant and have important implications for gender inequality in education levels. A simple calculation shows that compared with people born in Q2, schooling years increase by 0.27 and 0.20 on average for females and males born in Q4, respectively. Subsequently, the gender gap in schooling years shrinks by 0.07 for those born in Q4 compared with Q2 for the 1930-1990 cohort, which corresponds to a 5% decrease in the sample average gender gap.

Complementary to the estimates for educational attainment, we use the CEPS to estimate gendered BQEs on cognitive skills and academic performance—measured by exam scores for math, Chinese, and English—for junior high school students. The results are reported in Appendix Table A3. Although the estimates are less precise, partly due to the small sample size, the estimates of Q4 effects are positive. Compared with males, BQE estimates are larger for females for all dependent variables, though the differences are statistically insignificant.

Labor Market Outcomes Table 5 reports the estimated BQEs on labor market outcomes based on the mini-census 2005 sample. We use three dependent variables: log monthly earnings (Columns (1) - (2)), an indicator for being employed in the public sector (Columns (3) - (4)), and an indicator for having unemployment insurance (Columns (5) - (6)).[23] The results for labor market outcomes (Table 5) are consistent with those for educational outcomes (Table 4). People born in Q4 have better labor market outcomes than those born in other quarters across all three measures, and Q4 effects are larger for females than males. For example, the estimates show that the difference in log monthly earnings is 0.033 between males born in Q4 and Q1, and this difference increases to 0.043 for females. Gender differences in estimated Q4 coefficients are statistically significant across all three dependent variables.

Gender differences in BQEs on labor market outcomes are largely explained by the gender gap in BQEs on education. Specifically, we repeat the regressions reported in Table 5 and add schooling years as a control variable. Appendix Table A4 shows that the estimated coefficients on Q4 are smaller than those in Table 5. Moreover, gender differences in the coefficients on Q4 are statistically insignificant when we use earnings as dependent variables. When we use the indicator for being employed in the public sector as the dependent variable, the gender difference in the estimated coefficients on Q4 drops from 0.007 to 0.003. This indicates that education is a driver for the gender gap in BQEs on labor market outcomes. Therefore, we focus on BQEs on education in heterogeneity and mechanism analyses below.

Tables 4 and 5 show that for educational and labor market outcomes, the sizes of the coefficients on the Q4 dummy are consistently larger than those on Q2 and Q3 by one magnitude in

[23] When we use an indicator for being employed as a dependent variable, the estimates of BQEs are small and statistically insignificant for both males and females. Thus, we focus on the three labor market outcomes for the employed. The results are similar to those presented in Table 5 if we additionally include individuals who are unemployed.

Table 5: Birth Quarter Effects on Labor Market Outcomes by Gender

Dependent variable	Log monthly earnings		Working in the public sector (Yes=1)		Unemployment insurance coverage (Yes=1)	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Q2	-0.008**	-0.005	-0.003*	-0.005***	-0.004***	-0.003**
	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Q3	0.006	0.011***	0.001	0.001	-0.003***	-0.000
	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Q4	0.043***	0.033***	0.017***	0.011***	0.011***	0.007***
	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
p-value for Q2, Q3, and Q4 coefficient equality between gender subsamples	*0.006*		*0.003*		*0.000*	
Outcome mean	5.783	6.257	0.127	0.166	0.109	0.134
Han ethnicity (Yes=1)	Yes	Yes	Yes	Yes	Yes	Yes
Birth province FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	508,544	615,444	508,544	615,444	508,544	615,444
R-squared	0.145	0.206	0.074	0.052	0.137	0.122

Note: Data are from mini-census 2005. The sample includes individuals aged 25 to 60 who were employed at the time of the survey. Standard errors in parentheses are clustered at the province-by-birthyear level. For each dependent variable, we report the *p*-value from the Wald test for the equality of the Q2, Q3, and Q4 coefficients in the two gender subsamples. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

absolute value. Therefore, in the analyses below, we focus on the gender gap in Q4 effects—i.e., the differences in outcomes between people born in Q4 and Q1.

4.2 Robustness Analyses

We now present a series of robustness analyses for the baseline estimates of BQEs and their gender differences as reported in Section 4.1.

Sample Attrition A potential concern for our estimation is that the sample attrition rate might vary across QOB groups. Although we cannot fully rule out this possibility, the attrition issue would be less likely to materially affect our estimates. Given that the attrition rate is likely to be higher for people with poorer neonatal conditions, the potential sample attrition would lead to that our estimates serve as a lower bound for the BQE and its gender difference in terms of absolute values. To formally check the attrition issue, we calculate the cohort size by birth year, province, and gender, using census 1990. We then regress the cohort size on QOB dummies, age, gender, and their full interactions. The result shows that the estimated coefficients on triple-interaction terms are small and statistically insignificant (Appendix Table A5).[24] This suggests no gender difference in the seasonal patterns of sample attrition, which is captured by the linear relationship between cohort sizes and age. Finally, in the mechanism analysis in Section 5, we address the mortality selection issue rigorously and do not find evidence of seasonality in cohort losses driven by seasonality in agricultural production.

Excluding Special Time Periods We conduct robustness checks by excluding people born in some special time periods. First, we exclude people born after 1978, as these birth cohorts were affected by the one-child policy (OCP) and subject to potentially stronger gender selection. Second, we exclude people born after 1970, in order to purge out the impact of the fertility control policy of the "Later, Longer, and Fewer" Campaign and the Compulsory Education Law which was implemented around 1986. Third, we exclude people born during the Great Famine (between 1959-1961) as the mortality selection would be more severe during this period.[25] We report the results for the above three analyses in Appendix Table A7 with schooling years as the dependent variable. Reassuringly, our baseline findings on the BQE and its gender difference keep largely unchanged with these sample restrictions.[26]

Controlling for Seasonality in Maternal Characteristics As we have discussed in Section 3.4, maternal characteristics might differ significantly between children born in different quarters. Although such seasonality in maternal characteristics does not systematically vary between genders (as shown in Table 3), it might contribute to shaping the BQE on lifecycle outcomes and its gender difference. As a robustness check, in our regression, we additionally control for the average ma-

[24] In addition, in Appendix Table A5, the estimated coefficients on interaction terms between QOB dummies and gender are statistically insignificant. This also suggests the absence of systematic gender differences in sample attrition across QOBs.

[25] In an additional analysis, we interact the QOB dummies with the indicator for the years of the Great Famine (i.e., 1959-1961). In Appendix Table A6, we find that the between-QOB difference in schooling years is enlarged during the Great Famine for females and not for males, thus the gender difference in BQEs is larger for people born between 1959-1961 as compared to other cohorts. This finding is consistent with the observation in Figure 1 that the BQE and its gender difference spiked during the Great Famine. Note that, however, this result should be interpreted with caution because the mortality selection issue tends to be more severe for people born during the Great Famine (Gørgens et al., 2012; Meng et al., 2015).

[26] The rapid decline in the observed BQEs from 1930s to 1950s shown in Figure 1 is potentially because of the rapid expansion of primary education led by the government in the beginning years of the People's Republic of China. The primary school completion rate is 41% among people born during 1930-1939 and 81% among those born during 1950-1959. In Appendix Table A8, we find that the estimated Q4-Q1 difference is about two times larger among people born in the 1930s compared to those born in the 1950s. Based on the estimates of a regression with interactions between QOB dummies and province-cohort-level primary school completion rates, a back-of-the-envelope calculation reveals that the expansion of primary education can explain about 86 percent of the decrease in BQEs during this period. In addition, this mechanism is less likely to contribute to the decrease in BQEs after 1978, as the primary school completion rate in China has reached 97% for cohorts born in 1978.

ternal characteristics for each month of birth (MOB) in the baseline regression.[27] Appendix Table A9 presents the results with these variables of MOB-specific maternal characteristics as additional controls. We find that the estimation results on QOB dummies are similar to our baseline results after including these additional covariates. This result suggests that our observed gendered BQEs are less likely to be driven by the seasonality in maternal characteristics.

4.3 Heterogeneity across Provinces

BQEs and their gender differences exhibit substantial heterogeneity across provinces in China. In Appendix D, we first investigate the spatial distribution of BQE estimates and their gender gaps across provinces; we then correlate the estimated BQEs and gender differences with provincial characteristics. We summarize our main findings from the provincial heterogeneity analysis in the following, with a detailed description of methods and results presented in Appendix D.

First, the estimates of BQEs are positive and statistically significant across all provinces, and the BQE estimates for females exceed those for males in 27 of the 31 provinces.[28] This underscores the robustness of BQEs and the gender differences to a variety of regions with different geographic and socioeconomic characteristics.

Second, upon correlating BQE estimates with provincial characteristics, we discover that BQEs are larger in provinces with lower levels of economic development, higher fertility rates, lower health status, and lower education levels. Regarding the gender differences in BQEs, we observe that such differences in BQEs positively correlate with BQE estimates in the pooled sample, suggesting common driving factors underlying BQEs and their gender differences. Moreover, gender differences in BQEs tend to be larger in provinces with lower levels of health conditions and education. The differences are also larger in provinces with a higher degree of gender inequality, as proxied by the gender gap in life expectancy and female bargaining power within households.

In sum, the province-level analyses reveal consistent patterns that provide valuable insights into the potential mechanisms driving BQEs and their gender differences. We will further examine the underlying mechanisms in Sections 5 and 6.

5 Mechanism

In this section, we investigate the mechanism of agricultural seasonality through which the QOB differentially affects child lifecycle outcomes by gender. Specifically, we explore the role of agri-

[27] In the census data, we cannot precisely match individuals with their mothers. Therefore, we use the MOB-specific average maternal characteristics—i.e., those examined as dependent variables in Table 3—as a proxy, which captures the seasonal variation of individuals' maternal characteristics.

[28] The four negative differences in the estimates between females and males are small and statistically insignificant.

cultural seasonality. We first describe seasonality in agricultural production in China, which induces seasonal variations in household resources for child neonatal investment (Section 5.1). Next build a model which shows that seasonal variations in household resources, combined with son preference, result in a gender difference in BQEs on child neonatal investment, and subsequently, on lifecycle outcomes (Section 5.2). We then empirically examine the proposed mechanism using five analyses at the individual, province, and county levels (Sections 5.3 to 5.7).[29]

5.1 Seasonality in Agricultural Production and Seasonal Variations in Household Resources for Child Neonatal Investment in China

This section shows that household resources for child neonatal investment—including both food and parental childcare time—are most abundant for children born in Q4. We describe the seasonality in household resources during the neonatal period driven by the seasonality in agricultural production. We also discuss the presence of household seasonal liquidity constraints in China.

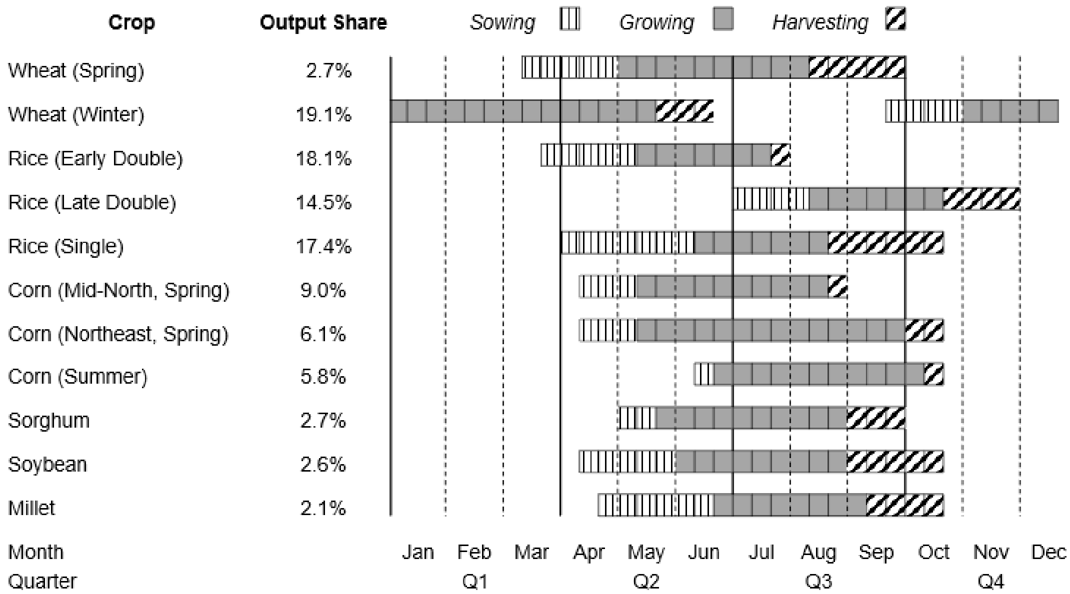
China covers 9.6 million square kilometers, approximately 15% of which is arable. Its primary crops are rice, wheat, and corn. Rice is mainly planted in southern China; in the northern part, wheat and corn are the main crops. Despite the vast size and diversified crops across the country, seasons for sowing, growing, and harvesting are similar. Figure 2 lists the calendar for 11 crops, which account for over 90% of total grain output in China (Ministry of Agriculture, 1980). Most crops are sown in Q2 and harvested in Q3 or Q4.

Based on the crop calendar, for children born in each quarter, we calculate the levels of food abundance during the *in utero* and neonatal periods separately. The *in utero* period includes the 10 months prior to the birth and the neonatal period includes the 4 months during and after the birth. The calculation consists of five steps. (i) For each crop, we assign the value of the abundance level for the 10 days prior to harvesting as 0 (the lowest level in a year) and the level for the last 10 days of the harvesting period as 1 (the highest level). Across every 10 days, we assume that the level linearly increases from 0 to 1 during the harvesting period, and similarly, linearly decreases from 1 to 0 during the period from the end of harvesting this year to the beginning of harvesting next year. Take wheat (spring) in Figure 2 as an example. We assign the value of the level as 0 for the first 10 days in August and as 1 for the last 10 days in September. The number increases by 0.2 per 10-day period during the harvesting period,[30] and decreases by $\frac{1}{31}$ per 10-day period from the

[29] Administrative divisions in China contain three levels: province, prefecture, and county. County-level units fall into three categories: counties (*Xian*, the most common county-level divisions); districts (*Qu*, mainly subdivisions of urban areas); and autonomous counties (*Zizhixian*, counties with one or more designated ethnic minorities). We term all three categories of county-level units "counties" throughout the paper.

[30] Solving a linear equation such as $Y = \beta t$, where t indexes every 10 days from the second 10 days in August ($t = 1$) to the last 10 days in September ($t = 5$), and Y equals 0 for the first 10 days in August and 1 for the last 10 days in September, we have $\beta = 0.2$.

Figure 2: Seasonal Agricultural Production in China



Note: Data sources: China Agriculture Yearbook (1980); US Department of Agriculture, Foreign Agricultural Service.

last 10 days in September to the first 10 days in August next year.[31] (ii) For each 10-day period, we take the average of the levels across the 11 crops listed in Figure 2, weighted by their output shares out of all crops in 1979. (iii) We sum the levels over the three 10-day periods in each month. (iv) For each birth month, we further sum the levels over the months in the *in utero* and neonatal periods separately. (v) Finally, we take the average of the summed levels across the 3 months for each QOB.

In addition to food, parental time allocation between work and childcare is important for child development during both the *in utero* and neonatal periods. Since agricultural work is labor intensive, seasonality in agricultural production induces seasonal variations in parental time allocation between work and childcare. For children born in each quarter, we calculate the levels of agricultural work intensity during the *in utero* and neonatal periods separately. The calculation consists of six steps. (i) For each crop, we assign its sowing time to each month proportionally. For example, for wheat (spring) shown in Figure 2, the sowing time is 0.4 (0.6) in March (April), and it is 0 in other months.[32] (ii) For each month, we generate the level of sowing intensity by averaging the sowing time across the 11 crops listed in Figure 2, weighted by their output shares in 1979. (iii) We calculate levels of growing and harvesting intensity in a similar way. (iv) We calculate the level of

[31] Solving a linear equation such as $Y = 1 - \beta t$, where t indexes every 10 days from the first 10 days in October ($t = 1$) to the first 10 days in August next year ($t = 31$), and Y equals 1 for the last 10 days in September and 0 for the first 10 days in August next year, we have $\beta = \frac{1}{31}$.

[32] For wheat (spring) shown in Figure 2, 40% of the sowing time is in March, 60% in April, and 0 in other months. We normalize total sowing time across the year as 1.

Table 6: Food Abundance and Agricultural Work Intensity by Quarters of Birth

	Food Abundance		Agricultural Work Intensity				
	Quarterly Average	Relative to within-year mean	Sowing	Harvesting	Growing	Overall	Relative to within-year mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Neonatal period (4 months during and after the birth month)							
Q1	1.63	(0.82)	0.53	0.08	0.23	0.28	(0.86)
Q2	1.44	(0.72)	0.49	0.49	0.69	0.55	(1.68)
Q3	2.37	(1.19)	0.25	0.61	0.31	0.39	(1.19)
Q4	2.56	(1.28)	0.06	0.15	0.10	0.11	(0.32)
Panel B. In utero period (10 Months prior to the birth month)							
Q1	5.22	(1.04)	0.69	0.98	0.91	0.86	(1.04)
Q2	5.32	(1.06)	0.78	0.73	0.60	0.70	(0.85)
Q3	4.79	(0.96)	0.86	0.66	0.88	0.80	(0.96)
Q4	4.69	(0.94)	1.00	0.96	0.95	0.97	(1.17)

Note: Q1, Q2, Q3, and Q4 represent children born in the first, second, third, and fourth quarters, respectively. The calculation is based on the crop calendar presented in Figure 2.

agricultural work intensity for each month by averaging the three levels of sowing, growing, and harvesting intensity. (v) For each birth month, we sum the levels over the months in the *in utero* and neonatal periods separately. (vi) We finally average the summed levels of intensity across the 3 months for each QOB.

Table 6 tabulates levels of food abundance and agricultural work intensity by QOBs in neonatal (Panel A) and *in utero* periods (Panel B).[33] Panel A shows that household resources are most abundant for children born in Q4 during their neonatal period. For example, the level of food abundance for children born in Q4 is 128% of the average level across QOBs in a year (Column (2)). Strikingly, the level of agricultural work intensity for children born in Q4 is only 32% of the average level in a year (Column (7)). This indicates that relative to parents of children born in other quarters, parents of children born in Q4 are largely absent from agricultural work, which enables them to spend more time on childcare during the child neonatal period. In addition, the lower intensity of agricultural work for mothers would raise the quantity and quality of breast milk for infants. By contrast, Panel B shows that the differences in household resources are small between children born in different quarters in their *in utero* period.

A crucial assumption that associates seasonal food abundance and agricultural work intensity with seasonality in neonatal conditions is the presence of household seasonal liquidity constraints. It is well documented in the literature that households usually face seasonal liquidity constraints

[33] We note that our constructed QOB-specific levels of food abundance and agricultural work intensity serve only as rough measures and are not precise quantitatively, though to a large extent they can qualitatively capture the cross-QOB variations.

and are unable to fully smooth consumptions across seasons in developing economies including China (Agneman et al., 2023; Beaman et al., 2023; Fink et al., 2020; Sun et al., 2013; Vaitla et al., 2009; Zhu et al., 2019). In our context, it is plausible to assume the presence of seasonal liquidity constraints. On one hand, the seasonal variation in agricultural work intensity can hardly be smoothed within a year. On the other hand, household consumption, particularly food consumption, would be largely affected by the seasonality in income from agricultural production. This is partly because of the lack of effective food preservation techniques and less developed financial and product markets.

To further substantiate the presence of household seasonal liquidity constraints, we provide evidence using seasonal food consumption data from household surveys in China. We utilize two datasets. The first is the 2010 wave of the CFPS, which contains data on household food expenditure for the preceding month at the time of the survey. The second is the CHNS (waves 1991, 1993, 1997, and 2000), which collects detailed individual-level food consumption records—which are then summarized as total nutritional intake in kilocalories—over the three days preceding the survey. Comparing households surveyed in different months within a year,[34] we find that households, on average, exhibit higher food consumption and nutritional intake in Q4 as compared to other quarters. Furthermore, household food consumption and nutritional intake are positively associated with the index of monthly food abundance calculated based on the crop calendar (step (iii) in calculating the food abundance index during the neonatal period as discussed above), as shown in Appendix Table A10. In summary, these findings suggest the existence of seasonal household liquidity constraints and the impact of agricultural seasonality on household food consumption patterns.[35]

5.2 Theoretical Analysis

Based on the stylized facts about the seasonality in agricultural production and household resources as documented above, we now propose a conceptual framework, which combines the seasonality in household resources, household seasonal liquidity constraints, and son preference in intrahousehold investment, to explain our findings on the BQE and its gender difference, and guide our further

[34]The survey time for CFPS spans all months from January to December, while CHNS only covers the months from July to December. In the CFPS sample, we control for province fixed effects, hukou status, household income in the past year, and schooling years of the household head. In the CHNS sample, leveraging the panel structure, we control for household fixed effects and survey year fixed effects, which strategy accounts for unobserved household heterogeneity and exploits the variation in the survey time for a household across waves.

[35]Due to data constraints, we lack detailed data on household seasonal consumption prior to the 1990s, so our analysis is based on household survey data from the 1990-2010 period. The result here may be interpreted as providing a lower bound for seasonal variation in household food consumption and nutritional intake during the 1930-1990 period. It is reasonable to believe that seasonal liquidity constraints would have been more severe before 1990 due to the lesser access to food preservation techniques and lower levels of financial and product market development.

investigation on the mechanism of agricultural seasonality.

5.2.1 A Model of Household Resources and the Gender Gap in Intrahousehold Investment in Children

Model Setup Consider a household that gives birth to a child of gender $G \in \{f, m\}$ (females and males) in season S.[36] For simplicity, we assume two seasons in a year: a season with abundant household resources to invest in children in their neonatal period ($S = H$) and a season with lean household resources ($S = L$). Parents are altruistic. They maximize utility from their own consumption (c) and investment in the child in the neonatal period (h), subject to resources that are constant between seasons (w) plus resources that vary between seasons (q_S), where $q_H > q_L$:[37]

$$\begin{aligned} \max \quad & u(c) + \beta^G v(h^G), \\ \text{s.t.} \quad & c + ph^G \leq w + q_S, \end{aligned} \tag{4}$$

where β^G represents the degree of parental altruism toward the child and p is the price of child investment relative to parental consumption. We assume that parents prefer boys to girls,[38] such that $\beta^f < \beta^m$.[39] We further assume that utility functions $u(\cdot)$ and $v(\cdot)$ are well behaved, such that they are strictly concave and second-order continuously differentiable.

Our model setup captures the main feature of an agricultural economy, in which agricultural production varies between seasons and households have limited ability to smooth consumption between seasons, as empirically supported in Section 5.1. For the purpose of illustration, we note that child investment, h^G, represents neonatal nutritional input by parents.[40]

[36] For simplicity, we consider one child in a family. Our paper focuses on child investment during the neonatal period. A family does not give birth to multiple children within a season, which we consider, except for twins and triplets.

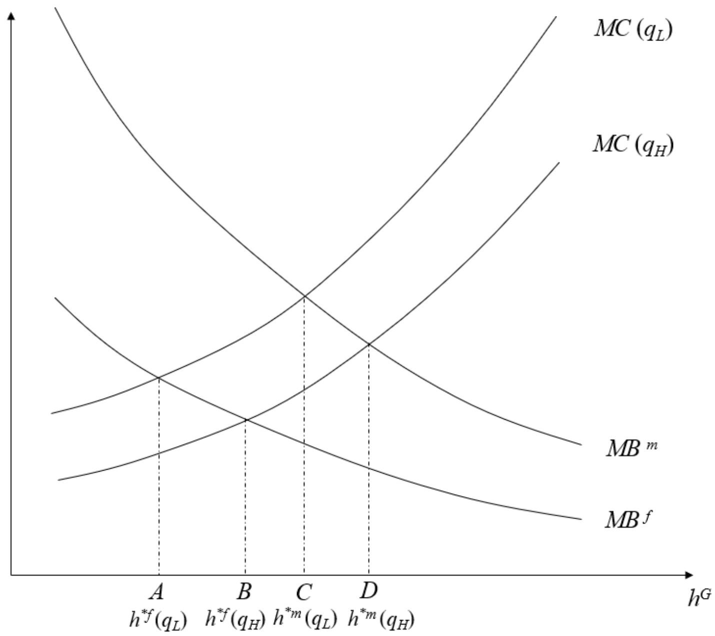
[37] In reality, household resource abundance would influence investment in children during the neonatal period in multiple respects. For instance, first, since children at that age are not consuming food directly, the food abundance in the neonatal period works through maternal food consumption and subsequently exerts influence on the quality of mothers' breastmilk (also on the extensive margin of breastfeeding or exclusive breastfeeding). Second, lower agricultural work load is associated with more parental time for childcare and also contributes to better nutritional status for mothers (Komatsu et al., 2019), which is associated with higher quality of mothers' breastmilk. Third, household resources can also influence the choice of seeking medical treatment, which is also a crucial factor during children's neonatal period.

[38] According to the literature, an alternative explanation for the greater weight on boys than girls is that boys may be in greater need of inputs because of their larger size and greater frailty during the neonatal period (Drevenstedt et al., 2008). While we cannot fully rule out this possibility, we believe parental son preference plays a role in our context, which is suggested by a larger gender difference in BQEs in provinces with a higher degree of gender inequality, as proxied by the gender gap in life expectancy and female bargaining power within households (Section 4.3).

[39] As shown in Section 3.4, the degree of parental son preference does not vary significantly between children born in different quarters (Appendix Table A1). Thus, we assume β^G to be constant between seasons of birth.

[40] We note that this framework can be used to analyze parental time allocation equivalently. The total time, which is fixed, can be divided into two parts: time for agricultural work and off-agriculture time. Seasonality in agricultural

Figure 3: Optimal Investments in Children between Seasons by Gender



Gender Gap in Intrahousehold Resource Allocation between Seasons The equilibrium condition with respect to h^G in Problem (4) is

$$pu'(w+q_S-ph^G)=\beta^G v'(h^G). \tag{5}$$

This condition depicts the tradeoff between the marginal cost (MC, the left-hand side) and marginal benefit (MB, the right-hand side) from child investment. Figure 3 plots this tradeoff. When child investment increases, parental consumption decreases, and MC from child investment—the marginal utility of parental consumption—increases. The slope of the MC curve is upward. By contrast, MB decreases with child investment, and the slope of the MB curve is downward.

We have two observations from Figure 3. First, for any given level of child investment, MB is higher for males than females; moreover, the ratio of MBs between males and females is constant. Thus, the line for MB is flatter for females than males. This observation yields the most important implication in our model: The MB for females is less sensitive to child investment than males. Second, when moving from a lean season to an abundant one, the line for MC moves downward.

work time is determined by natural conditions and agricultural technology. For the off-agriculture time, we do not consider off-farm work, because the hukou system restricted migration in China, and local labor markets for off-farm work did not exist before the 1990s. Therefore, parents allocate their time out of agricultural work between leisure and childcare. Then Problem (4) becomes the follows. Parents maximize $u(t_p)+\beta^G v(t_c^G)$, subject to $t_p+t_c^G=t_S^{NA}$, where t_p is parental leisure time, t_c^G is childcare time by child gender, and t_S^{NA} is the total non-agricultural-work time, which varies across seasons.

Figure 3 shows that the BQE is larger for girls than boys. Points A and B (C and D) represent the optimal investments for girls (boys) in a lean season and an abundant one, i.e., $h^{*f}(q_L)$ and $h^{*f}(q_H)$ ($h^{*m}(q_L)$ and $h^{*m}(q_H)$), respectively.[41] AB and CD correspond to BQEs on neonatal investment in girls and boys, respectively. We observe that $AB > CD$. The intuition is as follows. We interpret the MB curves in Figure 3 as the demand for child investment, and the MC curves as the supply. Because of son preference, the demand curve is more elastic for girls than boys. Consequently, the change in investment at the equilibrium is larger for girls than boys when the supply curve shifts.

We formally derive the gender gap in BQEs on intrahousehold investment in children. Specifically, the BQE—the difference in investments between children born in an abundant season and those born in a lean season—for children with gender G is

$$BQE^G = h\left(w, q_H, p; \beta^G\right) - h\left(w, q_L, p; \beta^G\right) = \int_{q_L}^{q_H} \frac{\partial h\left(w, q, p; \beta^G\right)}{\partial q} dq, \tag{6}$$

where

$$\frac{\partial h\left(w, q, p; \beta^G\right)}{\partial q} = \frac{pu''\left(w + q - ph^{*G}\right)}{p^2 u''\left(w + q - ph^{*G}\right) + \beta^G v''\left(h^{*G}\right)} > 0, \quad \forall q.$$

This yields the following proposition:

Proposition 1 (Gender gap in BQEs) *When $\beta^f < \beta^m$, the difference between girls born in abundant and lean seasons is larger than that for boys in terms of parental neonatal investment in children. That is,*[42]

$$h^{*f}(q_H) - h^{*f}(q_L) > h^{*m}(q_H) - h^{*m}(q_L). \tag{7}$$

This proposition corresponds to the fact that $AB > CD$ in Figure 3. Rearranging terms in Eq. (7), Proposition 1 has an important implication for the gender gap between seasons, which is summarized in the corollary below.

Corollary 1 (Gender gap in child investments between seasons) *Compared with children born in the abundant season, the gender inequality in intrahousehold neonatal investment is larger for children born in the lean season. That is,*

$$h^{*m}(q_L) - h^{*f}(q_L) > h^{*m}(q_H) - h^{*f}(q_H).$$

[41] The existence and uniqueness of h^{*G} is guaranteed when $u(\cdot)$ and $v(\cdot)$ satisfy the Inada condition, and are strictly concave and second-order continuously differentiable.

[42] In the theoretical model, this comparison is based on a ceteris paribus basis. For a given family, we consider four hypothetical scenarios in which parents give birth to a child (of gender f versus m) in a season (H versus L). We can illustrate these four different scenarios as four types of families, conditional on other parameters in the model being the same.

This corollary corresponds to $AC > BD$ in Figure 3. The result is consistent with the literature whereby for parents with son preference, a tighter resource constraint would lead to a larger gender gap (male relative to female) in their investment in children (Behrman, 1988; Duflo, 2012).

The Role of Economic Development Our model derives two channels through which economic development attenuates the gender gap in BQEs: (i) shrinking the gap in resources between seasons ($q_H - q_L$) and (ii) increasing resources that are constant between seasons (w).

First, economic development closes the gap in household resources between seasons. On the one hand, with technological progress in agricultural production and food preservation, seasonal variations in household resources induced by agricultural production seasonality decrease. On the other, with the development of product and credit markets, households are able to better smooth their consumption between seasons. This channel is represented by a decrease in $q_H - q_L$ in our model. Eq. (6) shows that $BQE^f - BQE^m$ decreases when $q_H - q_L$ decreases, holding $\frac{q_H+q_L}{2}$ and w constant. Second, household resources that do not vary between seasons (w) increase with economic development. In our model, when w increases, the impact of q_H and q_L on the marginal utility from parental consumption decreases. This is represented by a decrease in the gap between the two lines that denote $MC(q_L)$ and $MC(q_H)$ in Figure 3. The decrease in the gap between the two lines reduces the gender gap in BQEs on the investment, holding the two lines of MB^m and MB^f constant in Figure 3.[43] Our discussion is summarized in the following proposition.

Proposition 2 (Economic development reduces BQEs and their gender gap) *BQE^f, BQE^m, and $BQE^f - BQE^m$ decrease if (i) $q_H - q_L$ decreases, holding $\frac{q_H+q_L}{2}$ and w constant; or (ii) w increases, holding q_H and q_L constant.*

Proposition 2 yields an important implication for economic development and the gender gap between seasons, which is summarized in the corollary below.

Corollary 2 (Economic development reduces the difference between seasons in gender gaps in child neonatal investments) *The difference in gender gaps in child neonatal investments between seasons, $\left(h^{*m}(q_L) - h^{*f}(q_L)\right) - \left(h^{*m}(q_H) - h^{*f}(q_H)\right)$, decreases if (i) $q_H - q_L$ decreases, holding $\frac{q_H+q_L}{2}$ and w constant; or (ii) w increases, holding q_H and q_L constant.*

5.2.2 Lifecycle Effects of Neonatal Conditions

The literature has demonstrated that not only the total amount but also the timing of child investment is important for child development. In particular, the neonatal period is a critical stage in

[43] Mathematically, a sufficient condition for this conclusion is that the utility function for parental consumption is sufficiently concave, such that $u'''(\cdot) \geq 0$. This condition holds for the utility functions we commonly use, such as linear, quadratic, log, Cobb-Douglas, and CES.

shaping child lifecycle outcomes. For example, in the medical literature, Wiedmeier et al. (2011) highlight the importance of the first several days after birth and document long-term consequences of insufficient nutrient intake during the first 4 months after birth; Lucas et al. (1998) and Singhal et al. (2001) provide experimental evidence on the long-term effects of nutritional intake during the first month after birth on cognitive development and health.

The importance of neonatal conditions has also been documented in the economics literature (Bharadwaj et al., 2013; Carneiro et al., 2015; Cunha et al., 2010; Heckman et al., 2013). For example, Bharadwaj et al. (2013) find that neonatal health interventions have long-run effects on children's academic achievement in school, and Carneiro et al. (2015) show that the increased maternal time spent with a child during the neonatal period lead to lower high school dropout rates and higher wages in adulthood.

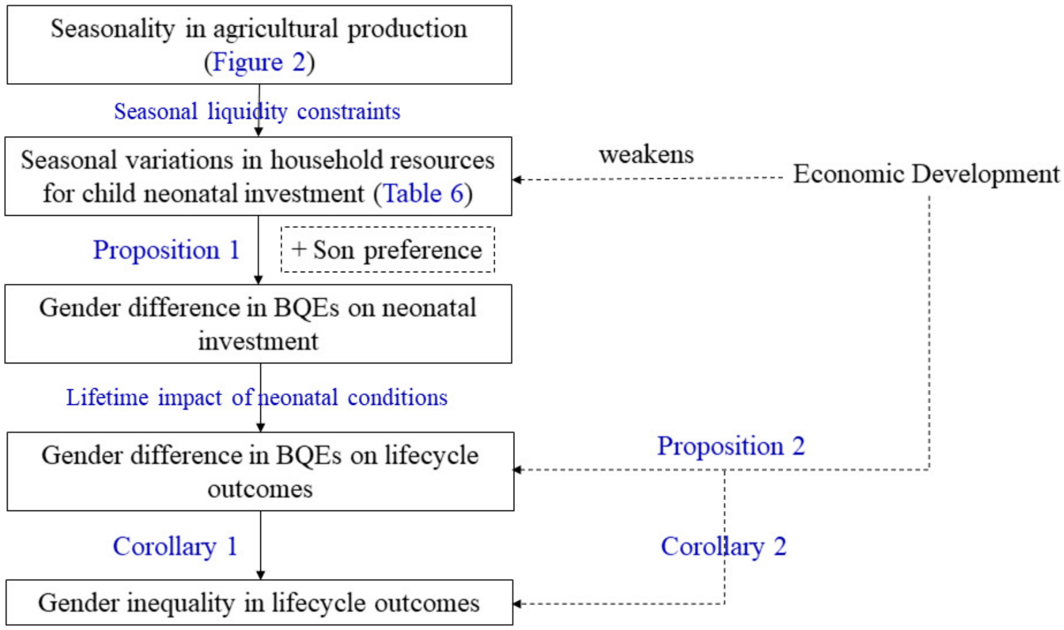
The persistence of the impact of seasonality in neonatal investment on lifecycle outcomes hinges on the condition that the deficiency in neonatal treatment cannot be fully remedied by treatments in later periods of life. We provide supportive evidence for the plausibility of this condition in our context of BQEs by examining the between-QOB differences in parental investment in children later in their adolescent period. Using the CEPS data, we do not find any significant difference in various measures of parental investment—in terms of educational expenditure, extracurricular tutoring, health insurance, time spent with children, and parenting styles (demandingness and responsiveness)—between children of different QOBs for either females or males (Appendix Table A11).[44] Given the finding of significant BQEs on cognitive skills and academic performance among children in the same dataset (Appendix Table A3), this result suggests a limited response of parental investment during children's later periods of life, and thus lends support to the theoretical assumption of the lifecycle effects of neonatal conditions.

5.2.3 Summary and Overview of Analyses on the Mechanism

Figure 4 visualizes our conceptual framework and provides a roadmap for subsequent empirical analyses on the mechanism. Based on agricultural production statistics in China, we have documented stylized facts whereby, with household seasonal liquidity constraints, seasonality in agricultural production shapes seasonal variations in household resources for child neonatal investment (Table 6). According to our model, with parental son preference, such seasonal variations lead to the gender gap in BQEs on child neonatal investment (Proposition 1), which further translates into the gender gap in BQEs on lifecycle outcomes, given the lasting impact of neonatal conditions. Moreover, economic development weakens the association between seasonal variations in household resources and agricultural production seasonality, and thus reduces the gender gap in BQEs

[44] Appendix B.1 presents details about the sample and variables for this analysis.

Figure 4: Conceptual Framework



(Proposition 2). The gender gap in BQEs—as well as its association with economic development—demonstrates the role of seasonality in household resources and economic development in shaping gender inequality in lifecycle outcomes (Corollaries 1 and 2).

In our subsequent analyses, we formally test the underlying mechanism regarding the role of agricultural seasonality. We first provide individual-level evidence on the effect of seasonal neonatal household resource abundance on individual lifecycle outcomes by gender (Section 5.3). We then study the role of agricultural production seasonality by exploiting provincial agricultural output and county-level natural-experimental weather shocks (Sections 5.4 and 5.5), examine the role of economic development using the quasi-experimental rural economic reform in 1979 (Section 5.6), and confirm the channel of intrahousehold neonatal investment using information on infant breastfeeding (Section 5.7). We examine alternative explanations in Section 6.

5.3 Individual-level Evidence for Agricultural Seasonality and Lifecycle Outcomes

In this section, we estimate the effect of seasonal household resource abundance during the neonatal period on lifecycle outcomes at the individual level. We make use of the measure of seasonal household resource abundance as constructed in Section 5.1. For each QOB, we assign a value of food abundance and a value of agricultural work intensity, as in Columns (1) and (6) in Panel

A of Table 6, respectively. We aggregate these two variables into a single index of QOB-specific household resource abundance during the neonatal period using the inverse covariance method as in Anderson (2008),[45] and re-estimate Eq. (1) using this index as the key dependent variable in place of the QOB dummies.

The results are presented in Panel A of Table 7 with educational outcomes as dependent variables based on the census data. We find that individuals born in quarters with more abundant household resources for neonatal investment have significantly higher education levels, and this effect is significantly stronger for females relative to males. This finding is consistent with our theoretical prediction on the gender-differentiated impact of neonatal household resources on lifecycle outcomes, implying the role of agricultural seasonality in shaping gendered BQEs on education through neonatal conditions.

To corroborate the results above, we further make use of the spatial variation in agricultural seasonality across China and measure seasonal household resource abundance by province and QOB. Specifically, we explore the variation in crop structures across provinces in China, and replicate the calculation in Section 5.1 for each province by replacing the countrywide crop output shares (shown in Figure 2) with the corresponding within-province crop output shares.[46] This gives QOB-specific neonatal food abundance and work intensity (as in Columns (1) and (6) in Panel A of Table 6) for each province. Again, aggregating the two variables into a single index (Anderson, 2008), we generate a measure of seasonal household resource abundance during the neonatal period at the province-by-QOB level.

As suggestive evidence, a province-level correlational analysis shows that the BQE as well as its gender difference are both larger in provinces with a larger seasonal variation in household resources for neonatal investment across QOBs, as shown in Appendix Figure A1.[47] Furthermore, in Panel B of Table 7, we use the province-by-QOB-level household resource abundance during the neonatal period as the key explanatory variable in individual-level regressions. Reassuringly, the results are consistent with those in Panel A, demonstrating the gender-differentiated effect of neonatal household resource abundance on lifecycle outcomes.

[45] The variable of agricultural work intensity is reversed when generating the index.

[46] The data on province-level crop structures are from *China Agricultural Yearbook (1980)*.

[47] In this analysis, we use province-level estimates of BQEs on education and their gender differences as presented in Appendix Table D1. To measure the within-province seasonal variation in household resources for neonatal investment across QOBs, we use the range (i.e., maximum minus minimum) of the household resource abundance index across QOBs in a province. In addition, as can be seen in Appendix Figure A1, the within-province seasonal variation in household resource abundance for child neonatal investment is large in northern provinces in China, such as Qinghai, Ningxia, Inner Mongolia, Liaoning, Jilin, and Heilongjiang. These province are characterised by a lengthy and cold winter, which is not conducive to crop cultivation, and thus these regions are dominated by the growth of single-season crops. In contrast, the primary regions for wheat (winter) production, including provinces like Henan, Shandong, and Anhui, exhibit less seasonality in household resource abundance. As can be seen in Figure 2, wheat (winter) significantly contributes to alleviating potential resource scarcity during the second quarter, as it begins being harvested in May.

Table 7: Household Resource Abundance in the Neonatal Period and Educational Attainment

	Schooling years		Junior high school completion (yes=1)		Senior high school completion (yes=1)	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. QOB-level measure of seasonality						
Household resource abundance	0.076***	0.052***	0.007***	0.005***	0.006***	0.005***
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
p-value for coefficient equality	*0.000*		*0.000*		*0.000*	
Outcome mean	6.780	8.150	0.484	0.631	0.161	0.221
Observations	7,816,218	8,127,660	7,816,218	8,127,660	7,816,218	8,127,660
R-squared	0.318	0.210	0.251	0.200	0.090	0.066
Panel B. Province-by-QOB-level measure of seasonality						
Household resource abundance	0.070***	0.049***	0.007***	0.005***	0.006***	0.004***
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
p-value for coefficient equality	*0.000*		*0.000*		*0.000*	
Outcome mean	6.780	8.150	0.484	0.631	0.161	0.221
Observations	7,816,218	8,127,660	7,816,218	8,127,660	7,816,218	8,127,660
R-squared	0.318	0.210	0.251	0.200	0.090	0.066

Note: Data are from censuses 1990, 2000, and 2010 and mini-censuses 2005 and 2015, and the sample includes individuals aged from 25 to 60. The key independent variable is the QOB-specific (province-by-QOB-specific) index of household resource abundance during the neonatal period in Panel A (Panel B), which is standardized with a mean of 0 and a standard deviation of 1. We control for the dummy of Han ethnicity, birth province fixed effects, birth year fixed effects, and census year fixed effects. Standard errors in parentheses are clustered at the province-by-birthyear level. For each dependent variable, we report the p-value from the Wald test for the equality of the coefficients on household resource abundance in the two gender subsamples. ***, ** and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

The results in Table 7 keep robust in a battery of sensitivity analyses. First, we use labor market outcomes as dependent variables (Appendix Table A12). Second, we measure the seasonality in neonatal household resource abundance at the month-of-birth (MOB) rather than quarter-of-birth (QOB) level (Appendix Table A13). Third, we examine the effects of the two aspects of seasonal household resources during the neonatal period—food abundance and parental time for childcare (the reverse of agricultural work intensity)—separately (Appendix Table A14).

5.4 Correlations between Agricultural Output and Birth Quarter Effects by Gender at the Province Level

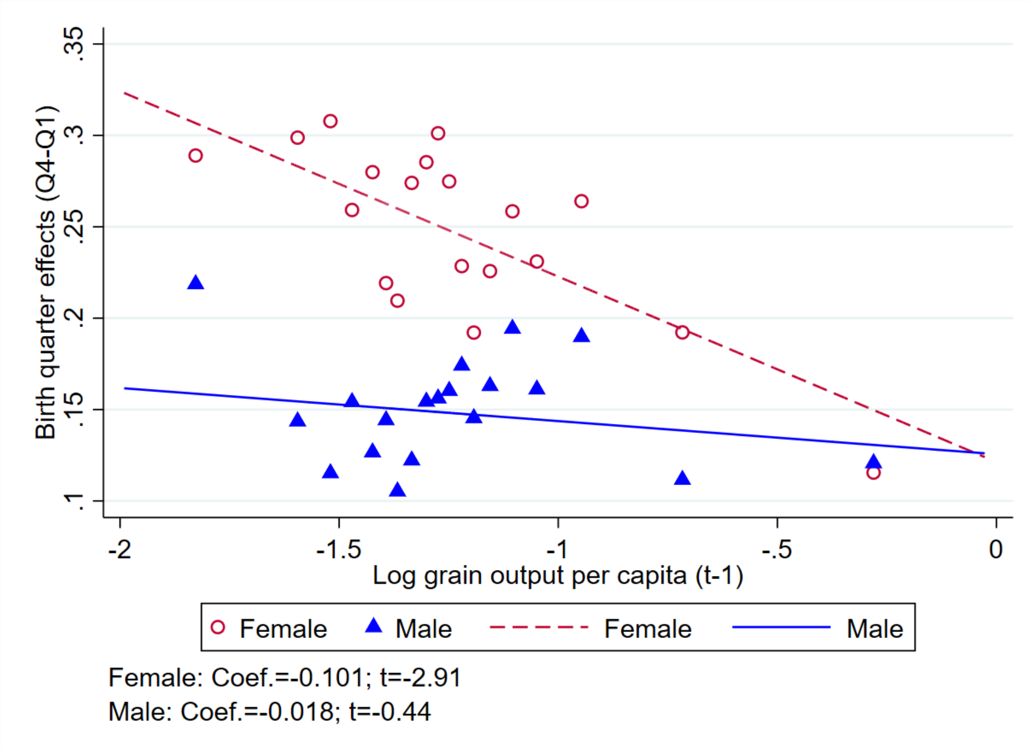
In the previous subsection, our analysis exploits QOB-level and province-by-QOB-level measures of seasonal household resource abundance for neonatal investment based on the crop calendar and (regional) crop production structures in China. However, these measures might not necessarily capture the impact of agricultural seasonality, as they could correlate with other natural, institutional, and cultural factors that might vary across QOBs and provinces, such as the seasonality in temperature, the timing of school starting, and the timing of festivals (Montero and Yang, 2022), which may shape the seasonality in lifecycle outcomes. To alleviate this concern, we leverage the cross-year variation in household resource seasonality within a province. This approach helps control for unobserved heterogeneities, of which the seasonal variations are likely constant across years.

Specifically, to this end, we exploit variations in agricultural output in the previous year and focus on the difference in education between those born in Q4 with those born in Q1. Since children born in Q1 depend more heavily on the grain harvested last year than those born in Q4 for neonatal investment, higher agricultural output in the previous year would reduce the difference in household resources for neonatal investment between children born in Q1 and those born in Q4 in a given year, thus reducing the gender gap in BQEs in the presence of son preference according to our conceptual framework (as outlined in Figure 4).[48]

To empirically test this prediction, we first study the correlations between BQEs and grain output per capita in the previous year by gender at the province-by-birthyear level. Figure 5 delineates the correlational analysis which controls for province and birth year fixed effects. We construct the figure in five steps. (i) Based on the pooled census sample, we calculate the difference in schooling years between people born in Q4 and Q1 (Q4-Q1 difference) by province, birth year, and gender. We collect data on grain output per capita by province and year from *China Compendium of Statistics 1949-2008*. (ii) We separately regress the two variables on province and year fixed effects, weighted by provincial population, and then compute the two residuals. (iii) We divide the residuals of grain output per capita into 19 bins and plot it on the horizontal axis, where we determine the number of bins by using the optimal binned scatter techniques as in Cattaneo et al. (2023). (iv) We plot the average residuals of the Q4-Q1 difference in schooling years within each bin on the vertical axis, where the Q4-Q1 difference corresponds to one-year-lagged grain output per capita. (v) We linearly fit the binned scatters for females and males separately, again weighted

[48] For children born in Q2, household resources during their neonatal period relate to some crops newly harvested in the year of birth, such as wheat (winter) and rice (early double) harvested in Q2 or early in Q3 (Figure 2). In the following analysis, we focus on the difference in schooling years between people born in Q4 and those in Q1 within a year. We use Q2 as the reference group for a robustness check.

Figure 5: Province-by-year-level Grain Output and Birth Quarter Effects by Gender



Note: The figure presents binned scatter plots of province-by-year-level birth quarter effects on schooling years against the logarithm of the previous-year grain output per capita in the province by gender. On the vertical axis, province-by-year-level birth quarter effects are defined as the difference between the average schooling years for individuals born in the fourth quarter (Q4) and those born in the first quarter (Q1) in the province-by-year cell for females and males, respectively. We exclude observations for birth years 1959, 1960, and 1961. The binned scatter plots are constructed using the method in Cattaneo et al. (2023). The two lines show the best linear fit estimated on the underlying province-by-year panel data using a weighted OLS regression for the two gender subsamples. Province and birth year fixed effects are controlled for. Coefficients show the estimated slopes of the best-fit lines, with t-statistics using standard errors clustered at the province level.

by provincial population.

We have three observations from Figure 5. First, for each bin of grain output per capita except for one, the Q4-Q1 difference is always larger for females than males. Second, the coefficients from regressing the Q4-Q1 difference on grain output per capita are negative for both males and females. Third, the coefficient is statistically significant only for females, and the size of the coefficient for females is much larger than that for males. The findings are consistent with our theory, since smaller seasonal variations in household resources for child neonatal investment are associated with a smaller gender gap in BQEs. We note that since grain output might correlate with unobserved factors that affect child neonatal investments across seasons, the results do not necessarily capture causal effects.

5.5 Causal Effect of Thermal Agricultural Productivity on the Gender Difference in BQEs at the County Level

The above correlational analysis at the province level might be subject to biases due to omitted factors, such as agricultural technology adoption and food policy changes, which may vary across provinces and years. To further eliminate these potential confounding factors and obtain causal estimates of the effect of previous-year agricultural output on the gender difference in BQEs, we use county-level weather shocks to agricultural productivity as a natural experiment, using weather records from 819 weather stations. Specifically, we construct a variable for thermal agricultural productivity (TAP) based on county-level weather records. TAP is one of the major determinants of agricultural output, and changes in TAP across years within a county are random (Ritchie and Nesmith, 1991; Yi et al., 2022).

Empirical Specification We estimate the following equation:

$$Y_{ct} = \beta TAP_{c,t-1} + \lambda_c + \eta_t + \varepsilon_{ct}, \tag{8}$$

where c and t index county and year. We have two types of dependent variables: BQEs and their gender difference. Using the pooled census sample, in Eq. (8) the BQE is defined as the average schooling years for those born in county c in Q4 of year t minus those born in Q1 of the same year. The gender difference in BQEs is defined as the BQE for females minus that for males. Controlling for county fixed effects (λ_c) and year fixed effects (η_t), the coefficient (β) of our interested independent variable of TAP in the previous year ($TAP_{c,t-1}$), defined below, captures the effect of random weather shocks to agricultural output in the previous year on the BQE or the gender difference. ε_{ct} is the error term. The regression is weighted by the number of individuals by county and birth year. Standard errors are clustered at the county level.

In estimating Eq. (8), we exclude years before 1956 because there were few weather stations and many missing values in weather records, and also the years 1959, 1960, and 1961 because of the Great Famine. We further excluded county-year cells with insufficient individual-level observations in the pooled census data for calculating BQEs for females or males. Our final sample includes 56,304 county-year observations spanning 2,833 counties in China. The summary statistics are presented in Appendix Table A16. The average BQE defined as the Q4-Q1 difference at the county-year level is larger for females than males, consistent with our finding in the baseline analysis.

Thermal Agricultural Productivity To capture random weather shocks to agricultural output, we construct the variable for TAP based on exposure to heat using weather records from 819 weather stations from the China Meteorological Administration. Following the agronomic literature (Ritchie and Nesmith, 1991), TAP for county c in year t is defined as

$$TAP_{ct} = \sum_{d=\text{Apr}\,1}^{\text{Sep}\,30} H_{ctd}, \tag{9}$$

where H_{ctd} is the "degree-day" on day d, defined as

$$H_{ctd} = \begin{cases} 0 & \text{if} \quad T_{ctd} < 8 \\ T_{ctd} - 8 & \text{if} \quad 8 \leq T_{ctd} < 33 \\ \frac{25}{8}\left[41 - T_{ctd}\right] & \text{if} \quad 33 \leq T_{ctd} < 41 \\ 0 & \text{if} \quad T_{ctd} \geq 41 \end{cases} \tag{10}$$

where T_{ctd} is the mean instrumental temperature on day d in weather records. Eq. (10) reflects the nonlinear relationship between yields and heat exposure (Ritchie and Nesmith, 1991). Specifically, when the temperature exceeds 8°C, plants start absorbing heat and yields increase until 33°C—above which yields decrease—and crops cannot survive in temperatures higher than 41°C. In Eq. (9), TAP is defined as the sum of degree-days in the growing season (Yi et al., 2022).

We construct a county-by-year panel dataset of TAP by linking each county to the nearest weather station based on the county's geographic coordinates. As a robustness check, we construct an alternative measure of TAP by linking each county to the three nearest weather stations and weight temperatures by the inverse of distances.

Identification Assumptions We aim to identify the causal effect of previous-year agricultural output on the gender gap in BQEs. Due to the unavailability of annual agricultural production information at the county level over such a long period, we instead estimate the effect of previous-year TAP and interpret the estimate β in Eq. (8) as the causal effect of TAP on the Q4-Q1 differences and their gender gap through agricultural output.

This interpretation hinges on three assumptions. First, TAP is a major determinant of agricultural output, which has been well documented in the agricultural literature (Ritchie and Nesmith, 1991; Yi et al., 2022). Second, within-county variation in TAP is random across years. Appendix Table A15 shows that it is not serially correlated conditional on county fixed effects. Third, TAP affects lifecycle outcomes differently for people born in different quarters in the following year mainly through its effect on agricultural output. This assumption cannot be directly tested. The biological literature suggests that extremely high temperatures may directly affect fetal development and neonatal outcomes (Martens et al., 2019; Ngo and Horton, 2016). We carefully examine this possibility and find that it is unlikely to explain our results for two reasons. (i) We follow the agronomic literature to construct our measure of TAP, which is different from the measure of extremely high temperatures used in the literature on fetal development. The correlation between the two measures is low. (ii) The result reported below shows significant gender differences in the effects of TAP on BQEs, whereas the literature on fetal development does not find gender differences in the effects of extremely high temperatures on neonatal outcomes (Chen et al., 2020).[49] In addition, the prevalence of diseases (such as malaria) is an important determinant of neonatal health (Currie and Schwandt, 2013), and weather (captured by TAP) might have a differential influence on the prevalence of diseases across seasons. We check this possibility in detail in our discussion on the alternation explanation of seasonal disease patterns later in Section 6.2.

Results Table 8 reports estimates of Eq. (8). In Columns (1) – (3), the dependent variables are the calculated BQEs for all people, for females, and for males, respectively. In Column (4), the dependent variable is the difference in calculated BQEs between females and males. Our interested independent variable of TAP in the previous year is measured by 100 degree-days, with a within-county standard deviation (SD) of 90.

Panel A shows a significant gender difference in the effects of the previous-year TAP on BQEs. Although the estimates in Columns (1) and (3) are insignificant, the estimate is economically and statistically significant in Column (2). For females, an increase in TAP by one within-county SD decreases the BQE on schooling years by about 0.02, which translates into a 10% decrease relative to the mean. The estimated effect of TAP on the gender difference in BQEs is also statistically significant (Column (4)).

The results remain robust in five sensitivity analyses. (i) When calculating temperature at the county level, we associate each county with the three nearest weather stations and weight temperatures by the inverse of Euclidean distance, instead of associating each county with the nearest station. (ii) We drop observations when the number of individuals is fewer than 30 in calculating BQEs for a given county in a given year. (iii) We exclude counties in Beijing, Tianjin, and Shanghai because the food supply in these counties depends less on local agricultural production. (iv) We exclude the six provinces to the west of the Heihe-Tengchong Line, since in those provinces the population density is lower than—and agricultural production differs from—the rest of China (Naughton, 2006).[50] (v) We use Q2 as the reference group and define BQEs as the differences in education between Q4 and Q2. Appendix Table A17 reports robustness analysis results.

We then examine the heterogeneity between rural and urban areas. In our theory proposed

[49] Prior studies show that weather during the prenatal period could affect infant mortality (Basagaña et al., 2011). This would be less likely to drive the estimation results in our context, because (i) as discussed, we do not find significant gender difference in the effect of previous-year TAP on the Q4-Q1 difference in cohort loss rates (Appendix Table A18), and (ii) since the previous-year TAP only affects children born in Q1 and does not affect those born in Q4 through the channel of prenatal temperature exposure, potentially higher mortality for those born in Q1 due to higher temperature would make our estimates serve as a lower bound for the effect of previous-year TAP on BQEs by gender.

[50] The six provinces are Inner Mongolia, Tibet, Gansu, Qinghai, Ningxia, and Xinjiang, which account for 57.1% of the area and about 5.6% of the population in China.

Table 8: Thermal Agricultural Productivity and Birth Quarter Effects at the County Level

Dependent variable	Difference in schooling years (Q4 minus Q1)			Gender difference (Females minus males)
	Overall	Female	Male	
	(1)	(2)	(3)	(4)
A. Whole sample				
Thermal agricultural productivity (t-1)	-0.007	-0.019***	-0.000	-0.019**
	(0.005)	(0.007)	(0.006)	(0.009)
Outcome mean	0.150	0.172	0.121	0.051
Observations	56,304	56,304	56,304	56,304
R-squared	0.083	0.068	0.067	0.056
B. Urban counties				
Thermal agricultural productivity (t-1)	-0.006	-0.012	-0.001	-0.011
	(0.006)	(0.009)	(0.009)	(0.013)
Outcome mean	0.134	0.158	0.105	0.053
Observations	26,547	26,547	26,547	26,547
R-squared	0.080	0.065	0.065	0.054
C. Rural counties				
Thermal agricultural productivity (t-1)	-0.004	-0.024**	0.006	-0.030**
	(0.007)	(0.011)	(0.010)	(0.014)
Outcome mean	0.163	0.190	0.123	0.067
Observations	25,533	25,533	25,533	25,533
R-squared	0.087	0.071	0.068	0.056
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note: Dependent variables are the differences in average schooling years (Q4 minus Q1) in Columns (1) – (3) based on the whole sample, the female sample, and the male sample, respectively. Specifically, it is the difference in individuals' average schooling years between those born in Q4 and those born in Q1 within each year of birth in each county, aggregated from the pooled census data. In Column (4), the dependent variable is the difference between the female BQE (in Column (2)) and the male BQE (in Column (3)). The key explanatory variable is thermal agricultural productivity (unit: 100 degree-days) in the previous year. County fixed effects and year fixed effects are controlled for. In Panel B, we use the subsample of counties with urbanization rates in 1990 no lower than the countrywide median, and in Panel C we use those lower than the median. County-level urbanization rate is calculated according to one's hukou type—i.e., agricultural or nonagricultural. The regression is weighted by the number of individuals in each county-by-cohort cell in the pooled census data. Standard errors in parentheses are clustered at the county level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

in Section 5.2, compared with urban areas, the economy in rural areas is characterized by lower abundance of resources (lower w) and larger seasonal variations in household resources (larger $(q_H - q_L)$) due to the higher reliance of household resources on local agricultural production.[51] Therefore, higher agricultural output in the previous year would have a stronger effect on BQEs for children born in rural areas than those born in urban areas. To examine this prediction, we classify all counties into two groups (urban or rural) according to the median value of urbanization rates in 1990;[52] we then repeat the estimations in Panel A for the two groups separately. Panels B and C of Table 8 report estimates for urban and rural groups, respectively. Consistent with our prediction, the estimated effects of TAP are significant for females in rural counties only.[53]

Potential Concern with Respect to Mortality Selection Potential mortality selection might bias our estimate of β in Eq. (8). TAP affects the food supply, which may in turn affect infant or early-childhood mortality. If this were the case, the sample used to calculate BQEs by county and year would be a truncated sample. We first note that if mortality selection did exist, our estimate serves as a lower bound for β in terms of absolute value. This is because the difference in schooling years between those born in Q4 and Q1 would be smaller if better endowed children are more likely to survive food shortages.

We then directly estimate the effect of the previous-year TAP on the Q4-Q1 difference in mortality rates by gender, and find that the estimated effect is small and statistically insignificant for both females and males. Following Yi et al. (2022), we proxy the mortality rate by calculating the cohort loss rate by county and birth quarter separately for females and males. Based on census 1990, for county c, year t, and quarter q, we define the cohort loss rate as $Loss_{ctq} = \frac{\tilde{P}_{ctq} - P_{ctq}}{\tilde{P}_{ctq}}$, where P_{ctq} and $\tilde{P}_{ctq}$ are the observed and predicted cohort sizes in 1990, respectively. We compute $\tilde{P}_{ctq}$ for each county by using the estimates in regressing the observed cohort size on a linear time trend from 1949 to 1989, quarter dummies, and their interactions.[54] Using this method, we calculate the cohort loss rate for the whole sample, females, and males, respectively. We then estimate Eq. (8) using the difference between $Loss_{ct4}$ and $Loss_{ct1}$ as the dependent variable. Appendix Table

[51] In the central planning economy, grain sales were centrally purchased and sold by the government. In urban areas, household food was rationed; household resources depended less on local agricultural production and were less subject to seasonality in agricultural production than rural areas.

[52] We calculate a county's urbanization rate as the share of people with an urban hukou in census 1990. As rural-to-urban migration was strictly regulated and rare before 1990 in China, this share serves as a proxy for the urbanization rate before 1990 in a county.

[53] The result is robust to alternative definitions of urban and rural counties. First, we define urban counties as the one-third with the highest urbanization rates and rural counties as the one-third with the lowest urbanization rates. We drop the other one-third of counties in the estimation. Second, we adopt the official urban vs rural division of county-level administrative units (*Qu* vs *Xian*) in 1982. We prefer our definition in the baseline analysis to the official division. The urbanization rate in some *Xians* in coastal provinces is higher than that in some *Qus* in inland provinces, although the urbanization rate on average is higher in *Qus* than *Xians*.

[54] We exclude years 1959, 1960, and 1961 in regressions due to the Great Famine.

A18 reports the results. The estimates are small and statistically insignificant, for both the overall cohort loss rate and the cohort loss rates for each gender. This suggests that potential mortality selection is less of a concern in our analysis.

5.6 Moderating Role of Economic Development in the Effect of Thermal Agricultural Productivity on the Gender Difference in BQEs

We have estimated the effect of agricultural production seasonality on the gender difference in BQEs. Our theory predicts that economic development reduces the gender gap in BQEs by mitigating the effect of agricultural production on household resources for child neonatal investment (Figure 4). In this section, we formally examine the role of economic development. Specifically, we exploit the market-oriented rural economic reform in 1979 as a quasi-experiment for economic development. We first present the institutional background about the reform, and then our empirical analysis.

China started to reform the agricultural sector in 1979. Prior to the reform, under the economic planning regime introduced in 1953, agricultural production was subject to the collective system in the form of cooperatives (before 1957), communes (1958-1959), and production teams (since 1960). Under the collective system, the incentive to work was low for farmers (Lin, 1990); they could only sell their grain to the government through centralized procurement at regulated low prices. In addition, interregional trade for agricultural products was prohibited. The government could reallocate agricultural products among regions through the procurement system, but the reallocation rule was rigid and lacked a basis in profitability or regional comparative advantage. Consequently, the growth of agricultural production was minimal before the reform: Grain output per capita was only 10% higher in 1978 than in 1952 (Lin, 1992).

When Deng Xiaoping came into power at the end of 1978, the government instituted systematic policy reforms intended to boost agricultural production.[55] Grain procurement prices were raised by 22.1% on average to enhance farmers' incentives. Market fairs and interregional trade for agricultural products were reinstated. This improved production efficiency through specialization, which is based on comparative advantage determined by regional agricultural endowment. Reinstating markets also helped rural households smooth their consumption over the seasonal cycle of agricultural production (Foster, 1995). In addition, in a development unexpected by the central government, some production teams started to adopt the Household Responsibility System (HRS), which contracted with individual households for the land, resources, and quotas of output given to the government. The system was successful and quickly spread across the country. By

[55] In December 1978, the Third Plenary Session of the 11th Central Committee of the Chinese Communist Party announced that China was shifting its focus to economic development and adopting the policy of reform and opening-up.

1984, 99% of villages in China had adopted the HRS.[56]

The reform dramatically enhanced agricultural productivity. The annual agricultural production growth rate was 7.7% during 1978-1984, in contrast to the rate of 2.9% during 1952-1978. The institutional change—i.e., the adoption of the HRS—accounted for nearly half of the agricultural growth in the period (Lin, 1992). The reform largely helped rural households solve the problem of food shortages and enabled them to enjoy food surpluses in good harvest years. Since 1985, encouraged by the success of the rural economic reform, the central government has also launched market-oriented reforms in the urban sector, such as the state-owned enterprise reform.

In sum, the rural economic reform can serve as a quasi-experiment for economic development due to its unexpected initiation, quick adoption, and significant and persistent impact on agricultural output. It provides us with a unique opportunity to directly examine the role of economic development in lessening household resource constraints and reducing the gender gap in BQEs. The reform induced a steady increase in agricultural productivity and, more importantly, enabled households to better smooth consumption across seasons, which corresponds to a higher w and a lower $(q_H - q_L)$ in our theory. We now test how the economic reform in 1979 mitigated the effect of agricultural production seasonality on the gender gap in BQEs.

Empirical Analysis We use the reform that began in 1979 as a quasi-experiment to examine its moderating role in the effect of TAP on the gender difference in BQEs. We estimate the following equation:

$$\begin{aligned} Y_{ct} =& \beta_1 TAP_{c,t-1} \times Rural_c \times Post_t + \beta_2 TAP_{c,t-1} + \beta_3 TAP_{c,t-1} \times Rural_c + \\ & \beta_4 TAP_{c,t-1} \times Post_t + \beta_5 Rural_c \times Post_t + \lambda_c + \eta_t + \nu_{ct} \end{aligned} \tag{11}$$

where $Post_t$ is an indicator for birth cohorts after 1979, and $Rural_c$ is an indicator for rural counties defined in Section 5.5. All other variables are defined as in Eq. (8). The sample for estimating Eq. (11) includes birth cohorts 1975-1984, where cohorts 1980-1984 are the treated group. Eq. (11) is similar to a triple-difference regression equation, in which the three variables, $TAP_{c,t-1}$, $Rural_c$, and $Post_t$, are fully interacted. When Y_{ct} denotes the gender gap in the Q4-Q1 differences in

[56] The HRS represents a pivotal property reform in China that transitioned the ownership of collectively-owned farmland to individual households under secure tenures (Lin, 1992). The HRS reform marked a significant shift from the previous collectivized system which forced farmers into production teams of 20-30 households; under the HRS, land was allocated to households based on the number of members, with secure tenure provided for 30 years. Through granting of land use rights and residual income rights from farming activities to individual households, the HRS reform addressed the free-rider problem and low work incentives inherent in the old system, thereby stimulating labor productivity and income among rural households (Lin, 1990, 1992). It has been well-documented that the HRS significantly increased agricultural output and household income, lifting hundreds of millions of rural households out of poverty (Almond et al., 2019; Lin, 1992; McMillan et al., 1989; World Bank, 2000). Moreover, early-life exposure to the HRS has been associated with improved adult outcomes, such as education, health, and labor market outcomes (Xu, 2021).

schooling years by county and cohort (female minus male), coefficient β_3 captures the pre-reform rural-versus-urban difference in the effects of TAP on the gender gap in BQEs, which we expect to be negative since the effect of TAP tends to be larger in rural areas. Coefficient β_1, similar to a triple-difference coefficient, captures the differential effects of $TAP_{c,t-1}$ on Y_{ct} between rural and urban counties across the reform. Since this reform mainly affects rural residents after 1979, we expect β_1 to be positive, and especially for females. That is, the reform attenuates the negative effect of TAP on BQEs for females and the gender difference in BQEs before the reform.[57]

Consistent with our prediction, in Table 9, Columns (2) and (4), the estimates of β_1 are significantly positive and those of β_3 are negative. Specifically, the rural-urban disparity in the impact of TAP on the gender difference in BQEs decreases by 54% (0.025 relative to 0.046) with the reform (Column (4)); this effect is mainly driven by females, since the reform canceled more than 80% of the rural-versus-urban difference in the effects of TAP before the reform (0.023 relative to 0.028). [58] We perform three robustness analyses: (i) To support the common trend assumption, we conduct a placebo test by defining 1966-1970 cohorts as the control cohorts and 1971-1975 as the treated cohorts. Appendix Table A19, Panel A shows that the estimates of β_1 are insignificant. (ii) We expand the estimation sample from 1975-1984 to 1970-1989 birth cohorts, still using 1980 as the cutoff in defining treated vs control cohorts. (iii) We use an alternative definition for rural versus urban counties, as discussed in Section 5.5. Appendix Table A19, Panels B and C, respectively, show that the estimates of β_1 reported in Table 9 remain robust in analyses (ii) and (iii).

The One-child Policy A potential issue concerning our findings on the moderating role of economic reform is the possibility of confounding effects from concurrent historical events, which may have impacted rural and urban areas differently. One of the most important events relavant to our context is the one-child policy (OCP) (Cameron and Meng, 2014; Zhang, 2017). The OCP, which aimed to limit most families to a single child, was introduced by Chinese central government in 1979 and subsequently implemented at varying times across different provinces. The policy could influence the abundance of household resources available for neonatal investment

[57] Almond et al. (2019) find that the adoption of the HRS increased gender selection in China. This effect is not likely to materially affect our estimates for the role of the rural economic reform, because we focus on the gender difference in BQEs, and there is little evidence for seasonality in gender selection (Section 3.4).

[58] Related to our study, in a similar historical context, Qian (2008)—who also uses the 1979 reform as a quasi-experiment for economic development—finds that an increase in households' total agricultural income does not lead to an increase in children's education or to a reduced gender gap in educational attainment; rather, these outcomes are only affected if there is an increase in female-earned agricultural income. Different from the setting in Qian (2008), the focus of our study is the between-QOB difference in education and its gender difference. As discussed in our conceptual framework, economic development influences gendered BQEs through two channels: the increase in total income (higher w) and the decrease in the between-season variations in household resources (lower $q_H - q_L$). The impact of the rural economic reform in 1979 can work through both two channels, where the first channel itself might have exerted moderate influence. This may potentially explain the subtle difference between our findings and those in Qian (2008).

Table 9: The Moderating Effect of the Agricultural Reform since 1979 on the Impact of Thermal Agricultural Productivity

Dependent variable	Difference in schooling years (Q4 minus Q1)			Gender difference (Female minus male)
	Overall	Female	Male	
	(1)	(2)	(3)	(4)
$TAP_{c,t-1} \times Rural_c \times Post_t$	0.011*	0.023**	-0.002	0.025**
	(0.006)	(0.010)	(0.009)	(0.013)
$TAP_{c,t-1} \times Rural_c$	-0.002	-0.028	0.018	-0.046
	(0.017)	(0.025)	(0.025)	(0.034)
$TAP_{c,t-1} \times Post_t$	0.004	-0.002	0.009*	-0.012
	(0.004)	(0.006)	(0.006)	(0.008)
$TAP_{c,t-1}$	-0.007	-0.001	-0.018	0.017
	(0.014)	(0.021)	(0.020)	(0.029)
Outcome mean	0.174	0.188	0.149	0.039
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	18,334	18,334	18,334	18,334
R-squared	0.156	0.147	0.138	0.139

Note: Definitions of the dependent variables are the same as in Table 8. The regression specification is in Eq. (11) in Section 5.6. The variable $TAP_{c,t-1}$ is thermal agricultural productivity (unit: 100 degree-days) in the previous year. The dummy variable $Rural_c$ takes the value of one for counties with urbanization rates lower than the countrywide median in 1990, and the dummy variable $Post_t$ takes the value of one for cohorts born since 1980. The cohorts included are born from 1975 to 1984. We control for all lower-order terms of the triple-interaction term, as well as the county fixed effects and year fixed effects. The regressions are weighted by the number of individuals in each county-by-cohort cell in the pooled census data. Standard errors in parentheses are clustered at the county level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

through a quantity-quality tradeoff mechanism by reducing fertility rates, which could then result in changes in the BQE and its gender difference, according to our theory in Section 5.2. Importantly, the enforcement of the OCP was stricter in urban areas compared to rural areas. Therefore, it is crucial to examine whether the estimation results about rural economic reforms in Table 9 are influenced by the impact of the OCP.

We examine the robustness of our results by considering the OCP in two ways. First, based on Eq. (11), we additionally control for the interaction term of $TAP_{c,t-1}$ with OCP_{pt}, a variable capturing the staggered rollout of the OCP across provinces, which takes the value of one for county-cohort observations with birth years after the implementation of the OCP in the county's province (Guo et al., 2024). In a more stringent specification, we further interact $TAP_{c,t-1} \times OCP_{pt}$ with the indicator for rural counties, $Rural_c$, allowing the moderating effect of the OCP to differ between rural and urban areas.[59] We find that, upon incorporating these OCP-related controls, the estimate of β_1 in Eq. (11) remains largely consistent with those in Table 9, as shown in Appendix Table A20.

Second, we use a subsample of counties as in Almond et al. (2019), which dataset contains information of 914 counties in China on the timings of implementation of two policies—the HRS reform and the OCP—collected from county gazetteers. We leverage this subsample to further distinguish the effect of the HRS and that of the OCP on BQEs and their gender difference. In Appendix Table A21, based on this subsample, we find that the implementation of the HRS significantly attenuated the impact of previous-year TAP on the BQE for females as well as the gender difference in BQEs in rural areas relative to urban areas, which finding is consistent with the results in Table 9. Furthermore, this effect remains largely consistent after we including the interaction term between previous-year TAP and the variable indicating county-level rollout of the OCP, and even allowing this interactive effect to differ between rural and urban areas.[60] In sum, the above findings suggest that our results on the rural-urban-differentiated changes in the effect of TAP on the gendered BQEs are not primarily driven by the impact of the one-child policy.

Education Expansions In addition to the OCP, other contemporaneous historical events may affect the influence of TAP for cohorts born before and after 1979 differently, and at the same time, their effects may vary between rural and urban areas. Were this the case, our estimates of β_1 in Eq. (11) would be biased. Here we consider two of such historical events related to the expansion of education in China, i.e., the initiation of the Compulsory Education Law (CEL) in 1986 and the college education expansion in 1999.

We examine whether the effect of the CEL might confound our estimates of the role of rural economic reform in mitigating the impact of TAP on the gender difference in BQEs. To this end, similar to the method for considering the OCP effect, we re-estimate Eq. (11) with additional controls for the interaction term between the variable of the CEL rollout across provinces and previous-year TAP.[61] This interaction term is further interacted with the rural county dummy in

[59] In both specifications, we control for all lower-order terms of the interaction terms containing OCP_{pt}. The main effect of OCP_{pt} is absorbed by the province-by-cohort fixed effects.

[60] Using the subsample of the counties in Almond et al. (2019), we estimate the following equation:

$$\begin{aligned} Y_{ct} =& \beta_1 TAP_{c,t-1} \times HRS_{c,t-1} \times Rural_c + \beta_2 TAP_{c,t-1} + \beta_3 TAP_{c,t-1} \times Rural_c + \beta_4 TAP_{c,t-1} \times HRS_{c,t-1} + \beta_5 HRS_{c,t-1} \times Rural_c \\ &+ \beta_6 HRS_{c,t-1} (+\delta_1 TAP_{c,t-1} \times OCP_{ct} \times Rural_c + \delta_2 TAP_{c,t-1} \times OCP_{ct} + \delta_3 OCP_{ct} \times Rural_c + \delta_4 OCP_{ct}) + \lambda_c + \eta_{pt} + \nu_{ct}, \end{aligned}$$

where c and t denote counties and cohorts (birth years), respectively. HRS_{ct} (OCP_{ct}) is an indicator which takes one if year t is after the implementation of the HRS reform (the OCP) in county c. All other variables are defined in the same way as in Eq. (11). In this equation, we expect β_1 to be positive when the gender difference in BQEs (female minus male) is the dependent variable, which indicates that the HRS reform significantly attenuated the negative impact of previous-year TAP on the gender difference in BQEs to a larger extent for rural areas relative to urban areas. In order to separate the effect of the HRS reform with the OCP, we additionally control for the interaction term between $TAP_{c,t-1}$ and OCP_{ct}, and, in some specifications, the triple interaction term, $TAP_{c,t-1} \times OCP_{ct} \times Rural_c$, which allows the interactive effect between the OCP and previous-year TAP to vary between rural and urban areas.

[61] We generate an indicator CEL_{pt} which takes the value of one if the cohort born in year t in province p was under

another specification. We control for the potential impact of college education expansion in a similar way, where we use province-by-cohort level college completion rates as a proxy to capture differential college expansion scales across provinces, and interact this variable with previous-year TAP and the rural county dummy. Appendix Tables A22 and A23 show results of these two analyses. Reassuringly, our estimates of β_1 in Eq. (11) remain largely unchanged with the inclusion of the (rural-urban differentiated) effect of the CEL or the expansion of college education.

5.7 Gender Differences in Birth Quarter Effects on Infant Breastfeeding

According to our theory, the gendered BQEs on lifecycle outcomes work through intrahousehold neonatal investment (Figure 4), but we have yet to investigate this mechanism directly. To complete our mechanism analysis, we now examine the gender gap in BQEs on child neonatal investment. Our theory predicts that the BQE is larger for females than males (Proposition 1), and the gender gap in BQEs is smaller for households with more resources (Proposition 2). We test the predictions using infant breastfeeding—a major input in the human capital production function in the neonatal period—as a proxy for neonatal investment (Der et al., 2006; Jayachandran and Kuziemko, 2011). We estimate BQEs on infant breastfeeding based on subsamples by gender and household resources.

Our empirical analysis uses data from the China Health and Nutrition Survey (CHNS). Our estimation sample includes all 1,291 infants born in 1990-2000 recorded in the CHNS. Appendix Table A24 provides summary statistics. We estimate Eq. (1) using an indicator for "ever breastfeeding" as the dependent variable.[62] Table 10 shows that female infants born in Q4 are significantly more likely to be breastfed than those born in Q1 (Column (1)), and we do not detect significant between-QOB difference in the probability of being breastfed among male infants (Column (2)).[63]

Furthermore, we divide our sample into two subsamples according to the degree of household resource constraints. We categorize infants in rural areas whose mothers do not complete junior high school education as the constrained group and the others as the less constrained group. We assume that households in the constrained group have more stringent resource constraints and are less able to smooth consumption across seasons. Table 10 shows that for the constrained group, infants born in Q4 are significantly more likely to be breastfed than those born in Q1 (Column (3)), and the BQE estimate is not significant for males (Column (4)). In contrast, we do not find statistically significant BQE estimates in the less constrained group (Columns (5) - (6)). The result

age 16 when the CEL was implemented in province p (Du et al., 2021).

[62] The ever-breastfeeding rate in our sample is 94.7% (94.4% for males and 95.0% for females), which is similar to statistics reported in the medical literature (Xu et al., 2009).

[63] We advise caution with respect to the result due to a small sample size. The CHNS provides the only publicly available data that contains information on infant breastfeeding.

is consistent with our model predictions, which suggests the role of economic development in closing the gender gap in BQEs on child neonatal investment.

Table 10: Birth Quarter Effects on Infant Breastfeeding by Gender

Dependent variable:	Full sample		Constrained group		Less constrained group	
Indicator for being breastfed	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Q2	0.032	0.004	0.088*	-0.058	-0.003	0.040
	(0.029)	(0.025)	(0.046)	(0.044)	(0.039)	(0.026)
Q3	0.039	-0.023	0.090	-0.039	0.014	-0.016
	(0.028)	(0.027)	(0.056)	(0.030)	(0.033)	(0.034)
Q4	0.063**	0.009	0.124**	0.006	0.038	0.013
	(0.028)	(0.024)	(0.041)	(0.021)	(0.039)	(0.031)
Outcome mean	0.947	0.950	0.953	0.962	0.940	0.945
Observations	586	705	190	234	396	471
Birth year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Survey year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Data are from the China Health and Nutrition Survey (CHNS), and the sample includes infants born during 1990-2000. The dependent variable is an indicator for "ever breastfeeding." Columns (1) - (2) report results for the constrained group. Columns (3) - (4) report results for the constrained group. Columns (5) - (6) report results for the less constrained group. We categorize infants in rural areas whose mothers do not complete junior high school as the constrained group and others as the less constrained group. Standard errors in parentheses are clustered at the province-by-birthyear level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

The results are robust in multiple sensitivity analyses. First, in addition to the extensive margin of breastfeeding, we explore the length of breastfeeding and use the indicator for being breastfed for more than four months after birth as the dependent variable (Appendix Table A25).[64] Second, we check the robustness of our heterogeneity results using another three methods of defining subsamples (Appendix Table A26): (i) we categorize infants born in villages without tap water supply as the constrained group; (ii) we categorize infants in rural areas whose household income is lower than the within-wave median among rural households at the time of the survey as the constrained group; (iii) we construct a score reflecting household wealth levels using information on multiple categories of household assets, and categorize infants in rural areas with a household asset score lower than the within-wave median among rural households as the constrained group.[65]

[64]The cutoff of four months is commonly used for the analysis about the length of breastfeeding in medical literature Xu et al. (2009).

[65]To construct the score for household assets, we use indicators for the ownership of the following assets: bicycles, tricycles, motorcycles, tractors, irrigation equipment, power threshers, televisions, washing machines, sewing

6 Alternative Explanations

Thus far, we have argued that seasonal variations in household resources for child neonatal investment, which result from seasonality in agricultural production, play a significant role in driving the BQE and its gender difference. We now discuss alternative explanations for our empirical results.

6.1 Compulsory Education Law and School Starting Age

Differences in school starting age may act as a potential mechanism underlying the relationship between QOB and individuals' lifecycle outcomes (Angrist and Krueger, 1991). We now explore this possibility in our context. According to China's Compulsory Education Law (CEL), the cutoff date for school entry is September 1: Parents cannot enroll their children in primary school if they have not reached age 6 before this cutoff date. Consequently, children born in the fourth quarter are generally older than their classmates, which could result in educational outcomes. Nevertheless, the CEL and the associated seasonality in school starting age are less likely to be the primary driver of our empirical results, for the following four reasons.

Firstly, the cutoff date of September 1st was not enforced until 1986 when China enacted the CEL. Therefore, the majority of individuals born in 1930-1990 would not have been affected by this law. Our findings on the gendered BQEs remain robust after removing cohorts affected by the law. Specifically, we exclude those born after 1970, who were under the age 15 when the CEL was introduced. This is shown in Columns (1)-(2) in Appendix Table A7.

Secondly, to scrutinize the potential mechanism of school starting age more thoroughly, we simulate a school starting age in months by month of birth (MOB), adhering to the rule mentioned above. For instance, for those born in October, they are unable to start primary school on September 1st in the year when they turn six, necessitating a wait of another 12 months. Therefore, they begin schooling at 6 years and 11 months.[66] When estimating Eq. (1), we include this simulated variable of school starting age as an additional control. Appendix Table A27 presents the results.[67] On one hand, we find the coefficient on school starting age to be significantly positive, which lends support to the role of school starting age in shaping lifecycle outcomes. On the other hand, the inclusion of

machines, electric fans, and telephones. We aggregate these 11 indicators into a score using the inverse covariance method as in Anderson (2008).

[66] As children can only be enrolled in primary school once they reach the age of six, combined with the fixed start of the school year on September 1st, this creates a situation where children born in October will miss the enrollment cut-off for the year they turn six. Consequently, these children must wait until the following September to begin school, effectively starting at the age of six years and eleven months. In contrast, children born in September can start school right as they turn six. This can be mathematically represented as follows: for an individual born in the x^{th} month of a calendar year, the age of starting school is 6 years plus $(9-x)$ months if $x \leq 9$, and 6 years plus $(21-x)$ months if $x \geq 10$.

[67] We focus on educational attainment as dependent variables.

this control does not largely alter our estimates of the coefficients on the QOB dummies, compared to those in Table 4. We continue to observe a significant gender difference in BQEs.

Thirdly, we conduct horse-race regressions, where we regress individual outcomes on two mechanism variables, i.e., the QOB-level index of household resource abundance during the neonatal period (as in Panel A of Table 7) and the school starting age variable as simulated above. In Panel A of Appendix Table A29, we find that, even after controlling for the seasonality in school starting age, the coefficients on the household resource abundance remain significantly positive, and are significantly larger for females than males, consistent with our finding in Table 7.

Fourthly, in our mechanism analysis, we find that BQEs and their gender gap vary significantly with previous-year thermal agricultural productivity (TAP). This effect is difficult to explain solely by the role of the CEL and school starting age, as it seems improbable that the impact of school starting age would fluctuate with agricultural productivity across different years of birth.

6.2 Seasonal Disease Patterns

The literature suggests that the disease environment affects lifecycle outcomes across birth months. For example, Currie and Schwandt (2013) find that in the United States, babies conceived in May have the shortest gestation periods and the lowest birth weights, due to their exposure to the peak prevalence of influenza at birth. The authors further provide evidence to support the seasonal influenza mechanism by analyzing the H1N1 pandemic in 2009. Lokshin and Radyakin (2012) find that in India, children born during the monsoon season have lower anthropometric scores compared to those born during fall-winter months. They propose a disease environment mechanism to explain their finding, given the heightened prevalence of diseases during the monsoon season in India.[68] In our context, seasonality in diseases may also contribute to the observed BQE and its gender difference. We now formally investigate this potential factor. Overall, while we cannot entirely rule out the possibility of the infectious disease environment mechanism, we believe it less likely to be the driver for our results.

Following the epidemiology literature, we examine the seasonality of infectious diseases in China in two respects. First, of the 29 classes A and B notifiable infectious diseases in China, six exhibit significant seasonality as documented by Zheng et al. (2023).[69] For each of these diseases, Zheng et al. (2023) provide an index ranging from 0 to 1 that captures the prevalence of the disease for each month within a year.[70] We construct a variable that captures overall monthly disease

[68] Lokshin and Radyakin (2012) also argue that the lower anthropometric scores for children born during the monsoon season are driven by increased malnutrition prevalence during this period in India.

[69] The six diseases include measles, bacillary and amoebic dysentery, malaria, dengue fever, brucellosis, and tuberculosis.

[70] Zheng et al. (2023) provide a comprehensive depiction of the seasonal characteristics of classes A and B notifiable infectious diseases in China during 2005-2020, based on data from China Information System for Disease Control and

prevalence by calculating a weighted average of the six indexes, using the number of cases of each disease as weights. Second, in addition to the more severe infectious diseases, such as classes A and B notifiable infectious diseases mentioned above, influenza also display significant seasonality in China, with this seasonality varying significantly across provinces in China.[71] In the literature, Yu et al. (2013) provide a week-level index ranging from 0 to 0.4 for each province to capture the seasonal distribution of influenza.[72] We aggregate this index at the province-by-month level for our analysis. In summary, we employ two variables to capture the prevalence of infectious diseases for individuals born in each month: (i) the month-of-birth (MOB) level prevalence of notifiable infectious diseases, and (ii) the province-by-MOB level prevalence of seasonal influenza.[73]

We perform two individual-level analyses to explore the potential influence of seasonal disease patterns in driving the estimated BQEs by gender. First, we re-estimate Eq. (1) by additionally controlling for the two variables of seasonal disease prevalence as constructed above. Appendix Table A28 presents the results. We find that, on one hand, individuals born in months with a higher prevalence of infectious diseases have significantly lower educational attainment, aligning with the literature on the impact of neonatal disease environment (Currie and Schwandt, 2013; Lokshin and Radyakin, 2012); on the other hand, the inclusion of these two controls does not considerably alter the estimated coefficients on QOB dummies (compared to those in Table 4), which continue to indicate a significant gender difference in BQEs on education.

Secondly, in Panel B of Appendix Table A29, we simultaneously include the index of neonatal household resource abundance (as in Panel A of Table 7) and the two variables on seasonal disease prevalence in a single regression specification. We find that, after accounting for the variables on seasonal disease prevalence, the estimates on the household resource abundance variable remain positive and significant, and continue to show a significant gender difference. Moreover, in Panel C of Appendix Table A29, we conduct a horse-race regression with the simulated school starting age (as constructed in Section 6.1) as an additional explanatory variable. We find that the gender-differentiated effects of neonatal household resource abundance remain significant after accounting for seasonality in school starting age and disease prevalence. In summary, these findings suggest that, while seasonality in neonatal disease environment may potentially influence lifecycle outcomes, it is unlikely to be the primary driver of the gender-differentiated BQEs, or their association with seasonality in household resource abundance during the neonatal period.

In addition, regarding our mechanism analysis at the county level, a potential concern we noted

Prevention.

[71] For example, Shu et al. (2010) document that seasonal influenza peaks in the winter months (December to February) in northern China and in the summer months (June to August) in southern China.

[72] Yu et al. (2013) characterize regional influenza seasonality patterns in China based on weekly reports from a national sentinel hospital-based surveillance network between 2005 and 2011.

[73] In our regression analysis, both variables are standardized with a mean of 0 and a standard deviation of 1.

in Section 5.5 pertains to the possibility that seasonal disease patterns could serve as a channel linking previous-year thermal agricultural productivity (TAP) and gendered BQEs, which could be a potential concern regarding our interpretation of the estimations that leverage natural-experimental variations in TAP. To mitigate this concern, we conduct sensitivity analyses in which we re-estimate Eq. (8) by excluding provinces with high prevalence for each of the six notifiable infectious diseases that exhibit significant seasonality (Zheng et al., 2023).[74] Reassuringly, our estimates of β in Eq. (8) remain stable when restricting the sample to non-hotspot provinces for specific diseases (see Appendix Table A30). This suggests that seasonal disease prevalence is unlikely to be a primary channel through which previous-year TAP influences gendered BQEs.[75]

7 Discussion and Conclusion

This article provides novel evidence on economic development and gender inequality through the lens of agricultural production seasonality and neonatal investment in developing countries. We note that our empirical setting has limitations. For instance, first, we do not provide direct causal evidence on the role of gender preference in shaping the gender difference in BQEs.[76] Second, the interpretation of our results largely hinges on the critical role of investment during the neonatal period; the BQEs might also result from seasonal variations in prenatal investment and heterogeneous exposure effects across three trimesters.[77] Overall, while we emphasize the mechanism related to agricultural seasonality and present substantial evidence to support this mechanism, which helps derive implications for economic development and gender equality in general, it is important to note that we remain receptive to other potential factors that could underlie the gender-differentiated BQEs and their variations across space and time, and it remains a challenge to precisely quantify contributions of various mechanisms.

We conclude by providing some suggestions for future research on economic development and

[74] For each notifiable infectious disease, Zheng et al. (2023) identify hotspot provinces for that disease using the local Moran I statistic.

[75] In addition to classes A and B notifiable infectious diseases, seasonal influenza might also be influenced by TAP and affect neonatal outcomes. As we have discussed, the seasonality in influenza varies significantly between northern and southern China (Shu et al., 2010; Yu et al., 2013). However, we find that the effect of TAP on the gender gap in BQEs among northern provinces is nearly the same as that in southern provinces. Moreover, the peak of seasonal influenza in northern China is in the winter months (December to February), which falls outside the time range for TAP calculation (April 1$^{\text{st}}$ to September 30$^{\text{th}}$, as in Eq. (9)). Hence, it is less likely that TAP could significantly impact the severity of seasonal influenza in northern China. In sum, the potential relationship between TAP and seasonal disease patterns is less likely to pose a major threat to our identifying assumption for estimating Eq. (8).

[76] As suggestive evidence, province-level correlational analysis shows that the gender difference in BQEs on education tends to be larger in provinces with a higher gender inequality in life expectancy and those with a lower female bargaining power within households (Appendix D.3).

[77] In the medical and economics literature, the relative importance of prenatal conditions across the three trimesters is still unclear (Almond and Mazumder, 2011; Karimi et al., 2021; Stein et al., 1995), though it is well established that the neonatal period is critical for child development.

gender equality. While our results demonstrate the role of economic development in closing gender gaps in educational and labor market outcomes, we cannot speak to whether there is an impact on noneconomic outcomes. In our context, son preference, rooted in cultural traditions, persists despite rapid economic development, as reflected by the rising sex ratio at birth in the first couple of decades since the economic reform in China (Ebenstein, 2010; Jayachandran, 2015). Although gender norms have been shown to be malleable through affirmative actions such as promoting women's political participation, providing employment opportunities for women, and reshaping students' gender attitudes (Beaman et al., 2009; Jensen, 2012; Dhar et al., 2022), will cultural institutions that favor males reform with with economic development? If yes, what are the potential mechanisms through which economic development affects the cultural determinants of gender inequality? These questions warrant future investigation.

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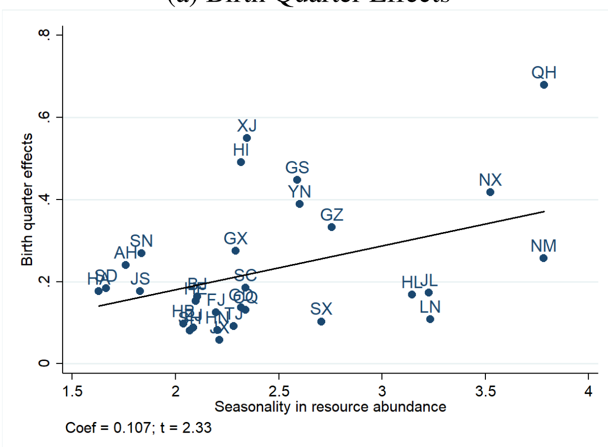
Online Appendix

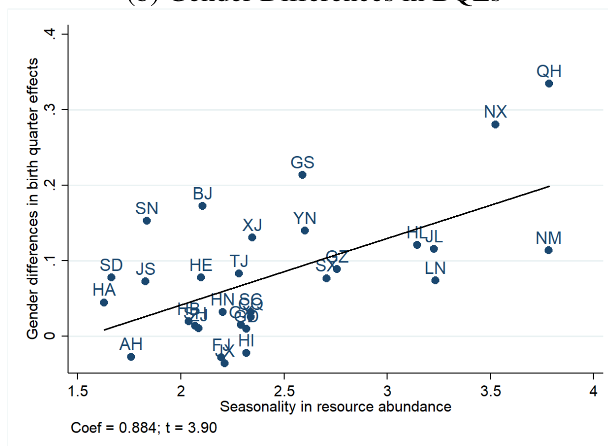
A Additional Figures and Tables

Figure A1: Seasonality in Household Resources, Birth Quarter Effects, and Gender Differences

(a) Birth Quarter Effects



(b) Gender Differences in BQEs



Note: In each figure, each point is a province. The horizontal axis is the seasonality in household abundance, defined as the difference between the maximum and minimum of the QOB-specific neonatal household resource abundance index (standardized) in each province. The vertical axis in (a) is province-level BQE estimates (Column (1) of Appendix Table D1), and that in (b) is province-level gender differences (female minus male) in BQE estimates (Column (4) of Appendix Table D1). We also report the regression coefficient and t-statistic from a univariate linear regression in each figure.

Table A1: Maternal Gender Attitudes and Birth Quarter of Newborns by Gender

Dependent variables (standardized):	At least one son (1)	Women focus on family (2)	Women marriage - important (3)	Having children - important (4)	Women on housework (5)
Female	-0.112**	-0.027	0.069	0.053	0.017
	(0.048)	(0.051)	(0.056)	(0.051)	(0.051)
Q2	0.038	0.005	0.023	0.053	0.036
	(0.047)	(0.051)	(0.052)	(0.053)	(0.052)
Q3	0.064	0.051	0.013	0.057	0.022
	(0.048)	(0.049)	(0.053)	(0.051)	(0.055)
Q4	0.042	-0.007	0.090*	0.096**	0.038
	(0.046)	(0.050)	(0.050)	(0.044)	(0.055)
Q2 $\times$ female	0.025	0.075	-0.014	-0.054	-0.003
	(0.070)	(0.071)	(0.073)	(0.071)	(0.070)
Q3 $\times$ female	-0.016	-0.018	-0.107	-0.040	-0.054
	(0.064)	(0.066)	(0.073)	(0.074)	(0.074)
Q4 $\times$ female	-0.094	0.048	-0.133	-0.090	-0.035
	(0.067)	(0.074)	(0.081)	(0.074)	(0.075)
p-value for joint significance of Q2, Q3, and Q4	*0.604*	*0.638*	*0.268*	*0.199*	*0.884*
p-value for joint significance of Q2×female, Q3×female, and Q4×female	*0.340*	*0.528*	*0.207*	*0.682*	*0.871*
Year-of-birth fixed effects	Yes	Yes	Yes	Yes	Yes
Province-of-birth fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	6,406	6,406	6,406	6,406	6,406
R-squared	0.115	0.049	0.033	0.015	0.021

Note: Data are from the China Family Panel Survey (the 2014 wave). Each observation is a mother with children younger than 15 years. Dependent variables are mothers' answers of whether they agree with the following five statements on a Likert scale from 1 (totally disagree) to 5 (totally agree). The statements for Columns (1) - (5) are: (1) "In order to continue the family lineage, women should give birth to at least one boy;" (2) "Men should focus on career, while women should focus on family;" (3) "Marrying well is more important for women than doing well;" (4) "Women should have at least one child;" (5) "Men should do half of the housework." All dependent variables are standardized with a mean of 0 and a standard deviation of 1. Q2, Q3, and Q4 are indicators for children's quarter of birth, with those born in Q1 as the omitted group. Female is an indicator for child gender. Standard errors in parentheses are clustered at the province-by-birthyear level. The table reports two *p*-values from each regression. The first is that from the F-test for the joint significance of Q2, Q3, and Q4, and the second is that from the F-test for the joint significance of Q2 $\times$ female, Q3 $\times$ female and Q4 $\times$ female. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A2: Summary Statistics for the CEPS Sample

	Female sample			Male sample		
	N	Mean	Std. dev.	N	Mean	Std. dev.
Cognitive test score	6,780	0.02	0.98	6,759	-0.02	1.02
Math exam score	6,650	0.05	0.95	6,574	-0.05	1.01
Chinese exam score	6,654	0.29	0.84	6,576	-0.30	1.03
English exam score	6,651	0.28	0.84	6,576	-0.29	1.03
Education expenditure (unit: 1,000 RMB yuan)	4,929	2.13	4.56	4,857	2.05	5.27
Extracurricular tutoring (Yes=1)	6,726	0.33	0.47	6,677	0.28	0.45
Health insurance (Yes=1)	6,542	0.89	0.32	6,511	0.89	0.31
Daily hours spent on children	6,773	3.95	4.14	6,754	3.74	4.09
Demandingness score	6,533	11.19	3.23	6,432	10.89	3.18
Responsiveness score	6,635	6.58	2.64	6,585	6.34	2.55
Paternal schooling years	6,780	10.30	3.03	6,759	10.22	3.08
Maternal schooling years	6,780	9.57	3.48	6,759	9.54	3.50

Note: The table presents summary statistics for the CEPS sample. The cognitive test score is standardized over the full sample, and exam scores for math, Chinese, and English are standardized within each class.

Table A3: Birth Quarter Effects on Cognitive Skills and Academic Performance by Gender

Dependent variable	Cognitive test score		Math exam score		Chinese exam score		English exam score	
	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Q2	0.016	0.011	-0.004	-0.088**	-0.039	-0.092***	0.030	-0.055*
	(0.030)	(0.032)	(0.031)	(0.039)	(0.030)	(0.035)	(0.030)	(0.031)
Q3	0.090***	0.040	0.020	-0.069*	-0.019	-0.045	0.053*	-0.046
	(0.030)	(0.032)	(0.035)	(0.037)	(0.033)	(0.036)	(0.031)	(0.036)
Q4	0.140***	0.081**	0.094**	-0.036	0.032	-0.046	0.095***	-0.019
	(0.034)	(0.036)	(0.041)	(0.039)	(0.039)	(0.036)	(0.033)	(0.041)
p-value for Q2, Q3, and Q4 coefficient equality between gender subsamples	*0.574*		*0.161*		*0.405*		*0.127*	
Outcome mean	0.016	-0.016	0.052	-0.053	0.293	-0.297	0.283	-0.287
Han ethnicity (Yes=1)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parental schooling years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,780	6,759	6,650	6,574	6,654	6,576	6,651	6,576
R-squared	0.214	0.189	0.022	0.023	0.019	0.016	0.026	0.027

Note: Data are from the China Education Panel Survey (CEPS) for academic year 2013-2014, and the sample includes junior high school students in grade 7 and grade 9, aged 11 to 17. The cognitive test score is normalized over the sample with a mean of 0 and a standard deviation of 1, and exam scores for math, Chinese, and English are normalized within each class with a mean of 0 and a standard deviation of 1. Standard errors in parentheses are clustered at the county-by-birthyear level. For each dependent variable, we report the *p*-value from Hausman's general specification test for the equality of the Q4 coefficients in the two subsamples. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A4: Birth Quarter Effects on Labor Market Outcomes by Gender: Controlling for Schooling Years

Dependent variable	Log monthly earnings		Working in the public sector (Yes=1)		Unemployment insurance coverage (Yes=1)	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Q2	-0.005	-0.002	-0.001	-0.003***	-0.002**	-0.002**
	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Q3	0.001	0.009***	-0.001	0.000	-0.005***	-0.001
	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Q4	0.017***	0.018***	0.006***	0.003***	0.003**	0.001
	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Schooling years	0.096***	0.096***	0.041***	0.050***	0.031***	0.035***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
p-value for Q2, Q3, and Q4 coefficient equality between gender subsamples	*0.225*		*0.022*		*0.002*	
Outcome mean	5.783	6.257	0.127	0.166	0.109	0.134
Han ethnicity (Yes=1)	Yes	Yes	Yes	Yes	Yes	Yes
Birth province FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	508,544	615,444	508,544	615,444	508,544	615,444
R-squared	0.256	0.326	0.266	0.244	0.257	0.236

Note: Data are from the mini-census 2005. The sample includes individuals aged 25 to 60 who were employed at the time of the survey. Standard errors in parentheses are clustered at province-by-birthyear level. Q2, Q3, and Q4 are dummies indicating an individual's quarter of birth, with the first quarter as the benchmark group. For each dependent variable, we report the *p*-value from the Wald test for the equality of the Q2, Q3, and Q4 coefficients in the two gender subsamples. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A5: Cohort Sizes by Quarter of Birth and Gender for Cohorts 1930-1990

Dependent variable: Province-QOB-gender-level cohort size	(1)	(2)
$Q2 \times male \times age$	0.003	0.003
	(0.069)	(0.070)
$Q3 \times male \times age$	0.059	0.059
	(0.085)	(0.086)
$Q4 \times male \times age$	-0.120	-0.120
	(0.086)	(0.087)
$Q2 \times male$	-27.059	-27.059
	(134.922)	(136.280)
$Q3 \times male$	-122.748	-122.748
	(165.510)	(167.176)
$Q4 \times male$	245.181	245.181
	(168.940)	(170.641)
p-value for the joint significance of the estimates on the three triple interaction terms	*0.103*	*0.109*
Province fixed effects	Yes	Yes
Cohort fixed effects	Yes	Yes
Cohort-QOB fixed effects	No	Yes
Province-QOB fixed effects	No	Yes
Provincial cohort linear trends	No	Yes
Observations	15,128	15,128
R-squared	0.830	0.910

Note: The analysis is based on census 1990 and restricted to people born after 1930. Each observation is a cohort in a quarter of birth (QOB) group in a province by gender. The dependent variable is the cohort size—i.e., the number of individuals in the province-QOB-cohort cell by gender. We estimate the following equation: $CohortSize_{qtgp} = \gamma_1 QOB_q \times male_g \times age_t + \gamma_2 QOB_q \times age_t + \gamma_3 QOB_q \times male_g + \gamma_4 QOB_q + \gamma_5 male_g \times age_t + \gamma_6 male_g + \lambda_p + \mu_t + \varepsilon_{qgtp}$, where q, t, g, p denote QOB, cohort, gender, and province, respectively. QOB_q is the vector of birth quarter indicators. Standard errors are clustered at the province-by-cohort level.

Table A6: Birth Quarter Effects on Educational Attainment by Gender

Dep. var.: schooling years	Female	Male
	(1)	(2)
Q2	-0.041***	-0.034***
	(0.005)	(0.004)
Q3	0.054***	0.059***
	(0.006)	(0.005)
Q4	0.212***	0.165***
	(0.007)	(0.006)
Q2 × Great Famine	-0.042**	-0.010
	(0.018)	(0.013)
Q3 × Great Famine	-0.033	-0.030*
	(0.025)	(0.017)
Q4 × Great Famine	0.090***	-0.003
	(0.027)	(0.019)
p-value for joint significance of Q2×famine, Q3×famine, and Q4×famine	*0.000*	*0.110*
p-value for Q2, Q3, and Q4 coefficient equality between gender subsamples	*0.000*	
p-value for Q2×famine, Q3×famine, and Q4×famine coefficient equality between gender subsamples	*0.000*	
Observations	7,816,215	8,127,658
R-squared	0.319	0.211

Note: Data are from censuses 1990, 2000, and 2010 and mini-censuses 2005 and 2015, and the sample includes individuals aged from 25 to 60. Standard errors in parentheses are clustered at the province-by-birthyear level. "Great Famine" is the indicator for individuals born during 1959-1961. In each column, we report the *p*-value for the joint significance of the interaction terms between the QOB dummies and the Great Famine indicator. We report the *p*-value from the Wald test for the equality of the Q2, Q3, and Q4 coefficients in the two gender subsamples. We also report the *p*-value from the Wald test for the equality of the coefficients on Q2×famine, Q3×famine, and Q4×famine in the two gender subsamples. ***, ** and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

Table A7: Birth Quarter Effects on Educational Attainment by Gender: Cohort Subsamples

Dep. var.: schooling years	Cohorts born before 1978		Cohorts born before 1970		Excluding cohorts born between 1959-1961	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(3)	(4)
Q2	-0.046***	-0.039***	-0.047***	-0.046***	-0.042***	-0.036***
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)
Q3	0.046***	0.053***	0.042***	0.049***	0.054***	0.056***
	(0.006)	(0.005)	(0.007)	(0.005)	(0.006)	(0.005)
Q4	0.221***	0.165***	0.212***	0.157***	0.218***	0.162***
	(0.007)	(0.006)	(0.008)	(0.007)	(0.007)	(0.006)
p-value for Q2, Q3, and Q4 coefficient equality between gender subsamples	*0.000*		*0.000*		*0.000*	
Outcome mean	6.517	7.983	6.084	7.741	6.732	8.089
Observations	7,259,272	7,570,779	6,009,070	6,320,667	7,315,536	7,605,768
R-squared	0.293	0.194	0.274	0.190	0.329	0.214

Note: Data are from censuses 1990, 2000, and 2010 and mini-censuses 2005 and 2015, and the sample includes individuals aged from 25 to 60. In Columns (1) and (2), we keep cohorts born before 1978; in columns (3) and (4), we keep cohorts born before 1970; in columns (5) and (6), we exclude cohorts born between 1959-1961. Standard errors in parentheses are clustered at the province-by-birthyear level. For each dependent variable, we report the *p*-value from the Wald test for the equality of the Q2, Q3, and Q4 coefficients in the two gender subsamples. ***, ** and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

Table A8: Primary School Expansion and Birth Quarter Effects on Educational Attainment by Cohorts

Dependent variable	Years of schooling		
	(1)	(2)	(3)
Cohorts	1930-1939	1950-1959	1930-1959
Q2	-0.023*	-0.033***	-0.032***
	(0.012)	(0.007)	(0.005)
Q3	0.182***	0.050***	0.064***
	(0.014)	(0.008)	(0.007)
Q4	0.352***	0.187***	0.186***
	(0.015)	(0.009)	(0.008)
Q2 × primary			0.076***
			(0.024)
Q3 × primary			-0.164***
			(0.029)
Q4 × primary			-0.356***
			(0.034)
primary			7.630***
			(0.224)
Census year FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Observations	879,987	4,325,536	7,479,084
R-squared	0.172	0.181	0.241

Note: Data are from censuses 1990, 2000, and 2010 and mini-censuses 2005 and 2015, and the sample includes individuals aged from 25 to 60. *Primary* is the province-cohort-level primary school completion rate, which is demeaned in Column (3). Columns (1) - (3) are based on subsamples of cohorts born between 1930-1939, 1950-1959, and 1930-1959, respectively. Standard errors in parentheses are clustered at the province-by-birthyear level. ***, ** and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

Table A9: Birth Quarter Effects on Educational Attainment by Gender: Controlling for Seasonal Maternal Characteristics

Dependent variable	Schooling years		Junior high school completion (Yes=1)		Senior high school completion (Yes=1)	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Q2	-0.004	-0.026***	-0.001	-0.004***	-0.001**	-0.003***
	(0.006)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)
Q3	0.032***	-0.022**	0.002	-0.003**	-0.001	-0.005***
	(0.009)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)
Q4	0.278***	0.173***	0.028***	0.015***	0.024***	0.017***
	(0.012)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)
p-value for Q2, Q3, and Q4 coefficient equality between gender subsamples	*0.000*		*0.000*		*0.000*	
Outcome mean	6.780	8.150	0.484	0.631	0.161	0.221
MOB-level maternal characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Han ethnicity (Yes=1)	Yes	Yes	Yes	Yes	Yes	Yes
Birth province FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth year FE	Yes	Yes	Yes	Yes	Yes	Yes
Census year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,816,218	8,127,660	7,816,218	8,127,660	7,816,218	8,127,660
R-squared	0.319	0.210	0.251	0.200	0.091	0.066

Note: Data are from censuses 1990, 2000, and 2010 and mini-censuses 2005 and 2015, and the sample includes individuals aged from 25 to 60. “MOB-level maternal characteristics” are month-of-birth (MOB)-specific maternal characteristics calculated using the newborn sample, as described in Section 4.2. Standard errors in parentheses are clustered at the province-by-birthyear level. For each dependent variable, we report the *p*-value from the Wald test for the equality of the Q2, Q3, and Q4 coefficients in the two gender subsamples. ***, ** and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

Table A10: Seasonality in Household Food Consumption and Nutritional Intake

Data source:	CFPS		CHNS	
Dependent variable:	Monthly food expenditure (unit: RMB yuan, in logarithm)		3-day nutritional intake (unit: kilocalorie)	
	(1)	(2)	(3)	(4)
Q4	0.208**		55.031***	
	(0.092)		(18.918)	
Monthly food abundance		0.069***		29.031***
		(0.020)		(8.685)
Controls	Yes	Yes	Yes	Yes
Outcome mean	5.889	5.889	2,317.9	2,317.9
Observations	13,664	13,664	37,888	37,888
R-squared	0.365	0.367	0.408	0.408

Note: Q4 is an indicator for months in the fourth quarter. Monthly food abundance is the month-level food abundance score constructed based on the crop calendar as in Section 5.1. The score is standardized across months with a mean of 0 and a standard deviation of 1. In Columns (1) - (2), data are from the China Family Panel Studies (CFPS, wave 2010); each observation is a household; the dependent variable is household food expenditure in logarithm during the past month at the survey time; we control for province fixed effects, household rural-urban status, log household income during the past year, and schooling years of the household head; standard errors are clustered at the county level. In Columns (3) - (4), data are from the China Health and Nutrition Survey (CHNS, waves 1991, 1993, 1997, and 2000); each observation is an individual in a survey year; the dependent variable is individual-level nutritional intake in kilocalories during the past three days at the survey time; we control for household fixed effects and survey year fixed effects; standard errors are clustered at the household level. ***, ** and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

Table A11: Quarter of Birth and Parental Investment in Children in Adolescence

	Education expenditure		Extracurricular tutoring		Health insurance	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Q2	0.012	-0.039	0.009	0.005	-0.005	0.010
	(0.032)	(0.048)	(0.017)	(0.014)	(0.010)	(0.015)
Q3	0.012	0.010	0.006	-0.011	0.012	0.009
	(0.031)	(0.037)	(0.014)	(0.014)	(0.011)	(0.013)
Q4	0.039	0.005	0.016	-0.003	0.008	0.011
	(0.036)	(0.046)	(0.013)	(0.014)	(0.012)	(0.014)
p-value for joint significance	*0.718*	*0.508*	*0.652*	*0.637*	*0.556*	*0.862*
Outcome mean	0.000	0.000	0.328	0.277	0.887	0.889
Observations	4,929	4,857	6,726	6,677	6,542	6,511
R-squared	0.333	0.268	0.433	0.397	0.134	0.150
	Hours with children		Demandingness		Responsiveness	
	Female	Male	Female	Male	Female	Male
	(7)	(8)	(9)	(10)	(11)	(12)
Q2	-0.050	0.010	0.003	-0.003	-0.023	0.036
	(0.034)	(0.038)	(0.035)	(0.036)	(0.035)	(0.034)
Q3	-0.008	-0.004	0.010	0.033	-0.013	0.003
	(0.034)	(0.040)	(0.033)	(0.032)	(0.032)	(0.034)
Q4	-0.019	0.015	-0.001	0.025	0.013	0.041
	(0.038)	(0.042)	(0.036)	(0.039)	(0.033)	(0.037)
p-value for joint significance	*0.463*	*0.999*	*0.998*	*0.816*	*0.730*	*0.684*
Outcome mean	0.000	0.000	0.000	0.000	0.000	0.000
Observations	6,773	6,754	6,533	6,432	6,635	6,585
R-squared	0.114	0.092	0.159	0.149	0.242	0.202

Note: Data are from the China Education Panel Survey (CEPS) for academic year 2013-2014, and the sample includes junior high school students in grade 7 and grade 9, aged 11 to 17. The dependent variable is annual educational expenditure in Columns (1) and (2), the indicator for extracurricular tutoring in Columns (3) and (4), the indicator for a child having health insurance in Columns (5) and (6), daily hours spent on children in Columns (7) and (8), a score for parental demandingness in Columns (9) and (10), and a score for parental responsiveness in Columns (11) and (12). All dependent variables, except for those in Columns (3) to (6), are standardized with a mean of 0 and a standard deviation of 1. In each regression, we report the p-value in the test for the joint significance of the three QOB dummies (Q2, Q3, and Q4). We control for the indicator for Han ethnicity and parental schooling years, as well as county fixed effects and birth year fixed effects. Standard errors in parentheses are clustered at the county-by-birthyear level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A12: Household Resource Abundance in the Neonatal Period and Labor Market Outcomes

	Log monthly earnings		State sector (yes=1)		Unemp. insur. (yes=1)	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. QOB-level measure of seasonality						
Household resource abundance	0.015***	0.010***	0.006***	0.005***	0.006***	0.003***
	(0.002)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
p-value for coefficient equality	*0.002*		*0.061*		*0.000*	
Outcome mean	5.783	6.257	0.127	0.166	0.109	0.134
Observations	508,544	615,444	508,544	615,444	508,544	615,444
R-squared	0.145	0.206	0.074	0.052	0.137	0.122
Panel B. Province-by-QOB-level measure of seasonality						
Household resource abundance	0.014***	0.010***	0.006***	0.004***	0.005***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
p-value for coefficient equality	*0.000*		*0.021*		*0.002*	
Outcome mean	5.783	6.257	0.127	0.166	0.109	0.134
Observations	508,544	615,444	508,544	615,444	508,544	615,444
R-squared	0.145	0.206	0.074	0.052	0.137	0.122

Note: Data are from mini-census 2005. The sample includes individuals aged 25 to 60 who were employed at the time of the survey. Dependent variables are defined in the same way as Table 5. Standard errors in parentheses are clustered at the province-by-birthyear level. The key independent variable is the QOB-specific (province-by-QOB-specific) index of household resource abundance during the neonatal period in Panel A (Panel B), which is standardized with a mean of 0 and a standard deviation of 1. Standard errors in parentheses are clustered at the province-by-birthyear level. For each dependent variable, we report the *p*-value from the Wald test for the equality of the coefficients on household resource abundance in the two gender subsamples. ***, ** and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

Table A13: Month-of-birth-specific Household Resource Abundance in the Neonatal Period and Educational Attainment

	Schooling years		Junior high school completion (yes=1)		Senior high school completion (yes=1)	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. MOB-level measure of seasonality						
Household resource abundance	0.077***	0.045***	0.007***	0.004***	0.006***	0.004***
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
p-value for coefficient equality	*0.000*		*0.000*		*0.000*	
Outcome mean	6.780	8.150	0.484	0.631	0.161	0.221
Observations	7,816,218	8,127,660	7,816,218	8,127,660	7,816,218	8,127,660
R-squared	0.318	0.210	0.251	0.200	0.090	0.066
Panel B. Province-by-MOB-level measure of seasonality						
Household resource abundance	0.062***	0.038***	0.006***	0.003***	0.005***	0.003***
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
p-value for coefficient equality	*0.000*		*0.000*		*0.000*	
Outcome mean	6.780	8.150	0.484	0.631	0.161	0.221
Observations	7,816,218	8,127,660	7,816,218	8,127,660	7,816,218	8,127,660
R-squared	0.318	0.210	0.251	0.200	0.090	0.066

Note: Data are from censuses 1990, 2000, and 2010 and mini-censuses 2005 and 2015, and the sample includes individuals aged from 25 to 60. The key independent variable is the month-of-birth (MOB)-specific (province-by-MOB-specific) index of household resource abundance during the neonatal period in Panel A (Panel B), which is standardized with a mean of 0 and a standard deviation of 1. Standard errors in parentheses are clustered at the province-by-birthyear level. For each dependent variable, we report the p-value from the Wald test for the equality of the coefficients on household resource abundance in the two gender subsamples. ***, ** and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

Table A14: Food Abundance and Agricultural Work Intensity in the Neonatal Period and Educational Attainment

	Schooling years		Junior high school completion (yes=1)		Senior high school completion (yes=1)	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. QOB-level measure of food abundance						
Food abundance	0.103***	0.082***	0.010***	0.008***	0.007***	0.007***
	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
p-value for coefficient equality	*0.000*		*0.000*		*0.233*	
Panel B. Province-by-QOB-level measure of food abundance						
Food abundance	0.081***	0.064***	0.008***	0.006***	0.006***	0.005***
	(0.003)	(0.003)	(0.000)	(0.002)	(0.000)	(0.000)
p-value for coefficient equality	*0.000*		*0.000*		*0.339*	
Panel C. QOB-level measure of agricultural work intensity						
Agricultural work intensity	-0.103***	-0.076***	-0.010***	-0.007***	-0.008***	-0.007***
	(0.003)	(0.002)	(0.000)	(0.000)	(0.002)	(0.000)
p-value for coefficient equality	*0.000*		*0.000*		*0.000*	
Panel D. Province-by-QOB-level measure of agricultural work intensity						
Agricultural work intensity	-0.031***	-0.017***	-0.003***	-0.002***	-0.003***	-0.002***
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
p-value for coefficient equality	*0.000*		*0.000*		*0.000*	
Outcome mean	6.780	8.150	0.484	0.631	0.161	0.221
Observations	7,816,218	8,127,660	7,816,218	8,127,660	7,816,218	8,127,660

Note: Data are from censuses 1990, 2000, and 2010 and mini-censuses 2005 and 2015, and the sample includes individuals aged from 25 to 60. The key independent variable is the QOB-specific (province-by-QOB-specific) index of food abundance during the neonatal period in Panel A (Panel B), and the QOB-specific (province-by-QOB-specific) index of agricultural work intensity during the neonatal period in Panel C (Panel D), respectively. All the indexes are standardized with a mean of 0 and a standard deviation of 1. Standard errors in parentheses are clustered at the province-by-birthyear level. For each dependent variable, we report the *p*-value from the Wald test for the equality of the coefficients on the key independent variable in the two gender subsamples. ***, ** and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

Table A15: Serial Correlation in Thermal Agricultural Productivity

Dependent variable	Current-year thermal agricultural productivity			
	(1)	(2)	(3)	(4)
Thermal agricultural productivity (t-1)	0.986***	0.496***	0.006	-0.010
	(0.000)	(0.003)	(0.007)	(0.007)
Thermal agricultural productivity (t-2)		0.496***		0.001
		(0.003)		(0.006)
Outcome mean	23.52	23.53	23.52	23.53
County FE	No	No	Yes	Yes
Observations	80,623	74,216	80,623	74,210
R-squared	0.971	0.979	0.985	0.986

Note: The dependent variable is the current year thermal agricultural productivity (TAP, unit: 100 degree-days) and the explanatory variables are the TAP of the previous 1 or 2 years. The first two columns do not control for county fixed effects and the last two columns control for them. Standard errors are clustered at the county level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A16: Summary Statistics for the County-level Analysis

	All counties		Urban counties		Rural counties	
	Mean	SD	Mean	SD	Mean	SD
Previous-year TAP	24.60	6.23	24.29	6.22	24.71	6.16
BQE for all people	0.15	1.19	0.13	1.15	0.16	1.20
BQE for males	0.12	1.71	0.11	1.65	0.12	1.70
BQE for females	0.17	1.79	0.16	1.72	0.19	1.82
Gender difference in BQEs (female versus male)	0.05	2.44	0.05	2.35	0.07	2.48
Observations	56,304		26,547		25,533	

Note: This table presents the mean and standard deviation (SD) for variables used in estimating Eq. (8) in Section 5.5. Each observation is a cohort in a county. We classify all counties into two groups (urban vs rural) according to the median value of urbanization rates in 1990. The urbanization rate in 1990 is missing for some counties due to changes in administrative divisions. BQEs and their gender differences are calculated from the pooled census sample. The unit for the previous-year TAP is 100 degree-days.

Table A17: Robustness Checks on the Effects of Thermal Agricultural Productivity

Dependent variable	Difference in average schooling years (Q4 minus Q1)			Gender difference (Female minus male)
	Overall	Female	Male	
	(1)	(2)	(3)	(4)
A. Weighted average of the nearest three weather stations				
Thermal agricultural productivity (t-1)	-0.004	-0.016**	0.003	-0.019**
	(0.004)	(0.007)	(0.006)	(0.009)
Observations	56,304	56,304	56,304	56,304
R-squared	0.083	0.068	0.067	0.056
B. Excluding county-by-cohort observations with fewer than 30 individuals				
Thermal agricultural productivity (t-1)	-0.007	-0.019***	0.000	-0.019**
	(0.005)	(0.007)	(0.007)	(0.010)
Observations	46,057	46,057	46,057	46,057
R-squared	0.096	0.080	0.079	0.066
C. Excluding Beijing, Tianjin and Shanghai				
Thermal agricultural productivity (t-1)	-0.007	-0.020***	0.002	-0.021**
	(0.005)	(0.007)	(0.007)	(0.010)
Observations	54,947	54,947	54,947	54,947
R-squared	0.084	0.069	0.068	0.057
D. Excluding provinces to the west of the Heihe-Tengchong Line				
Thermal agricultural productivity (t-1)	-0.008	-0.020***	0.001	-0.021**
	(0.005)	(0.007)	(0.007)	(0.010)
Observations	50,538	50,538	50,538	50,538
R-squared	0.077	0.064	0.063	0.053
E. Using the Q4-Q2 differences to define BQEs				
Thermal agricultural productivity (t-1)	-0.006	-0.016**	0.001	-0.017*
	(0.005)	(0.007)	(0.007)	(0.010)
Observations	54,047	54,047	54,047	54,047
R-squared	0.038	0.021	0.018	0.005

Note: Definitions of dependent variables and regression specifications are the same as those in Table 8. The key explanatory variable is county-level thermal agricultural productivity (TAP) in 100 degree-days for the previous year. In Panel A, we replace the TAP of the weather station nearest to the county with the weighted average of the TAP of the three nearest weather stations using the inverses of distances as weights. In Panel B, we exclude county-by-cohort observations with fewer than 30 individuals in the pooled census data. In Panel C, we exclude Beijing, Tianjin, and Shanghai. In Panel D, we exclude the six provinces to the west of the Heihe-Tengchong Line—Inner Mongolia, Tibet, Gansu, Qinghai, Ningxia, and Xinjiang. In Panel E, we replace the dependent variables as BQEs defined using Q4-Q2 differences. In all regressions, county fixed effects and year fixed effects are controlled for. The regression is weighted by the number of individuals in each county-by-cohort cell in the pooled census data. Standard errors in parentheses are clustered at the county level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A18: Robustness Check: Mortality Selection

Dependent variable	Difference in cohort loss rates (Q4 minus Q1)		
	Overall	Female	Male
	(1)	(2)	(3)
Thermal agricultural productivity (t-1)	-0.003	-0.003	-0.002
	(0.003)	(0.003)	(0.003)
Outcome mean	0.004	0.001	0.004
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	67,083	67,083	67,083
R-squared	0.061	0.040	0.041

Note: The dependent variable is the difference in birth-quarter-specific cohort loss rates between Q4 and Q1 in each county-cohort cell, as defined in Section 5.5. The key explanatory variable is county-level thermal agricultural productivity (unit: 100 degree-days) in the previous year. County fixed effects and year fixed effects are controlled for. The regression is weighted by the number of individuals in each county-by-cohort cell in the census 1990 data. Standard errors in parentheses are clustered at the county level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A19: Robustness Checks on the Moderating Effect of the Agricultural Reform

Dependent variable:	Difference in average schooling years (Q4 minus Q1)			Gender difference (Female minus male)
	Overall	Female	Male	
	(1)	(2)	(3)	(4)
Panel A. Placebo test				
$TAP_{c,t-1} \times Rural_c \times Post71_t$	0.002	-0.001	0.004	-0.005
	(0.004)	(0.006)	(0.005)	(0.008)
Observations	19,725	19,725	19,725	19,725
R-squared	0.153	0.138	0.140	0.126
Panel B. Alternative cohort interval				
$TAP_{c,t-1} \times Rural_c \times Post_t$	0.005	0.014***	-0.004	0.018*
	(0.005)	(0.007)	(0.007)	(0.010)
Observations	33,809	33,809	33,809	33,809
R-squared	0.096	0.090	0.081	0.080
Panel C. Alternative definition of treated and control Groups				
$TAP_{c,t-1} \times Rural\_1_c \times Post_t$	0.012	0.022*	-0.006	0.028*
	(0.008)	(0.012)	(0.010)	(0.016)
Observations	11,978	11,978	11,978	11,978
R-squared	0.158	0.151	0.137	0.133

Note: Definitions of dependent variables and regression specifications are the same as in Table 8. In each regression, we control for all lower-order terms of the triple-interaction term, as well as county fixed effects and year fixed effects. In Panel A, we use cohorts born during 1966-1975, and the dummy $Post71_t$ takes the value of 1 for cohorts born since 1971. In Panel B, we use cohorts born during 1970-1989. In Panel C, we use cohorts born during 1975-1984, and we define urban counties as the one-third with the highest urbanization rates and rural counties ($Rural\_1_c$) as the one-third with the lowest urbanization rates. Regressions are weighted by the number of individuals in each county-by-cohort cell in the pooled census data. Standard errors in parentheses are clustered at the prefecture level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A20: The Moderating Effect of the Agricultural Reform since 1979 on the Impact of Thermal Agricultural Productivity: Controlling for the Impact of One-child Policy

	Difference in schooling years (Q4 minus Q1)			Gender difference
	Overall	Male	Female	(Female minus male)
	(1)	(2)	(3)	(4)
Panel A.				
$TAP_{c,t-1} \times Rural_c \times Post_t$	0.017**	0.004	0.029***	0.026**
	(0.007)	(0.009)	(0.010)	(0.013)
$TAP_{c,t-1} \times OCP_{pt}$	-0.001	0.006	0.012	0.006
	(0.011)	(0.014)	(0.017)	(0.021)
Outcome mean	0.174	0.188	0.149	0.039
Observations	18,334	18,334	18,334	18,334
R-squared	0.173	0.153	0.163	0.148
Panel B.				
$TAP_{c,t-1} \times Rural_c \times Post_t$	0.008	-0.007	0.025**	0.032**
	(0.008)	(0.012)	(0.012)	(0.016)
$TAP_{c,t-1} \times OCP_{pt}$	-0.555*	-0.715*	-0.289	0.426
	(0.288)	(0.401)	(0.436)	(0.572)
$TAP_{c,t-1} \times OCP_{pt} \times Rural_c$	0.019*	0.025	0.010	-0.015
	(0.011)	(0.015)	(0.017)	(0.022)
Outcome mean	0.174	0.188	0.149	0.039
Observations	18,334	18,334	18,334	18,334
R-squared	0.173	0.153	0.163	0.148
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes

Note: Definitions of the dependent variables are the same as in Table 8. The regression specification is based on in Eq. (11) in Section 5.6 with additional control variables. In Panel A, we additionally control for $TAP_{c,t-1} \times OCP_{pt}$, where OCP_{pt} is an indicator for birth year t following the implementation of the OCP in province p. The other notations are the same as those in Table 9. In Panel B, we additionally control for $TAP_{c,t-1} \times OCP_{pt} \times Rural_c$. In all regressions, we control for all lower-order terms of the interaction terms, as well as the county fixed effects and province-by-year fixed effects. The regressions are weighted by the number of individuals in each county-by-cohort cell in the pooled census data. Standard errors in parentheses are clustered at the county level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A21: Household Responsibility System Reform, One-child Policy, and the Impact of Thermal Agricultural Productivity

	Difference in schooling years (Q4 minus Q1)			Gender difference
	Overall	Male	Female	(Female minus male)
	(1)	(2)	(3)	(4)
Panel A.				
$TAP_{c,t-1} \times Rural_c \times HRS_{c,t-1}$	0.009	-0.017	0.037**	0.054**
	(0.011)	(0.016)	(0.016)	(0.022)
Observations	9,557	9,557	9,557	9,557
R-squared	0.166	0.145	0.152	0.136
Panel B.				
$TAP_{c,t-1} \times Rural_c \times HRS_{c,t-1}$	0.009	-0.016	0.037**	0.053**
	(0.011)	(0.016)	(0.016)	(0.022)
$TAP_{c,t-1} \times OCP_{ct}$	-0.003	-0.012	0.003	0.015
	(0.008)	(0.011)	(0.014)	(0.018)
Observations	9,557	9,557	9,557	9,557
R-squared	0.166	0.145	0.152	0.136
Panel C.				
$TAP_{c,t-1} \times Rural_c \times HRS_{c,t-1}$	-0.006	-0.031	0.025	0.056*
	(0.013)	(0.019)	(0.022)	(0.030)
$TAP_{c,t-1} \times OCP_{ct}$	-0.018	-0.025	-0.010	0.015
	(0.012)	(0.016)	(0.018)	(0.024)
$TAP_{c,t-1} \times OCP_{ct} \times Rural_c$	0.021*	0.020	0.017	-0.003
	(0.012)	(0.016)	(0.020)	(0.026)
Observations	9,557	9,557	9,557	9,557
R-squared	0.166	0.145	0.152	0.136
Outcome mean	0.206	0.167	0.216	0.049
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes

Note: Definitions of the dependent variables are the same as in Table 8. The regressions are based on the subsample of 914 counties as in Almond et al. (2019). HRS_{ct} (OCP_{ct}) is an indicator which takes one if year t is after the implementation of the HRS reform (the OCP) in county c. All remaining notations have the same meaning as in (9). In Panel A, we include the triple-interaction term $TAP_{c,t-1} \times Rural_c \times HRS_{c,t-1}$ and all lower-order terms of the interaction term. In Panel B, we further include the interaction term $TAP_{c,t-1} \times OCP_{c,t}$ and their lower-order terms. In Panel C, we additionally include the triple interaction term $TAP_{c,t-1} \times OCP_{c,t} \times Rural_c$ on the basis of Panel B. In all regressions, we control for all lower-order terms of the interaction terms, as well as the county fixed effects and province-by-year fixed effects. The regressions are weighted by the number of individuals in each county-by-cohort cell in the pooled census data. Standard errors in parentheses are clustered at the county level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A22: The Moderating Effect of the Agricultural Reform since 1979 on the Impact of Thermal Agricultural Productivity: Controlling for the Impact of Compulsory Education Law

	Difference in schooling years (Q4 minus Q1)			Gender difference
	Overall	Male	Female	(Female minus male)
	(1)	(2)	(3)	(4)
Panel A.				
$TAP_{c,t-1} \times Rural_c \times Post_t$	0.017**	0.004	0.029***	0.026**
	(0.007)	(0.009)	(0.010)	(0.013)
$TAP_{c,t-1} \times CEL_{pt}$	-0.057	-0.121*	0.006	0.126*
	(0.047)	(0.072)	(0.040)	(0.072)
Outcome mean	0.174	0.188	0.149	0.039
Observations	18,334	18,334	18,334	18,334
R-squared	0.173	0.153	0.163	0.148
Panel B.				
$TAP_{c,t-1} \times Rural_c \times Post_t$	0.014*	-0.001	0.028**	0.029**
	(0.008)	(0.012)	(0.012)	(0.016)
$TAP_{c,t-1} \times CEL_{pt}$	0.021	-0.005	0.049	0.054
	(0.022)	(0.031)	(0.031)	(0.041)
$TAP_{c,t-1} \times CEL_{pt} \times Rural_c$	0.021	0.035*	0.008	-0.027
	(0.014)	(0.019)	(0.021)	(0.028)
Outcome mean	0.174	0.188	0.149	0.039
Observations	18,334	18,334	18,334	18,334
R-squared	0.174	0.154	0.164	0.148
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes

Note: Definitions of the dependent variables are the same as in Table 8. The regression specification is based on in Eq. (11) in Section 5.6 with additional control variables. In Panel A, we additionally control for $TAP_{c,t-1} \times CEL_{pt}$, where CEL_{pt} is a dummy variable which takes the value of one if the cohort born in year t in province p was under age 16 when the CEL was implemented in province p. The other notations are the same as those in Table 9. In Panel B, we additionally control for $TAP_{c,t-1} \times CEL_{pt} \times Rural_c$. In all regressions, we control for all lower-order terms of the interaction terms, as well as the county fixed effects and province-by-year fixed effects. The regressions are weighted by the number of individuals in each county-by-cohort cell in the pooled census data. Standard errors in parentheses are clustered at the county level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A23: The Moderating Effect of the Agricultural Reform since 1979 on the Impact of Thermal Agricultural Productivity: Controlling for the Impact of Collge Education Expansion

	Difference in schooling years (Q4 minus Q1)			Gender difference
	Overall	Male	Female	(Female minus male)
	(1)	(2)	(3)	(4)
Panel A.				
$TAP_{c,t-1} \times Rural_c \times Post_t$	0.016**	0.003	0.029***	0.026**
	(0.007)	(0.009)	(0.010)	(0.013)
$TAP_{c,t-1} \times College_{pt}$	-0.526*	-0.504	-0.357	0.147
	(0.269)	(0.354)	(0.408)	(0.532)
Outcome mean	0.174	0.188	0.149	0.039
Observations	18,334	18,334	18,334	18,334
R-squared	0.173	0.154	0.163	0.148
Panel B.				
$TAP_{c,t-1} \times Rural_c \times Post_t$	0.016*	0.005	0.029**	0.024
	(0.009)	(0.012)	(0.012)	(0.017)
$TAP_{c,t-1} \times College_{pt}$	-1.029	0.436	-0.855	-1.292
	(5.725)	(8.227)	(8.155)	(11.294)
$TAP_{c,t-1} \times College_{pt} \times Rural_c$	-0.030	-0.111	-0.019	0.092
	(0.213)	(0.305)	(0.309)	(0.427)
Outcome mean	0.174	0.188	0.149	0.039
Observations	18,334	18,334	18,334	18,334
R-squared	0.174	0.154	0.163	0.148
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes

Note: Definitions of the dependent variables are the same as in Table 8. The regression specification is based on in Eq. (11) in Section 5.6 with additional control variables. In Panel A, we additionally control for $TAP_{c,t-1} \times College_{pt}$, where $College_{pt}$ is the college education completion rate among the cohort born in year t in province p, which is calculated based on the 2015 mini-census data. The other notations are the same as those in Table 9. In Panel B, we additionally control for $TAP_{c,t-1} \times College_{pt} \times Rural_c$. In all regressions, we control for all lower-order terms of the interaction terms, as well as the county fixed effects and province-by-year fixed effects. The regressions are weighted by the number of individuals in each county-by-cohort cell in the pooled census data. Standard errors in parentheses are clustered at the county level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A24: Summary Statistics for the CHNS Sample

	Female sample			Male sample		
	N	Mean	Std. dev.	N	Mean	Std. dev.
Breastfeeding (Yes=1)	586	0.947	0.224	705	0.950	0.217
Breastfeeding for more than four months (Yes=1)	445	0.901	0.299	525	0.890	0.313
Maternal junior high school completion (Yes=1)	586	0.645	0.479	705	0.630	0.483
Tap water (Yes=1)	586	0.642	0.480	705	0.607	0.489
Urban (Yes=1)	586	0.317	0.466	705	0.302	0.460
Annual household income (1,000 RMB yuan)	586	26.29	44.58	705	22.98	31.55
Household asset score (standardized)	586	0.012	1.055	705	-0.010	0.952

Note: The sample contains infants born during 1990-2000 in multiple waves of the China Health and Nutrition Survey (CHNS). The urban dummy takes 1 if the household is in an urban area.

Table A25: Birth Quarter Effects on Infant Breastfeeding by Gender

Dependent variable:	Full sample		Constrained group		Less constrained group	
Indicator for being breastfed	Female	Male	Female	Male	Female	Male
for $\geq$ 4 months	(1)	(2)	(3)	(4)	(5)	(6)
Q2	0.042	0.017	0.039	-0.091	0.020	0.066
	(0.042)	(0.039)	(0.086)	(0.074)	(0.054)	(0.044)
Q3	0.008	-0.027	-0.026	-0.043	-0.003	-0.021
	(0.044)	(0.041)	(0.099)	(0.053)	(0.053)	(0.051)
Q4	0.088**	-0.014	0.140*	-0.025	0.060	-0.015
	(0.044)	(0.045)	(0.073)	(0.075)	(0.055)	(0.054)
Outcome mean	0.901	0.890	0.898	0.910	0.902	0.880
Observations	445	525	138	167	307	358
Birth year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Survey year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Data are from the China Health and Nutrition Survey (CHNS), and the sample includes infants born during 1990-2000. The dependent variable is an indicator for being breastfed for more than four months after birth. Columns (1) - (2) report results for the constrained group. Columns (3) - (4) report results for the constrained group. Columns (5) - (6) report results for the less constrained group. We categorize infants in rural areas whose mothers do not complete junior high school as the constrained group and others as the less constrained group. Standard errors in parentheses are clustered at the province-by-birthyear level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A26: Birth Quarter Effects on Infant Breastfeeding by Gender: Robustness

	Constrained		Less constrained	
	Female	Male	Female	Male
	(1)	(2)	(3)	(4)
Panel A. Constrained group: the infants in villages without tap water supply				
Q2	0.071	-0.025	0.005	0.010
	(0.046)	(0.038)	(0.035)	(0.030)
Q3	0.117**	-0.020	-0.007	-0.012
	(0.048)	(0.024)	(0.032)	(0.035)
Q4	0.140***	0.004	0.024	0.006
	(0.049)	(0.022)	(0.034)	(0.032)
Outcome mean	0.953	0.971	0.947	0.940
Observations	213	272	415	481
Panel B. Constrained group: the infants with low levels of household annual income in rural areas				
Q2	0.074	-0.011	0.011	-0.002
	(0.051)	(0.047)	(0.038)	(0.025)
Q3	0.068	-0.025	0.023	-0.003
	(0.048)	(0.044)	(0.035)	(0.030)
Q4	0.095**	-0.009	0.048	0.010
	(0.043)	(0.041)	(0.039)	(0.025)
Outcome mean	0.964	0.933	0.941	0.961
Observations	222	268	406	485
Panel C. Constrained group: the infants with low levels of household wealth in rural areas				
Q2	0.041	0.011	0.013	-0.015
	(0.033)	(0.046)	(0.044)	(0.027)
Q3	0.033	-0.043	0.033	-0.008
	(0.034)	(0.041)	(0.039)	(0.031)
Q4	0.059**	0.002	0.063	-0.002
	(0.029)	(0.046)	(0.042)	(0.026)
Outcome mean	0.974	0.945	0.935	0.954
Observations	227	272	401	481
Birth year fixed effects	Yes	Yes	Yes	Yes
Survey year fixed effects	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes

Note: Data are from the China Health and Nutrition Survey (CHNS), and the sample includes infants born during 1990-2000. The dependent variable is an indicator for "ever breastfeeding." Columns (1) - (2) report results for the constrained group. Columns (3) - (4) report results for the less constrained group. In Panel A, we categorize infants in villages without a tap water supply as the constrained group and others as the less constrained group. In Panel B, we categorize infants in rural areas whose household income is lower than the within-wave median among rural households at the time of the survey as the constrained group. In Panel C, we categorize infants in rural areas with a household asset score lower than the within-wave median among rural households as the constrained group. Standard errors in parentheses are clustered at the province-by-birthyear level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A27: Birth Quarter Effects on Educational Attainment by Gender: Controlling for School Starting Age by Month of Birth

Dependent variable	Years of schooling		Junior high school completion (Yes=1)		Senior high school completion (Yes=1)	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Q2	-0.024***	-0.013***	-0.002***	-0.002***	-0.002***	-0.001**
	(0.005)	(0.004)	(0.001)	(0.000)	(0.001)	(0.001)
Q3	0.064***	0.071***	0.007***	0.006***	0.003***	0.005***
	(0.006)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)
Q4	0.198***	0.142***	0.020***	0.013***	0.013***	0.012***
	(0.007)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)
Simulated school starting age	0.087***	0.088***	0.009***	0.007***	0.008***	0.009***
	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)
p-value for Q2, Q3, and Q4 coefficient equality between gender subsamples	*0.000*		*0.000*		*0.000*	
Outcome mean	6.780	8.150	0.484	0.631	0.161	0.221
Han ethnicity (Yes=1)	Yes	Yes	Yes	Yes	Yes	Yes
Birth province FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth year FE	Yes	Yes	Yes	Yes	Yes	Yes
Census year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,816,218	8,127,660	7,816,218	8,127,660	7,816,218	8,127,660
R-squared	0.319	0.210	0.251	0.200	0.090	0.066

Note: Data are from censuses 1990, 2000, and 2010 and mini-censuses 2005 and 2015, and the sample includes individuals aged from 25 to 60. We control for the simulated variable of month-of-birth (MOB)-level school starting age in months, as defined in Section 6.1. Standard errors in parentheses are clustered at the province-by-birthyear level. For each dependent variable, we report the *p*-value from the Wald test for the equality of the Q2, Q3, and Q4 coefficients in the two gender subsamples. ***, ** and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

Table A28: Birth Quarter Effects on Educational Attainment by Gender: Controlling for Seasonal Disease Prevalence by Month of Birth

Dependent variable	Years of schooling		Junior high school completion (Yes=1)		Senior high school completion (Yes=1)	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Q2	-0.015***	-0.015***	-0.001***	-0.002***	-0.002***	-0.002**
	(0.005)	(0.004)	(0.001)	(0.000)	(0.001)	(0.001)
Q3	0.044***	0.060***	0.006***	0.005***	0.000	0.003***
	(0.006)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)
Q4	0.200***	0.155***	0.020***	0.014***	0.014***	0.013***
	(0.007)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)
Seasonal notifiable diseases	-0.018***	-0.014***	-0.002***	-0.001***	-0.001***	-0.000*
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Seasonal influenza prevalence	-0.024***	-0.008***	-0.002***	-0.000	-0.003***	-0.001***
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
p-value for Q2, Q3, and Q4 coefficient equalities between gender subsamples	*0.000*		*0.000*		*0.000*	
Outcome mean	6.780	8.150	0.484	0.631	0.161	0.221
Han ethnicity (Yes=1)	Yes	Yes	Yes	Yes	Yes	Yes
Birth province FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth year FE	Yes	Yes	Yes	Yes	Yes	Yes
Census year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,816,218	8,127,660	7,816,218	8,127,660	7,816,218	8,127,660
R-squared	0.317	0.207	0.250	0.198	0.090	0.066

Note: Data are from censuses 1990, 2000, and 2010 and mini-censuses 2005 and 2015, and the sample includes individuals aged from 25 to 60. We control for two variables as defined in Section 6.2. One is an index for the prevalence of six notifiable diseases in China in the month of birth (MOB), and the other is an index of the prevalence of seasonal influenza at the province-by-MOB level. Standard errors in parentheses are clustered at the province-by-birthyear level. For each dependent variable, we report the p-value from the Wald test for the equality of the Q2, Q3, and Q4 coefficients in the two gender subsamples. ***, ** and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

Table A29: Household Resource Abundance in the Neonatal Period, School Starting Age, Seasonal Disease Patterns, and Educational Outcomes

Dependent variable	Years of schooling		Junior high school completion (Yes=1)		Senior high school completion (Yes=1)	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A.						
Household resource abundance	0.037***	0.018***	0.003***	0.002***	0.003***	0.002***
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Simulated school starting age	0.187***	0.165***	0.019***	0.014***	0.015***	0.015***
	(0.007)	(0.007)	(0.001)	(0.001)	(0.001)	(0.001)
p-value for coefficient equality	*0.000*		*0.000*		*0.000*	
Observations	7,816,218	8,127,660	7,816,218	8,127,660	7,816,218	8,127,660
Panel B.						
Household resource abundance	0.056***	0.036***	0.005***	0.003***	0.005***	0.004***
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Seasonal notifiable diseases	-0.029***	-0.023***	-0.003***	-0.002***	-0.002***	-0.001***
	(0.003)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Seasonal influenza prevalence	-0.044***	-0.027***	-0.004***	-0.002***	-0.004***	-0.003***
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
p-value for coefficient equality	*0.000*		*0.000*		*0.000*	
Observations	7,816,218	8,127,660	7,816,218	8,127,660	7,816,218	8,127,660
Panel C.						
Household resource abundance	0.033***	0.015***	0.003***	0.002***	0.003***	0.002***
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Simulated school starting age	0.174***	0.158***	0.017***	0.013***	0.014***	0.015***
	(0.007)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)
Seasonal notifiable diseases	-0.011***	-0.006***	-0.001***	-0.001***	-0.000	0.001**
	(0.003)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Seasonal influenza prevalence	-0.046***	-0.030***	-0.005***	-0.002***	-0.004***	-0.003***
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
p-value for coefficient equality	*0.000*		*0.000*		*0.025*	
Observations	7,816,218	8,127,660	7,816,218	8,127,660	7,816,218	8,127,660
Outcome mean	6.780	8.150	0.484	0.631	0.161	0.221
Han ethnicity (Yes=1)	Yes	Yes	Yes	Yes	Yes	Yes
Birth province FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth year FE	Yes	Yes	Yes	Yes	Yes	Yes
Census year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Data are from censuses 1990, 2000, and 2010 and mini-censuses 2005 and 2015, and the sample includes individuals aged from 25 to 60. The key independent variable is the QOB-specific index of household resource abundance during the neonatal period (as in Table 7). We control for the variable of school starting age (as in Appendix Table A27) in Panels A and C, and control for two variables of seasonal disease patterns in Panels B and C. All four variables are standardized with a mean of 0 and a standard deviation of 1. Standard errors in parentheses are clustered at the province-by-birthyear level. For each dependent variable, we report the *p*-value from the Wald test for the equality of the coefficients on household resource abundance in the two gender subsamples. ***, ** and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

Table A30: Robustness Checks on the Effects of Thermal Agricultural Productivity: Excluding Hotspot Provinces for Specific Notifiable Infectious Diseases

Dependent variable	Difference in average schooling years (Q4 minus Q1)			Gender difference (Female minus male)
	Overall	Female	Male	
	(1)	(2)	(3)	(4)
Panel A. Excluding hotspot provinces of measles				
Thermal agricultural productivity (t-1)	-0.007	-0.020***	0.001	-0.021**
	(0.005)	(0.007)	(0.007)	(0.010)
Observations	54,441	54,441	54,441	54,441
R-squared	0.033	0.017	0.017	0.006
Panel B. Excluding hotspot provinces of bacillary and amoebic dysentery				
Thermal agricultural productivity (t-1)	-0.008	-0.021***	0.001	-0.022**
	(0.005)	(0.007)	(0.007)	(0.010)
Observations	55,417	55,417	55,417	55,417
R-squared	0.036	0.020	0.019	0.007
Panel C. Excluding hotspot provinces of malaria				
Thermal agricultural productivity (t-1)	-0.005	-0.019***	0.001	-0.020**
	(0.005)	(0.007)	(0.007)	(0.010)
Observations	50,739	50,739	50,739	50,739
R-squared	0.034	0.018	0.018	0.006
Panel D. Excluding hotspot provinces of dengue fever				
Thermal agricultural productivity (t-1)	-0.007	-0.018**	0.000	-0.018*
	(0.005)	(0.007)	(0.007)	(0.010)
Observations	52,185	52,185	52,185	52,185
R-squared	0.036	0.021	0.019	0.008
Panel E. Excluding hotspot provinces of brucellosis				
Thermal agricultural productivity (t-1)	-0.012**	-0.025***	-0.003	-0.022**
	(0.005)	(0.008)	(0.007)	(0.011)
Observations	44,806	44,806	44,806	44,806
R-squared	0.037	0.021	0.019	0.006
Panel F. Excluding hotspot provinces of tuberculosis				
Thermal agricultural productivity (t-1)	-0.007	-0.020***	0.000	-0.020**
	(0.005)	(0.007)	(0.007)	(0.010)
Observations	50,969	50,969	50,969	50,969
R-squared	0.032	0.017	0.016	0.006

Note: Definitions of dependent variables and regression specifications are the same as those in Table 8. The key explanatory variable is county-level thermal agricultural productivity (TAP) in 100 degree-days for the previous year. In each panel, we exclude provinces that are identified as hotspots of a notifiable infectious disease in Zheng et al. (2023). In all regressions, county fixed effects and year fixed effects are controlled for. The regression is weighted by the number of individuals in each county-by-cohort cell in the pooled census data. Standard errors in parentheses are clustered at the county level. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

B Data and Variables

B.1 CEPS Data, Sample and Variables

We now introduce the China Education Panel Survey (CEPS) and describe the sample and variables for estimations based on the CEPS data. We present the summary statistics in Appendix Table A2.

CEPS Data

The CEPS uses a stratified, multistage sampling design with probability proportional to size (PPS). A school-based, nationally representative sample of approximately 20,000 students (in grades 7 and 9) is randomly selected from 438 classrooms in 112 schools in 28 county-level units in China. The CEPS data for our analysis are drawn from the baseline survey, which was conducted by the National Survey Research Center at Renmin University of China in the 2013-2014 academic year. The CEPS administers separate questionnaires to sample students, parents, homeroom teachers, main subject teachers, and school administrators.

The CEPS complements the population censuses, because it provides multi-dimensional information on child human capital development. First, an internationally standard cognitive test score is used to measure student cognitive skills. Second, we use administrative transcript records for math, Chinese, and English scores on the most recent midterm or final exam to measure students' academic performance.

In addition, the CEPS includes detailed measures of parental investment in children during the adolescent period, which enables us to examine whether the impact of seasonal neonatal conditions can be reinforced or compensated by parental investment in children's later periods of life.

CEPS Sample

We use data from the CEPS (2013-2014 wave) to examine BQEs on human capital development among adolescents. The CEPS sample contains junior high school students in the 7th and 9th grades aged 11 to 17. We drop observations with missing information on parental education. We also exclude individuals whose county of hukou registration differs from the current residential county. The sample contains 13,539 students, of whom 6,759 (50%) are male; 6,957 (51%) are in the 7th grade and 6,582 (49%) are in the 9th grade.

Variables in the CEPS Data

(i) *Cognitive Skills* We use the cognitive test score to measure cognitive skills. The CEPS conducts a cognitive skill test separately for 7th and 9th grade students that contains 20 and 22 questions, respectively, for the two grades. The test does not refer to knowledge included in the school curriculum, but rather measures students' ability with respect to logical thinking and problem solving. Three dimensions of ability are examined: language, spatial reasoning, and calculation/logic.

The score is standardized by a 3-parameter logistic model. The test's internal and external validity have been widely examined and accepted in China (Jiang and Dong, 2020). The score is nationally comparable, so we normalize the score across the CEPS sample in our analysis. The score is higher for girls by 0.04 standard deviation than for boys (Appendix Table A2, Panel C).

(ii) *Exam Scores in Three Major Subjects* We measure students' academic performance using scores in three major subjects: math, Chinese, and English. The CEPS collects transcripts of the most recent major exam (midterm or final) at the survey time, provided by the administrative offices of junior high schools. Exam scores are comparable across students within a class, so we normalize the scores by class.

(iii) *Measures of Parental Investment* We employ six variables to capture the multi-dimensional aspects of parental investment in children. The first two variables are about educational investment, including educational expenditure (in 1,000 RMB yuan) during the past year and an indicator for children taking extracurricular tutoring. The third variable is an indicator for children having health insurance, which serves as a proxy for parental health investment in children. The fourth variable measures parental time input in children. It is the number of hours spent on children per day as reported by parents. The last two variables are measures of parenting styles, including demandingness and responsiveness (Zhang et al., 2020). In the survey, parents are asked whether they are strict to their children regarding the following eight things on a scale from 0 (not strict at all) to 2 (very strict): (1) exams and homework, (2) behavior at school, (3) going to school on time, (4) going back home on time, (5) making friends, (6) dressing, (7) time spent on surfing the Internet, and (8) time spent on watching TV. We add up the eight answers and generate a measure of demandingness ranging from 0 to 16. In addition, parents are asked how often they discuss with children regarding the following five things on a scale of 0 (never) to 2 (often): (1) things happening at school, (2) relationship with friends, (3) relationship with teachers, (4) children's emotions, (5) children's worries and concerns. We add up the five answers and generate a measure of responsiveness ranging from 0 to 10.

(iv) *Parental Education* We use two variables to measure parental education: paternal and maternal schooling years.

C More Discussions on the Identification Strategy

C.1 Proof of the Statement in Section 3.2

In Section 3.2, we claim that conditions (i) and (ii) hold *if and only if* conditions (i') and (ii') hold. Under this equivalence, if we provide empirical evidence in support of conditions (i') and (ii'), then conditions (i) and (ii) will also get supported, and *vice versa*. We now prove this statement. Specifically, we provide proof for the "if" part. Due to the highly symmetric mathematical structure, the subsequent proof of the "only if" part is trivial.

Throughout our analysis below, we regard ξ, $female$, and $Q4$ as three random variables, and the latter two are Bernoulli random variables which can only take values of 0 and 1.

Condition (i') states that

$$\mathbb{E}\left(female \mid Q4=1\right)=\mathbb{E}\left(female \mid Q4=0\right).$$

Since $female$ can only take values of 0 and 1, we have

$$\mathbb{P}(female=1 \mid Q4=1)=\mathbb{P}(female=1 \mid Q4=0).$$

Thus,

$$\begin{aligned}
\mathbb{P}(female=1) =& \mathbb{P}(female=1 \mid Q4=1)\times\mathbb{P}(Q4=1)+\mathbb{P}(female=1 \mid Q4=0)\times\mathbb{P}(Q4=0)\\
=& \mathbb{P}(female=1 \mid Q4=1)\times\left[\mathbb{P}(Q4=1)+\mathbb{P}(Q4=0)\right]\\
=& \mathbb{P}(female=1 \mid Q4=1).
\end{aligned}$$

This then implies that

$$\begin{aligned}
\mathbb{P}(\text{ female }=1, Q4=1) &= \mathbb{P}(\text{ female }=1 \mid Q4=1)\times\mathbb{P}(Q4=1)\\
&= \mathbb{P}(\text{ female }=1)\times\mathbb{P}(Q4=1).
\end{aligned}$$

As both $female$ and $Q4$ are dummy variables, these two random variables are independent. This corresponds to the fact that sex ratio is balanced across QOBs. The independent condition then gives

$$\mathbb{E}\left(Q4 \mid female=1\right)=\mathbb{E}\left(Q4 \mid female=0\right),$$

as in condition (i).

Condition (ii') states that

$$\mathrm{Cov}(\xi, female \mid Q4=1)=\mathrm{Cov}(\xi, female \mid Q4=0).$$

Note that

$$\mathbb{E}(\xi) = \mathbb{E}(\xi \mid female = 1) \times \mathbb{E}(female) + \mathbb{E}(\xi \mid female = 0) \times (1 - E(female)),$$

and

$$\begin{aligned}\mathbb{E}(\xi \times female) =& \mathbb{E}(\xi \times female \mid female = 1) \times \mathbb{E}(female) + \mathbb{E}(\xi \times female \mid female = 0) \times (1 - \mathbb{E}(female)) \\ =& \mathbb{E}(\xi \mid female = 1) \times \mathbb{E}(female).\end{aligned}$$

Thus, we can express $\mathrm{Cov}(\xi, female)$ as

$$\begin{aligned}\mathrm{Cov}(\xi, female) =& \mathbb{E}(\xi \times female) - \mathbb{E}(\xi) \times \mathbb{E}(female) \\ =& \mathbb{E}(\xi \mid female = 1) \times \mathbb{E}(female) - [\mathbb{E}(\xi \mid female = 1) \times \mathbb{E}(female) + \\ & \mathbb{E}(\xi \mid female = 0) \times (1 - \mathbb{E}(female))] \times \mathbb{E}(female) \\ =& (1 - \mathbb{E}(female)) \times \mathbb{E}(female) \times [\mathbb{E}(\xi \mid female = 1) - \mathbb{E}(\xi \mid female = 0)] \\ =& \mathrm{Var}(female) \times [\mathbb{E}(\xi \mid female = 1) - \mathbb{E}(\xi \mid female = 0)].\end{aligned}$$

Thus, according to condition (ii’), we have

$$\mathrm{Var}(female \mid Q4 = 1) \times [\mathbb{E}(\xi \mid female = 1, Q4 = 1) - \mathbb{E}(\xi \mid female = 0, Q4 = 1)]$$

$$= \mathrm{Var}(female \mid Q4 = 0) \times [\mathbb{E}(\xi \mid female = 1, Q4 = 0) - \mathbb{E}(\xi \mid female = 0, Q4 = 0)].$$

According to condition (i’), $\mathrm{Var}(female \mid Q4 = 1) = \mathrm{Var}(female \mid Q4 = 0)$, and thus

$$\mathbb{E}(\xi \mid female = 1, Q4 = 1) - \mathbb{E}(\xi \mid female = 0, Q4 = 1)$$

$$= \mathbb{E}(\xi \mid female = 1, Q4 = 0) - \mathbb{E}(\xi \mid female = 0, Q4 = 0).$$

Rearranging terms, we have

$$\mathbb{E}(\xi \mid female = 1, Q4 = 1) - \mathbb{E}(\xi \mid female = 1, Q4 = 0)$$

$$= \mathbb{E}(\xi \mid female = 0, Q4 = 1) - \mathbb{E}(\xi \mid female = 0, Q4 = 0).$$

According to condition (i), we have

$$\mathrm{Var}(Q4 \mid female = 1) \times [\mathbb{E}(\xi \mid female = 1, Q4 = 1) - \mathbb{E}(\xi \mid female = 1, Q4 = 0)]$$

$$= \mathrm{Var}(Q4 \mid female = 0) \times [\mathbb{E}(\xi \mid female = 0, Q4 = 1) - \mathbb{E}(\xi \mid female = 0, Q4 = 0)].$$

This then gives

$$\text{Cov}(\xi, Q4 \mid female = 1) = \text{Cov}(\xi, Q4 \mid female = 0),$$

as in condition (ii). *Q.E.D.*

C.2 Discussion on Condition (iii) in Section 3.2

In this subsection, we make supplementary discussions on condition (iii) as presented in Section 3.2. As we have discussed, the effect of unobserved parental characteristics (ξ_{icp}^{G}) on children's lifecycle outcomes might differ between boys and girls, i.e., δ^{f} and δ^{m} might be different, and such a gender difference might bias our estimates of $\beta^{f} - \beta^{m}$.

We now evaluate this potential bias using an omitted variable bias (OVB) formula. For simplicity, we focus on the gendered coefficients for Q4. As in Section 3.2, to illustrate, consider the following regression:[78]

$$Y_{icp} = \alpha^{G} + \beta^{G} Q4_{icp} + \upsilon_{icp}^{G}, \tag{1}$$

where $\upsilon_{icp}^{G} = \delta^{G}\xi_{icp}^{G} + e_{icp}^{G}$. Ignoring ξ_{icp}, since it is unobserved, the OLS estimator of β^{G} in Eq. (1) satisfies

$$\text{plim}(\hat{\beta}^{G}) = \beta^{G} + \delta^{G}\gamma^{G},$$

where γ^{G} is the regression coefficient of ξ_{icp}^{G} on $Q4_{icp}$ by gender.

We now evaluate the magnitude of the potential bias arising from $\delta^{G}\gamma^{G}$. As ξ_{icp}^{G} is unobserved, we cannot precisely evaluate this magnitude by estimating γ^{G}. As a preliminary investigation, we use the observed maternal schooling years as a proxy variable for ξ_{icp}^{G}. Table 3, Column (1) shows that $\hat{\gamma}^{f}$ and $\hat{\gamma}^{m}$ equal -0.043 and -0.059, respectively. The difference between the two estimates is minimal and statistically insignificant. Based on the parent-offspring matched sample (22,313 pairs) for the 1970-1988 cohorts in China based on the China Family Panel Studies (CFPS) in Fan et al. (2021), we regress children's schooling years on maternal schooling years, controlling for province and birth year fixed effects. The estimates of δ^{f} and δ^{m} are 0.361 and 0.301, respectively. We then calculate estimated $\delta^{f}\gamma^{f}$, $\delta^{m}\gamma^{m}$, and their difference. We find that $\hat{\delta}^{f}\hat{\gamma}^{f} - \hat{\delta}^{m}\hat{\gamma}^{m} = 0.0019$. In this case, the bias, if any, is negligible.

D Heterogeneity Analysis at the Province Level

In Section 4, we have documented gender differences in BQEs on educational and labor market outcomes at the national level. In this section, we first investigate the spatial pattern of BQE

[78] As in Section 3.2, we omit other covariates, such as X_{icp}, λ_{c}^{G}, and μ_{p}^{G}, in the regression. We also omit other QOB dummies by assuming that our estimation sample includes only children born in Q1 and Q4.

estimates and their gender gaps across provinces. We then correlate estimated BQEs and gender differences with provincial characteristics.

D.1 Province-level Estimates and Spatial Patterns

We now investigate the spatial patterns of BQEs by separately estimating Eq. (1) for the 31 provinces in China based on the pooled census sample. We assign an individual to the province in which they were born and use schooling years as our main dependent variable.[79] We focus on the coefficient estimate for the Q4 indicator.

Appendix Table D1, Column (1) shows BQE estimates for the full sample in each province and Columns (2) and (3) for females and males, respectively. Column (4) reports the BQEs for females minus those for males (Column (2) minus Column (3)), with the *p*-values of these differences in Column (5) based on Hausman's general specification tests.

The estimates of BQEs are positive and statistically significant across all provinces (Column (1)), which indicates the robustness of BQEs to a variety of regions with different geographic and socioeconomic characteristics. A thematic map shows that the estimates vary across provinces (Appendix Figure D1(a)). The estimates of BQEs are smaller for more developed provinces, such as Shanghai, Zhejiang, and Tianjin, and larger in less developed ones, such as Qinghai, Tibet, and Xinjiang. In addition, the estimates are small in major grain-producing provinces with abundant food crops, such as Jiangxi, Hunan, and Hubei.

Columns (2) and (3) show that the estimates are positive and statistically significant for both females and males across all provinces. In addition, the correlation coefficient of estimates between females and males is as high as 0.90. This suggests the robustness of BQEs between genders.

Despite high correlation in BQEs between genders, Column (4) shows that the estimates are larger for females than males in 27 of the 31 provinces. The four negative differences in the estimates between females and males are small and statistically insignificant (Column (5)). Gender differences in the estimates are larger in less developed provinces, such as Qinghai, Ningxia, and Gansu.

The spatial patterns of BQE estimates and their gender differences remain robust in three sensitivity analyses. First, we use two alternative measures of education—indicators for junior and senior high school completion—as outcome variables. Second, we restrict the estimation sample to cohorts born after 1960, most of whom entered the labor market after the economic reform in 1979. Third, we restrict the estimation sample to non-migrants.

[79] Information on birth province is recorded in censuses 2000 and 2010 only. In mini-censuses 2005 and 2015, we use the hukou registration province to proxy for the province of birth. Census 1990 does not contain information on birth or hukou registration province, so we use the residential province as a proxy, which is less of a concern because migration was strictly restricted before the 1990s in China. The documented spatial patterns in BQEs and their gender gaps are robust to restricting the pooled census sample to non-migrants only.

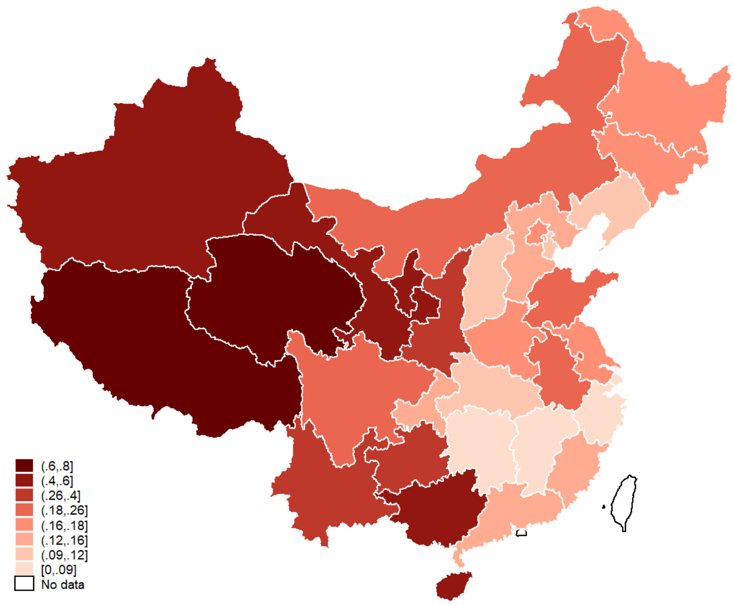
Table D1: Estimates of Birth Quarter Effects and Gender Differences in Each Province

Province	Observations	Estimated Q4 coefficient			Difference	*P*-value
		Full Sample	Female Sample	Male Sample	(2)-(3)	
		(1)	(2)	(3)	(4)	(5)
Beijing (BJ)	172,038	0.164***	0.250***	0.077*	0.173	0.000
Tianjin (TJ)	176,907	0.092**	0.125***	0.042	0.083	0.053
Hebei (HE)	871,752	0.153***	0.188***	0.110***	0.078	0.000
Shanxi (SX)	450,901	0.103***	0.145***	0.068***	0.077	0.001
Inner Mongolia (NM)	313,784	0.257***	0.312***	0.198***	0.114	0.004
Liaoning (LN)	607,308	0.108***	0.146***	0.072**	0.074	0.002
Jilin (JL)	393,474	0.173***	0.228***	0.112***	0.116	0.001
Heilongjiang (HL)	509,608	0.168***	0.226***	0.105***	0.121	0.000
Shanghai (SH)	242,259	0.081**	0.082**	0.068*	0.014	0.725
Jiangsu (JS)	950,490	0.177***	0.207***	0.134***	0.073	0.001
Zhejiang (ZJ)	599,578	0.088***	0.091***	0.080***	0.011	0.690
Anhui (AH)	743,931	0.240***	0.235***	0.262***	-0.027	0.466
Fujian (FJ)	406,955	0.125***	0.110***	0.138***	-0.028	0.400
Jiangxi (JX)	502,415	0.058**	0.032	0.068***	-0.036	0.170
Shandong (SD)	1,180,777	0.184***	0.213***	0.135***	0.078	0.001
Henan (HA)	1,094,577	0.177***	0.198***	0.153***	0.045	0.070
Hubei (HB)	741,623	0.098***	0.113***	0.093***	0.020	0.434
Hunan (HN)	828,001	0.082***	0.099***	0.067***	0.032	0.151
Guangdong (GD)	892,087	0.137***	0.140***	0.130***	0.010	0.613
Guangxi (GX)	534,944	0.275***	0.288***	0.273***	0.015	0.578
Hainan (HI)	97,526	0.491***	0.481***	0.503***	-0.022	0.765
Chongqing (CQ)	362,936	0.131***	0.146***	0.120***	0.026	0.455
Sichuan (SC)	1,109,218	0.185***	0.203***	0.171***	0.032	0.102
Guizhou (GZ)	409,220	0.333***	0.360***	0.271***	0.089	0.029
Yunnan (YN)	536,330	0.389***	0.455***	0.315***	0.140	0.000
Tibet (XZ)	35,901	0.630***	0.650***	0.636***	0.014	0.918
Shaanxi (SN)	490,067	0.269***	0.344***	0.191***	0.153	0.000
Gansu (GS)	354,048	0.448***	0.527***	0.313***	0.214	0.000
Qinghai (QH)	75,334	0.679***	0.844***	0.509***	0.335	0.001
Ningxia (NX)	67,525	0.418***	0.567***	0.286***	0.281	0.001
Xinjiang (XJ)	190,521	0.550***	0.608***	0.477***	0.131	0.014

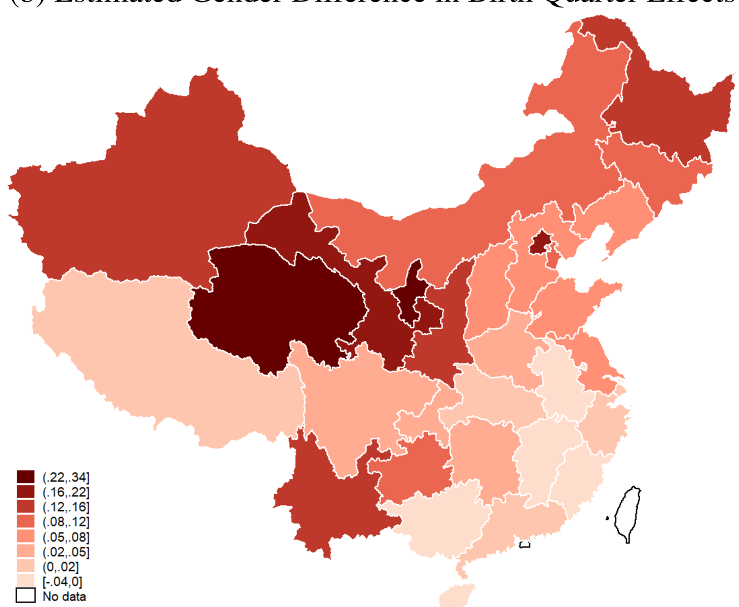
Note: The table reports the coefficients on Q4 from regressions specified the same as those in Table 4, where the dependent variable is schooling years. Columns (1) to (3) contain estimates based on the full sample, female sample, and male sample for each province, respectively, with levels of statistical significance calculated based on standard errors clustered at the cohort level. Column (5) contains the *p*-value from the Wald test for the equality of Q4 coefficients in the two gender subsamples. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Figure D1: Province-level Estimates of Birth Quarter Effects on Schooling Years and Gender Differences

(a) Birth Quarter Effect Estimates



(b) Estimated Gender Difference in Birth Quarter Effects



Note: Figure (a) plots province-level estimates for the coefficient of Q4 in Eq. (1) with schooling years as the dependent variable, as reported in Appendix Table D1, Column (1). Figure (b) plots the gender difference (female versus male) in Q4 coefficient estimates, as reported in Appendix Table D1, Column (4). Darker colors stand for higher values of the estimates.

D.2 Correlates of Birth Quarter Effects

Why do some provinces show higher BQEs than others? As a first step in answering this question, we correlate our BQE estimates with socioeconomic characteristics at the province level. Such correlations do not necessarily imply causality. The goal of this analysis is to show some stylized facts that shed light on the mechanism and motivate our causal analysis in Section 5.

Appendix Figure D2 plots the coefficients from univariate regressions of BQE estimates (Appendix Table D1, Column (1)) on socioeconomic characteristics at the province level, where all variables are standardized.[80] Appendix Figures D2(a) and D2(b) report coefficients from unweighted and weighted univariate regressions, respectively. In Appendix Figure D2(c), we replace BQE estimates based on schooling years (Appendix Table D1, Column (1)) with those based on the indicator for junior high school completion as the dependent variable in the unweighted univariate regressions.

We categorize province-level socioeconomic characteristics into four groups: economic, demographic, health, and educational variables. Cohorts in the pooled census sample were born between 1930 and 1990, so we measure province-level characteristics during this period, depending on data availability. We use GDP per capita, life expectancy at birth, and infant mortality rates measured in multiple years.

Panel A shows that estimated BQEs consistently negatively correlate with GDP per capita at the province level. Panel B shows that BQEs positively correlate with total fertility rate and negatively correlate with the share of only children. Panel C reveals that BQEs are smaller in provinces with better health status, proxied by higher life expectancy and lower infant mortality rates. Panel D shows that BQEs negatively correlate with multiple measures of education levels.

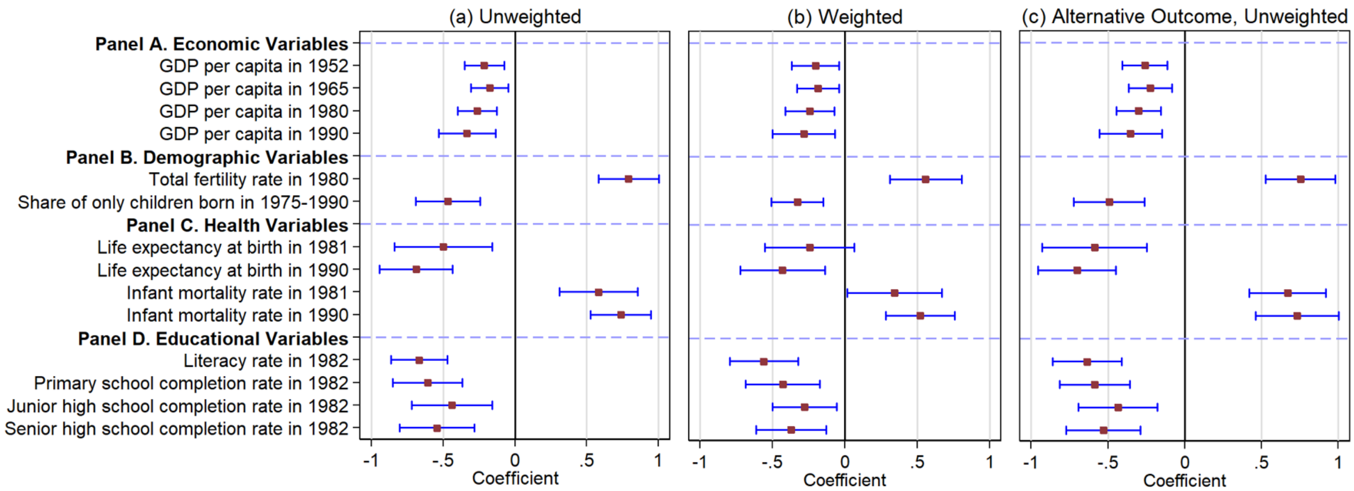
D.3 Correlates of Gender Differences in Birth Quarter Effects

We now examine correlations between the gender difference in BQEs and socioeconomic characteristics at the province level. Appendix Figure D3 plots univariate regression coefficients. In addition to the four groups of province-level variables shown in Appendix Figure D2, we add two groups in Appendix Figure D3. One is BQE estimates for the pooled sample of females and males at the province level. The other group includes gender differences in health and education (male relative to female) and female intrahousehold bargaining power, measured by the share of female household heads.

The first row in Appendix Figure D3(a), Panel A shows that gender differences in BQE estimates (Appendix Table D1, Column (4)) positively correlate with BQE estimates based on the pooled sample (Appendix Table D1, Column (1)). The pattern is robust in the second row, where

[80] Appendix Table D2 reports data sources and summary statistics for provincial characteristic variables.

Figure D2: Correlations between Birth Quarter Effect Estimates and Socioeconomic Characteristics at the Province Level



Note: These figures plot coefficients with 95% confidence intervals from univariate regressions of Q4 coefficient estimates on socioeconomic characteristics at the province level. Q4 coefficient estimates, as well as all provincial characteristics, are standardized. In Figures (a) and (c), we use unweighted regressions. In Figure (b), we weight the regressions with the number of individuals in each province in the pooled census sample. The outcome variable in estimating provincial BQEs is schooling years for Figures (a) and (b) and the indicator for junior high school completion for Figure (c).

the independent variable is BQE estimates for the indicator of junior high school completion. The pattern is also robust in Appendix Figures D3(b) and D3(c). This suggests some common factors that may simultaneously drive both BQEs and their gender difference.

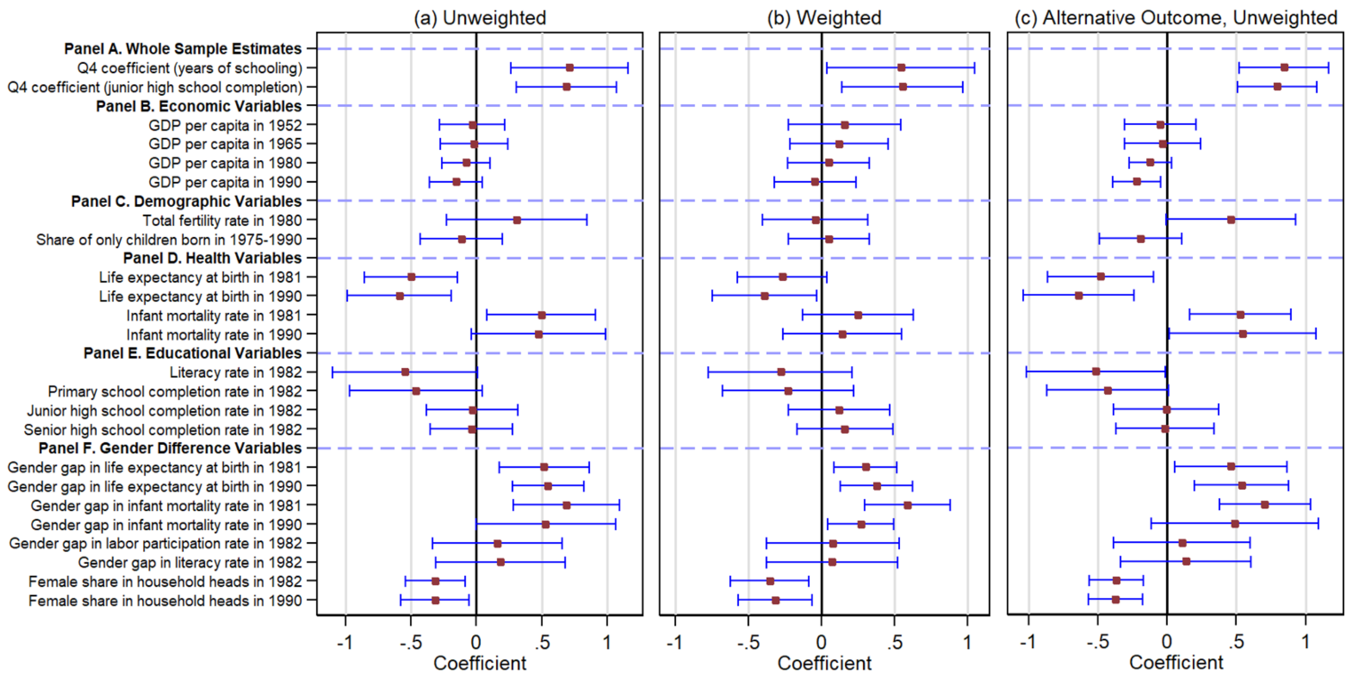
We do not detect significant correlations between gender differences in BQEs and economic and demographic variables (Panels B and C). We find that gender differences negatively correlate with life expectancy and positively correlate with infant mortality rate (Panel D). We also find weak evidence on negative correlations between gender differences in BQEs and provincial literacy and primary school completion rates (Panel E).

Notably, we find that gender differences in BQEs positively correlate with both gender differences in life expectancy (male minus female)—a measure of the gender bias in health resource allocation—and negatively correlate with female bargaining power (Panel F).[81] This result sheds light on the role of gender preference in shaping the gender gap in BQEs.

Summary Thus far, we have studied spatial variations in gendered BQEs. We find significant

[81] Because the infant mortality rate is higher for males than females in adverse conditions (Fuse and Crenshaw, 2006), the positive correlation between the gender difference in infant mortality rates and the gender difference in BQEs at the province level (Appendix Figure D3, Panel F) may reflect the fact that larger gender differences in BQEs are associated with tighter resource constraints.

Figure D3: Correlations between the Estimated Gender Difference in Birth Quarter Effects and Provincial Characteristics



Note: These figures plot the coefficients with 95% confidence intervals from univariate regressions of the gender differences in Q4 coefficient estimates on socioeconomic characteristics at the province level. Beijing and Tibet are excluded from the sample. All variables are standardized. In Figures (a) and (c), we use unweighted regressions. In Figure (b), we weight the regressions with the number of individuals in each province in the pooled census sample. The outcome variable in estimating provincial BQEs is schooling years for Figures (a) and (b) and the indicator for junior high school completion for Figure (c).

correlations of BQEs and their gender gaps with provincial socioeconomic variables. Of course, correlational analyses have some limitations. For example, while BQE estimates—the dependent variables in univariate regressions—are based on the sample of cohorts during 1930-1990, the independent variables of provincial socioeconomic characteristics are snapshot measures in a single year. Also, independent variables of socioeconomic characteristics, such as education, life expectancy, and GDP per capita, may correlate with each other. In spite of that, province-level analyses reveal some consistent patterns that motivate our examination of the mechanism underlying the gender difference in BQEs.

Table D2: Summary Statistics for Provincial Characteristics Variables

Variable	Data Source	Obs	Mean	Std. Dev.	Min	Max
Log GDP per capita in 1952	China Compendium of Statistics 1949-2008	30	4.78	0.53	4.05	6.46
Log GDP per capita in 1965	China Compendium of Statistics 1949-2008	30	5.41	0.47	4.79	6.95
Log GDP per capita in 1980	China Compendium of Statistics 1949-2008	31	6.12	0.54	5.38	7.91
Log GDP per capita in 1990	China Compendium of Statistics 1949-2008	31	7.40	0.44	6.68	8.68
Total fertility rate in 1980	China Population Statistics Yearbook	31	2.60	1.04	1.10	5.23
Share of only children born in 1975-1990	One-Percent Population Survey in 2005	31	0.20	0.13	0.07	0.51
Life expectancy at birth in 1981	Almanac of China's Population	30	67.39	3.60	60.00	72.91
Life expectancy at birth in 1990	National Bureau of Statistics in China	31	68.02	3.53	59.64	74.90
Infant mortality rate in 1981 (‰)	China Health Statistics Yearbook	30	40.28	23.66	16.10	115.00
Infant mortality rate in 1990 (‰)	China Health Statistics Yearbook	31	31.15	20.02	8.80	96.20
Literacy rate in 1982	Population Census 1982	31	0.67	0.12	0.25	0.85
Primary school completion rate in 1982	Population Census 1982	31	0.62	0.13	0.24	0.83
Junior high school completion rate in 1982	Population Census 1982	31	0.33	0.11	0.08	0.61
Senior high school completion rate in 1982	Population Census 1982	31	0.12	0.06	0.03	0.29
Gender gap in life expectancy at birth in 1981	Almanac of China's Population	31	-3.43	1.07	-6.35	-1.31
Gender gap in life expectancy at birth in 1990	National Bureau of Statistics in China	31	-3.63	0.91	-5.14	-0.95
Gender gap in infant mortality rate in 1981	Almanac of China's Population	29	3.64	5.56	-4.69	19.17
Gender gap in infant mortality rate in 1990	Almanac of China's Population	30	-0.83	6.58	-17.00	19.30
Gender gap in literacy rate in 1982	Population Census 1982	31	0.22	0.07	0.09	0.35
Gender gap in primary school completion rate in 1982	Population Census 1982	31	0.29	0.08	0.14	0.42
Female share in household heads in 1982	Population Census 1982	31	0.19	0.06	0.08	0.36
Female share in household heads in 1990	Population Census 1990	31	0.16	0.06	0.07	0.34

Note: Data source: Department of Comprehensive Statistics of National Bureau of Statistics (2009); Department of Population Statistics of National Bureau of Statistics (1981, 1987, 1990); Population Research Institute of Chinese Academy of Social Sciences (1981, 1990); Ministry of Health, PRC (2003).