Intrahousehold Resource Allocation, Son Preference, and Fertility Restrictions: A Tale of Birth Order*

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Abstract

Birth order is crucial for child development, yet the evidence of the heterogeneous effects of birth order by gender preferences and fertility control policies is limited. This paper aims to study the sources of birth order effects and how birth order effects on child health interact with gender preference and the family planning policy. We develop a stylized model that incorporates parents' fertility and child investment decisions. The model can not only help understand birth order effects in a general framework in which parents have no gender preferences but also explain why birth order effects arise in the presence of son preference and fertility control policies and how birth order effects interact with them. Using China Family Panel Studies (2010–2018), we find a negative birth order effect on health outcomes in rural China. Consistent with the model predictions, we find that: 1) a higher family income narrows birth order differences in child health, which suggests that the early stage of skill formation plays a more important role in human capital than the late stage; 2) in regions with stricter enforcement of the one-child policy, richer families are less likely to have multiple children, and birth order effects in stricter regions are stronger compared to families in less strict regions; 3) in regions with higher son preferences, richer families are more likely to have multiple children, and birth order effects in high-son-preference regions are less prominent compared with those in lower-son-preference regions.

Keywords: Birth order, intrahousehold-resource allocation, gender preference, one child policy
JEL codes: J61, O10, O13, O38

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1 Introduction

Undernutrition is detrimental to children's survival, growth, and development. Furthermore, it slows down the socioeconomic progress of a country. According to a report by the United Nations International Children's Emergency Fund in 2009, China has the second largest number of stunted children among developing countries. This problem is particularly acute in rural China, where one in five children is stunted.[1] A simple variance analysis using a rural sample drawn from China Family Panel Studies (CFPS) (2010–2018) suggests that about 65% of the total variation in the height-for-age (HFA) z-score, a widely used measurement of child health status, can be explained by within-family variations. Understanding the reasons behind the differences in the nutrition status of children within a family is crucial in improving health and well-being, especially for those who may be disadvantaged. By doing so, we can effectively support children's growth and ensure a healthy future.

Through intrahousehold analyses, a considerable amount of research finds that birth order affects health (e.g., Black et al., 2016; Jayachandran and Pande, 2017; Brenøe and Molitor, 2018; Pruckner et al., 2021), cognitive and non-cognitive abilities (e.g., De Haan et al., 2014; Lehmann et al., 2018; Black et al., 2018; Zhang et al., 2022), education and earnings (e.g., Black et al., 2005; Booth and Kee, 2009; De Haan, 2010). However, the evidence of how birth order effects interact with socioeconomic factors, such as gender preferences and fertility control policies, is limited.[2] In particular, gender preferences may increase or narrow the differences in resource allocation within families, and family planning policies may affect fertility choices that are closely related to intrahousehold behaviors.

As for the potential mechanisms of birth order effects, scholars have proposed various hypotheses, such as parental preferences (Jayachandran and Kuziemko, 2011; Lin et al., 2020), resource dilution (De Haan, 2010; Bishwakarma and Villa, 2019; Esposito et al., 2020), and biological mechanism (Brenøe and Molitor, 2018; Pruckner et al., 2021).[3] However, researchers have yet to reach a consensus on why birth order effects arise. Moreover, most studies on the effects of birth order in most existing literature lack a theoretical economic framework. It is still unclear why the later-born child performs worse in some cases but better in others than the earlier-born child. We define that a negative (positive) birth order effect exists if the later-born child performs worse

[1] Source: `https://digitallibrary.un.org/record/674645?ln=en` (accessed on May. 11, 2023).

[2] Gender preferences and fertility restriction policies are not confined to certain countries or regions. In countries deeply affected by Confucianism (e.g., South Korea) and societies where property and land rights favor males over females (e.g., India and Muslim-majority countries), the preference for sons is prevalent. Additionally, a large number of countries and regions have implemented fertility restriction policies to reduce the unprecedented population growth rate. India carried out the first population program in the world in 1962. By 1996, a total number of 82 countries had a population reduction policy (see De Silva and Tenreyro (2017) for more details).

[3] Parents may have preferences for certain children and hence adjust resource allocations to children. The biological mechanism suggests that birth order effects are driven by maternal age at childbirth. Compared with earlier-born children, later-born children are usually born to an older mother with a higher risk of chromosomal and congenital disabilities. Hence, the later-born have a disadvantage in health. Resource dilution theory states that first-born children have exclusive access to resources before their siblings are born and therefore have better child outcomes.

(better) than the earlier-born child.

The primary goal of the current study is to understand the sources of birth order effects and how such effects on children's nutrition status interact with gender preferences and fertility policies. China sets an ideal stage to answer this research question. First, son preference is deeply rooted in traditional Chinese culture, especially in rural areas. Second, China implemented a strict fertility control policy, the one-child policy (OCP), in 1979, which has affected millions of people for over three decades. Couples have to obey the birth quota regulation of the fertility policy. Heavy fertility fines were imposed if women had unapproved pregnancies. Third, sex selection technology, such as ultrasound, was available in all counties in China by the mid-1990s (Chen et al., 2013). Given the enforcement of the OCP, parents with stronger son preferences are more likely to use such technology.[4] The interactions among son preference, OCP, and sex selection technology in China provide us with a valuable opportunity to explore the allocation of resources within families and can thus offer important lessons for countries that have the cultural norm of son preference and those that implement fertility control policies.

This paper proceeds in two steps. First, we develop a stylized intrahousehold resource allocation model to understand why birth order effects arise not only in a general framework where no gender preference exists but also in a specific Chinese setting where son preferences and a family planning policy exist. Second, we present empirical evidence on birth order effects in rural China. We document how the nutrition status of children changes with birth order. We also examine the predictions generated from the theoretical framework on how birth order effects interact with gender, family income, son preference, and the enforcement of OCP.

In the first step, we construct a stylized framework to describe the factors that lead to birth order effects by sequentially considering parental fertility and investment decisions. Parents first decide whether to have one or two children. After making the fertility decisions, forward-looking parents maximize their lifetime utility by making once-and-for-all decisions on consumption and child investments in each period, similar to Behrman et al. (1982) and Behrman and Taubman (1986). Inspired by Cunha and Heckman (2007), human capital production has two stages (the early and late stages) and is characterized by self-productivity and dynamic complementarity.

The stylized framework starts from a baseline model with a gender-neutral preference, which highlights the importance of three factors in determining birth order effects: children's birth endowments, family income, and efficiency factors in human capital production (factors independent of parental investment and human capital stock). By taking into account these factors, the model provides a deeper insight into the direction of birth order effects. For instance, if birth endowments increase with birth order or the family income increases in the life cycle, later-born children tend to have better outcomes. Conversely, if the efficiency factor in the early stage of skill formation is more significant than that in the late stage, the later-born children tend to perform

[4]The Chinese government has issued regulations to ban sex-selection abortion since 1994. However, the ban is difficult given that abortion remains legal in China and sex detection is available in antenatal care.

worse. Ultimately, the direction of birth order effects is determined by which factors have the dominant impact.

Drawing on the rural China setting, we further extend the baseline model by incorporating son preference, sex selection technology, and penalties for violating the OCP. Based on the theoretical model, we can derive the following predictions. 1) A higher family income narrows birth order differences in child health, which suggests that the early stage of skill formation plays a more important role in human capital than the late stage. 2) In regions with stricter enforcement of the one-child policy (i.e., strict regions), richer families are less likely to have multiple children, and birth order effects in strict regions are more substantial than in less strict regions. 3) In high-son-preference (HSP) regions, richer families are more likely to have multiple children, and birth order effects in HSP regions are less prominent than in lower-son-preference (LSP) regions.

In the second step, we estimate birth order effects on the HFA z-score in a family-by-wave fixed effect model, drawing data from CFPS and focusing on children living in rural multiple-child families. Given that birth order is highly correlated with family size, we use the relative birth order (Ejrnæs and Pörtner, 2004) as our major measurement to disentangle birth order effects from family size effects. We show that the last child has an HFA z-score that is 0.5 standard deviations lower on average than that of the first child. The result of negative birth order effects on the HFA z-score in China is in line with those observed in earlier studies in other countries.[5] The identification strategy relies on the assumption that the family size is predetermined or at least not endogenous to the outcomes of existing children. To examine this assumption, we simulate the outcomes of "hypothetical" second-born children. The simulation shows that even if all observed one-child families are assumed to follow the optimal stopping rule, which predicts that parents will stop having more children if they have a "bad" child, more than half of the birth order effects will still be observed. The negative birth order effect remains robust in a series of robustness tests, including using birth order dummies, using alternative health-related outcomes, and examining various subsamples.

Furthermore, we test the theoretical predictions using the same data set. We first show that the negative birth order effect on the HFA z-score is 0.15 standard deviations smaller (in magnitude) in high-income families than in low-income families, thereby suggesting that the efficiency factor at the early stage of skill formation is larger than that at the late stage.

Then, we present evidence on the interaction between birth order effects and son preferences. Combining one- and multiple-child families, parents in HSP regions earn around 400 RMB less annually than those in LSP regions. However, if we only focus on multiple-child families, parents in HSP regions earn 343 RMB higher than those in LSP regions annually. Accordingly, rich families are positively selected into the multiple-child sample in HSP regions. Intuitively, son preferences affect birth order effects in two ways. One is the direct effect, that is, boys gain more

[5] The negative birth order effects on HFA z-score are also reported in the Philippines (Horton, 1988), England (Hatton and Martin, 2010), India (Jayachandran and Pande, 2017), and South African countries (Bishwakarma and Villa, 2019).

investments than girls due to son preference, and children at a higher birth order are more likely to be boys due to sex selection. This outcome suggests that birth order effects are smaller in regions with stronger son preferences. The other one is the indirect effect, that is, rich families are more likely to have multiple children in HSP regions, and an increase in family income can narrow birth order differences. Consistent with the intuition, the results show that the birth order effects are 0.23 standard deviations smaller (in magnitude) in HSP regions than in LSP regions.

Finally, we examine how the enforcement of the OCP affects birth order effects. Taking one- and multiple-child families together, parents in stricter regions earn about 125 RMB higher than those in less strict regions per year. Considering multiple-child families only, however, parents in stricter regions earn about 241 RMB less than those in less strict regions per year. In other words, rich families are negatively selected into the multiple-child sample in stricter regions. Hence, although the OCP has no direct effect on birth order effects, it indirectly affects sample selection. In regions with stricter OCP, low-income families are more likely to have multiple children, and a decrease in family income can widen the birth order differences. Consistent with the negative selection issue, the birth order effect on HFA z-score in stricter regions is 0.14 standard deviations larger than in less strict regions.

As noted earlier, previous studies have provided empirical evidence on the effects of birth order on child outcomes. However, the majority of these studies need well-grounded economic theoretical guidance. To address this theory-to-evidence gap, we develop a stylized model that extends the traditional literature on intrahousehold resource allocation. Many previous studies have focused on a single-period family utility model in which family size is predetermined (e.g., Behrman et al., 1982; Behrman and Taubman, 1986; Behrman, 1988; Yi et al., 2015).[6] We construct a model that incorporates both the fertility and human capital investment decisions of parents.[7] In addition, the model combines the literature on intrahousehold resource allocation with the recent research progress on the economics of human capital (Cunha and Heckman, 2007). Yi et al. (2015) allow for multidimensionality in skills and model the production of health and socioemotional skills simultaneously. Unlike Yi et al. (2015), we consider a multiple-stage evolution of skill (health) and allow the productivity at the early and late stages to be different. Thus, the current study contributes to the literature on birth order by being the first to demonstrate that birth order effects can be driven by differential efficiency factors across different stages of child development.

This study is also related to the literature on the crucial role of family income in child development. Unanimous evidence shows that families with higher long-term income have more child

[6]One exception is Gugl and Welling (2010) who model the effects of parental decisions on consumption and child investments across three periods. However, family size is predetermined in Gugl and Welling (2010)'s model.

[7]In our model, forward-looking parents decide whether to have one or two children by comparing the jointly intertemporal utility of having one and two children. In models related to the "quantity–quality trade-off" (Becker and Lewis, 1973; Barro and Becker, 1989; Bagger et al., 2021), family size is a choice variable that directly enters the one-period utility function. In models assuming that fertility is decided sequentially (Ejrnæs and Pörtner, 2004; Wei et al., 2022), parents decide whether to have a child based on the endowments of their existing children.

investments and have children with better skills (see Francesconi and Heckman (2016) for a literature review). With few exceptions, previous studies consider single-child models (Francesconi and Heckman, 2016) and hence focus on between-family analysis. The model proposed in the present study complements the literature by analyzing the role of family income in multiple-child families in an intrahousehold analysis. Results suggest that a sufficiently large family income will help mitigate birth order differences. This finding also has important policy implications. Specifically, policy interventions, such as transferring income to families when multiple children are competing for family resources, can help weaken the inequality among siblings.

The study contributes to the literature on son preference. The social norm of son preference can alter parents' childbearing and child-rearing behavior (Yi et al., 1993; Chen et al., 2007; Almond et al., 2010; Jayachandran and Pande, 2017) and lead to gender differences in health outcomes (Chen et al., 2007; Jayachandran and Kuziemko, 2011; Jayachandran and Pande, 2017). Meanwhile, the prevalence of diagnostic ultrasound in China results in parents with strong son preference to practice sex selection, which significantly increases the sex ratio (Chen et al., 2013). To the best of our knowledge, this study is the first to consider both son preference and sex selection in a theoretical model and an empirical analysis to investigate birth order effects. The research adds to the literature by showing that son preferences have direct and indirect impacts on birth order effects on child health.

Finally, the study contributes to our understanding of the effect of OCP on family outcomes. As Zhang (2017) points out, identifying the causal impact of the OCP on family outcomes can be difficult due to the endogeneity of the enforcement of this fertility policy. Several studies have attempted to construct indicators to measure the enforcement of the OCP.[8] Inspired by Li and Zhang (2017), we modify their excess fertility rate and create a quantitative indicator to measure OCP enforcement, which captures not only the strictness of the local statutory fertility policy but also the harshness of the actual policy compliance. Using this modified measure, we show that the enforcement of OCP can lead to a negative selection issue regarding parents' fertility behavior and indirectly influence the birth order effects on health.

The rest of this paper is organized as follows. Section 2 provides the background information on the culture of son preference and the OCP in China. Section 3 derives the theoretical model. Section 4 describes the data set and the empirical strategy. Section 5 reports the evidence on birth order effects on child health in rural China. Section 6 presents the empirical results corresponding to the model predictions in Section 3. Section 7 concludes the paper.

[8]For instance, McElroy and Yang (2000) and Huang et al. (2021) exploit the cross-sectional and temporary variations in fertility fines, which may suffer from endogenous problems (Zhang, 2017).

2 Background

2.1 Son Preference in China

The tradition of preference for sons has been deeply rooted in China. At least two possible reasons explain why Chinese parents have long favored sons over daughters. First, the son preference can arise from cultural norms. Chinese society is deeply influenced by Confucianism, which emphasizes the importance of continuing the family line. Parents favor sons because only a son can carry on the family name. Second, economic incentives can also explain son preferences. In places where agriculture is the principal economic activity (particularly in rural China), males usually have a comparative advantage over females since farming is physically demanding. As a result, in rural areas, sons tend to provide a higher economic return to their parents. Another example of economic incentives is family support, the most common eldercare model. Daughters usually leave home after they get married, while married sons and their wives tend to live with parents and take responsibility for eldercare. Therefore, parents value sons more than daughters.

2.2 China's Fertility Control Policy Since 1979

To curb China's rapid population growth, the OCP was first introduced in 1979 and lasted for more than three decades.[9] In the beginning, parents were only allowed to have one child, and the second or higher-parity births would receive punishment, including heavy fines and, in extreme cases, forced abortion and sterilization. The one-child-per-couple rule incurred strong resistance, particularly in rural areas where most families live on agriculture and parents have a strong preference for sons. As a result, the Chinese government relaxed the policy by allowing mothers to have a second child under certain conditions. Specifically, in 1984, the government established a localized birth control policy in which the implementation of OCP varied from one province to another. Urban couples were still subject to the OCP. Rural couples were allowed to have two children if they met some criteria. One important exemption is the 1.5 Child Policy, which allows mothers in several rural provinces with first-born girls to have a second child. Exemptions are also granted to ethnic minorities and those in hazardous occupations. Gu et al. (2007) compile local regulations throughout the 1990s and identify 22 exemptions that allow a second or third child.

On the other hand, sanctions for unauthorized births vary from place to place and from urban to rural. Parents with births outside the plan are forced to pay regular or one-time income deductions as above-quota birth fines, which usually accounts for 10–20 percent of family income for 7 to 14 years (Zhang, 2017). Besides fertility fines, urban residents may lose job promotions, be demoted, or even be discharged. Meanwhile, rural residents with unauthorized births are

[9] In the early 1970s, the Chinese government promoted a family planning campaign with the propaganda theme "two are just fine." See Zhang (2017) for a detailed review of the evolution of family planning policy in China.

commonly forced to pay a one-time fine.

To boost the birth rate and slow down the trend of population aging in recent years, the Chinese government began to relax the birth restrictions. In 2014, the Selective Two-child Policy was implemented, which allowed couples to have two children if at least one spouse was a single child. The family-planning policy was further relaxed in 2016 when the Universal Two-child Policy for all couples came into effect. In 2021, the Three-child Policy was announced at a meeting of the Politburo of the Chinese Communist Party.

2.3 Ultrasound and Prenatal Sex Selection

The first ultrasound machine in China was manufactured in 1979. Since then, portable ultrasound devices have been sent to hundreds of cities across the country. According to Chen et al. (2013), by the mid-1990s, all county hospitals and clinics, most township clinics, and family planning stations were armed with ultrasound machines. Ultrasound machines were initially designed for monitoring fetal development and other diagnostic purposes. They can also accurately identify the sex of a fetus approximately 20 weeks into a pregnancy. The ultrasound diagnostic service is relatively inexpensive and affordable for ordinary families. In addition, it makes sex selection easier, safer, and painless. Since the introduction of ultrasound machines in China, it has been the most popular form of prenatal sex selection.

With the popularization of ultrasound, the sex ratio at birth has significantly risen in China since the 1980s (Ebenstein, 2010; Chen et al., 2013). The number of male births per 100 female births is even over 120 in the mid-1990s. Conscious of the serious consequences of using ultrasound to conduct prenatal sex determination, the government passed a ban on sex-selective abortion in 1994 and tightened the ban from 2001 onwards (Das Gupta, 2019). However, the implementation of the ban had limited achievement. Doctors tended to provide the prenatal sex identification service to their friends, relatives, or people who offered bribes (Chen et al., 2013). According to Das Gupta (2019), the sex ratio at birth in China remained similar between the 2000 and 2010 censuses (i.e., around 120 boys per 100 girls).

3 Theoretical Model: Why Do Birth Order Effects Arise?

In this section, we develop a stylized model with an altruistic motive to understand the emergence of birth order effects. The model consists of two stages. In the first stage ($t = 0$), parents decide whether to have one or two children. The second stage contains three periods ($t = 1, 2, 3$). During the initial period ($t = 1$), parents make a forward-looking decision on household consumption, child investment, and, if necessary, savings and borrowing, for all three periods. Before reaching adulthood, each child spends two periods with their parents during which they receive early- and late-childhood health investments, respectively. In one-child families, the child is born at $t = 1$. In two-child families, children are born sequentially, that is, the first child is born at $t = 1$, and the second child is born at $t = 2$. The model is solved backwards by first resolving parents' investment in the second stage and then analyzing their fertility decision in the first stage.[10]

Preferences. Parents are altruistic; they care about both their own consumption in each period and their children's ultimate quality (specifically, their adult health). Let i denote the order in which a child is born[11] and N denote the total number of children (i.e., family size) in the family ($N \in \{1, 2\}$). Consumption in period t is represented by c_t ($t \in \{1, 2, 3\}$). The adult health of the child born in order i is defined as h_i.

Parental preferences in a family with N children can be represented as follows:

$$\mathrm{U}_N = \mathrm{U}(c_1, c_2, c_3, H_N),$$

where $H_N = \begin{cases} \{h_1\} & \text{if } N = 1 \\ \{h_1, h_2\} & \text{if } N = 2 \end{cases}$. U_N is assumed to be an increasing, concave, and twice continuously differentiable function that satisfies the standard Inada conditions in each argument.

To derive the analytic results, we further assume that preferences are additive separable and specify the distinct parental utility functions in the following forms:

$$\mathrm{U}_1 = log(c_1) + log(c_2) + log(c_3) + \delta log(h_1), \tag{3.1}$$

$$\mathrm{U}_2 = log(c_1) + log(c_2) + log(c_3) + \delta[log(h_1) + log(h_2)], \tag{3.2}$$

where $\delta > 0$ captures parents' altruism to children. For simplicity, δ is assumed to be the same across families. Eqs. (3.1) and (3.2) assume that parents exhibit "equal concern" (Behrman et al., 1982) for both children, i.e., they place the same weight on children. This assumption will be relaxed in the extended model in Section 3.2. In addition, weimplicitly assume that the intertemporal discount factor is 1, which implies parents value today's utility as much as the future's.

More general forms of Eqs. (3.1) and (3.2) are not meant to restrict the discount factor (denoted as β, $\beta > 0$) to be 1. When $\beta < 1$, parents tend to place more weight on the present than on the future, while the opposite is true when $\beta > 1$. Since child 1 always becomes an adult earlier than child 2, a non-unitary β would naturally lead to more weight on h_1 (when $0 < \beta < 1$) or h_2 (when $\beta > 1$).[12] To rule out birth order effects driven by the discount factor, we assume β to be 1. However, in Appendix D.1, we discuss a more general model allowing a flexible value of β.

[10] Assuming no uncertainty in this model, this two-stage model is equivalent to a model in which parents decide their fertility and investment simultaneously.

[11] Without loss of generality, for children in one-child families, $i = 1$.

[12] Intuitively, if $0 < \beta < 1$, parents prioritize today over the future; hence, they assign more weight to the first child, given that the first child becomes an adult first. Conversely, if $\beta > 1$, parents place more weight on the second child.

Technology for Human Capital Production. Building upon Cunha and Heckman (2007), we assume that skill formation contains two stages (indexed by j): an early stage ($j = 1$) and a late stage ($j = 2$). Parents have full and perfect information about the technology of human capital. Each child i is born with an endowment (i.e., initial conditions) denoted as $h_{i,0}$. In each stage j, $h_{i,j-1}$ represents the accumulated health stock from the previous stage $j-1$, and $I_{i,j}$ denotes parental investments in child health in the current stage j. In addition, a_j refers to an "efficiency factor" in stage j, capturing various factors that contribute to skill formation and operate independently of the health stock $h_{i,j-1}$.[13] Formally, the human capital production function for child i in stage j is specified as the following recursive form:

$$h_{i,j} = f_j(h_{i,j-1}, I_{i,j}, a_j), \quad \text{j=1,2.} \tag{3.3}$$

Similar to Cunha and Heckman (2007), we assume that the human capital production function f_j is strictly increasing and strictly concave in investment $I_{i,j}$ and twice continuously differentiable in each argument. Moreover, f_j is the same for all children in a family but can be different across families.

To obtain the analytic solutions, we now assume specific function forms for f_j ($j = 1, 2$). Without loss of generality, early investment ($I_{i,1}$) produces an interim level of health: $h_{i,1} = h_{i,0}(a_1 + I_{i,1})$. The late investment ($I_{i,2}$), interacting with $h_{i,1}$, produces adult health: $h_{i,2} = h_{i,1}(a_2 + I_{i,2})$. Thus, inserting $h_{i,1}$ into $h_{i,2}$, the adult health h_i is expressed as follows:

$$h_i = h_{i,0}(a_1 + I_{i,1})(a_2 + I_{i,2}). \tag{3.4}$$

A more general approach to modeling skill formation is to allow heterogeneous parameters for $I_{i,1}$ and $I_{i,2}$. However, as we take the log of adult health in Eqs. (3.1) and (3.2), it can be demonstrated that the more general function can be reduced to Eq. (3.4) (see Appendix D.2).

By construction, the technology illustrated in Eq. (3.4) characterizes the important properties emphasized by Cunha and Heckman (2007). *Self-Productivity* is $\frac{\partial h_{i,2}}{\partial h_{i,1}} = a_2 + I_{i,2}$. *Investment Productivity* for $I_{i,1}$ and $I_{i,2}$ are $\frac{\partial h_{i,1}}{\partial I_{i,1}} = h_{i,0}(a_2 + I_{i,2})$ and $\frac{\partial h_{i,2}}{\partial I_{i,2}} = h_{i,0}(a_1 + I_{i,1})$, respectively. *Dynamic Complementarity* is implied by $\frac{\partial^2 h_{i,2}}{\partial h_{i,1} \partial I_{i,2}} = 1 > 0$, which suggests that the stock $h_{i,1}$ enhances the productivity of late investment $I_{i,2}$.

In the following sections, we investigate birth order effects in a model with credit constraints, which is more applicable to the situation in rural China. Nonetheless, the framework can also be adapted to situations without credit constraints, as elaborated in Appendix C. To facilitate our

[13] In the skill evolution model of Heckman and Zhou (2021), they also include a variable that depends on age, similar to the a_j in our model.

analysis in this study, let us consider an extreme case in which families are not allowed to save or borrow against *any* future income to fund consumption or investments (Del Boca et al., 2014; Del Boca et al., 2016).

3.1 Baseline Model: No Gender Preference or Fertility Restriction Policy

Assuming the case of no borrowing or saving, we start by considering a baseline model in which parents have complete control over family size (i.e., no fertility restriction policies) and do not favor one child over the other.

3.1.1 The Second Stage: Investment Decisions

The Two-child Case.—In a two-child family, parents face the following budget constraints:

$$\begin{aligned} c_1 + I_{1,1} &= Y_1, \\ c_2 + I_{1,2} + I_{2,1} &= Y_2, \\ c_3 + I_{2,2} &= Y_3, \end{aligned}$$

where Y_1, Y_2, and Y_3 are exogenously income. To provide a general framework, we do not restrict the relative sizes of Y_1, Y_2, and Y_3.

Thus, parents' optimization problem is characterized as follows:

$$\begin{aligned} \max_{c_1,c_2,c_3,I_{1,1},I_{1,2},I_{2,1},I_{2,2}} \quad & \mathrm{U}_2 = log(c_1) + log(c_2) + log(c_3) + \delta[log(h_1) + log(h_2)] \\ \text{s.t.} \quad & c_1 + I_{1,1} = Y_1, \\ & c_2 + I_{1,2} + I_{2,1} = Y_2, \\ & c_3 + I_{2,2} = Y_3, \\ & h_i = h_{i,0}(a_1 + I_{i,1})(a_2 + I_{i,2}), \quad i \in \{1,2\}. \end{aligned} \tag{M1}$$

Based on the first-order conditions, we can solve the optimal child investments, denoted by the superscript $*$, as follows:

$$
\begin{aligned}
c_1^* &= \frac{Y_1 + a_1}{1+\delta}, \\
c_2^* &= \frac{Y_2 + a_1 + a_2}{1+2\delta}, \\
c_3^* &= \frac{Y_3 + a_2}{1+\delta}, \\
I_{1,1}^* &= \frac{\delta Y_1 - a_1}{1+\delta}, \\
I_{1,2}^* &= \frac{\delta Y_2 - a_2 + \delta(a_1 - a_2)}{1+2\delta}, \\
I_{2,1}^* &= \frac{\delta Y_2 - a_1 + \delta(a_2 - a_1)}{1+2\delta}, \\
I_{2,2}^* &= \frac{\delta Y_3 - a_2}{1+\delta}.
\end{aligned}
\tag{3.5}
$$

From Eq. (3.5):

$$
\begin{aligned}
\frac{\partial U_2}{\partial c_1^*} &= \frac{\partial U_2}{\partial I_{1,1}^*} = \frac{1+\delta}{Y_1 + a_1}, \\
\frac{\partial U_2}{\partial c_2^*} &= \frac{\partial U_2}{\partial I_{1,2}^*} = \frac{\partial U_2}{\partial I_{2,1}^*} = \frac{1+2\delta}{Y_2 + a_1 + a_2}, \\
\frac{\partial U_2}{\partial c_3^*} &= \frac{\partial U_2}{\partial I_{2,2}^*} = \frac{1+\delta}{Y_3 + a_2}.
\end{aligned}
\tag{3.6}
$$

The interpretation of Eq. (3.6) is straightforward: in each period t, the marginal utility of household consumption must be equal to the marginal utility of investment in child 1 (or child 2).

Using Eq.(3.4), the optimal adult health for each child can be solved as follows:

$$
\begin{aligned}
h_1^* &= h_{1,0}(a_1 + I_{1,1}^*)(a_2 + I_{1,2}^*) = h_{1,0}\frac{\delta(Y_1 + a_1)}{1+\delta}\frac{\delta(Y_2 + a_1 + a_2)}{1+2\delta}, \\
h_2^* &= h_{2,0}(a_1 + I_{2,1}^*)(a_2 + I_{2,2}^*) = h_{2,0}\frac{\delta(Y_2 + a_1 + a_2)}{1+2\delta}\frac{\delta(Y_3 + a_2)}{1+\delta}.
\end{aligned}
$$

Accordingly, we can derive the ratio of optimal adult health as follows:

$$
\frac{h_1^*}{h_2^*} = \frac{h_{1,0}}{h_{2,0}}\frac{Y_1 + a_1}{Y_3 + a_2}. \tag{3.7}
$$

Before proceeding to interpret Eq. (3.7), it is important to understand the ratio of adult health, $\frac{h_1^*}{h_2^*}$. If $\frac{h_1^*}{h_2^*} > 1$, the first child has better health than the second child, indicating a negative birth order effect. If $\frac{h_1^*}{h_2^*} < 1$, the first child has worse health than the second child, indicating a positive birth order effect. If $\frac{h_1^*}{h_2^*} = 1$, there is no birth order difference in health. Thus, we measure birth order effects by using the magnitude of $\frac{h_1^*}{h_2^*}$ relative to 1.[14]

Eq. (3.7) provides a general framework to help us understand why birth order effects arise, which is summarized in the following proposition:

Proposition 1. *In the presence of credit constraints, suppose parents display equal concern for their children.*

(1) $h_{1,0}(Y_1 + a_1) > h_{2,0}(Y_3 + a_2) \iff \frac{h_1^*}{h_2^*} > 1$ *(negative birth order effects).*

(2) $h_{1,0}(Y_1 + a_1) < h_{2,0}(Y_3 + a_2) \iff \frac{h_1^*}{h_2^*} < 1$ *(positive birth order effects).*

(3) $h_{1,0}(Y_1 + a_1) = h_{2,0}(Y_3 + a_2) \iff \frac{h_1^*}{h_2^*} = 1$ *(no birth order differences).*

Proposition 1 implies that the birth order effect ($\frac{h_1^*}{h_2^*}$) is jointly determined by the interplay of three factors: the relative size of birth endowments ($h_{1,0}$ and $h_{2,0}$), the relative size of family income in the first and third periods (Y_1 and Y_3), and the relative size of efficiency factors in the early and late stages (a_1 and a_2). The relative size of each factor can be greater than, less than, or equal to 1. Consequently, $\frac{h_1^*}{h_2^*}$ can be greater than, less than, or equal to 1. The direction and magnitude of the birth order effects depend on the relative significance of these factors. Positive or negative birth order effects emerge based on which factors exert a dominant influence on the outcomes.

The roles of birth endowments and family income in shaping birth order effects are intuitive. Birth endowments directly affect skill formation due to self-productivity. Specifically, a better birth endowment can be considered a higher human capital stock, leading to better adult health. Similarly, higher family income facilitates child investment, thus enhancing human capital through investment productivity.

To understand how efficiency factors contribute to the birth order effect, it is convenient to isolate their roles by assuming there is no heterogeneity by birth endowment ($h_{1,0} = h_{2,0}$) or by family income ($Y_t = Y$, $t = 1, 2, 3$). In this case, Eq. (3.7) is reduced to:

$$\frac{h_1^*}{h_2^*} = \frac{Y + a_1}{Y + a_2}. \tag{3.7$'$}$$

The following proposition summarizes the implications derived from (3.7′).

Corollary 1. *In the presence of credit constraints, suppose that parents display equal concern for their children, there is no heterogeneity by birth endowment, and family income is constant over time.*

(i) $a_1 > a_2 \iff \frac{h_1^*}{h_2^*} > 1$ *(negative birth order effects);* $a_1 < a_2 \iff \frac{h_1^*}{h_2^*} < 1$ *(positive birth order effects);* $a_1 = a_2 \iff \frac{h_1^*}{h_2^*} = 1$ *(no birth order differences).*

[14]Notably, the difference between adult health ($h_1^* - h_2^*$) is not suitable for determining birth order effects. As richer parents tend to invest more in their children, the adult health of children from high-income families tends to be better than those from low-income families (see Francesconi and Heckman (2016) for a literature review). Therefore, the adult health difference is always positively correlated with family income, making it an inadequate indicator to measure sibling inequality.

(ii) $a_1 > a_2 \iff \frac{\partial h_1^*/h_2^*}{\partial Y} < 0$ *(negative birth order effects decrease with income);* $a_1 < a_2 \iff \frac{\partial h_1^*/h_2^*}{\partial Y} > 0$ *(positive birth order effects increase with income);* $a_1 = a_2 \iff \frac{\partial h_1^*/h_2^*}{\partial Y} = 0$.

Using Eq. (3.7′), the proof of Corollary 1 is considered trivial. This corollary has two implications. Part (i) states that under the conditions of equal concern, constant family income, and no birth order difference in birth endowment, $\frac{h_1^*}{h_2^*}$ depends on the relative size of the efficiency factors in the early and late stages, a_1 and a_2. From Eq. (3.5), if $a_1 > a_2$, we observe $I_{1,1}^* > I_{2,1}^*$, $I_{1,1}^* < I_{2,2}^*$, and $c_1 > c_3$. Intuitively, in the first period, child 1 is the only child and exclusively enjoys family resources. In the second period, two children coexist and compete for resources. Due to the limited family resources, child 2 is allocated fewer resources than child 1 in the early stage ($I_{2,1}^* < I_{1,1}^*$). Consequently, in the third period, parents tend to compensate child 2's early-stage disadvantage by cutting expenditures on consumption ($c_3 < c_1$) and allocating more resources to child 2 in his/her late stage. However, given that the late stage is less important than the early stage (i.e., $a_2 < a_1$), parents' investment can not fully compensate for child 2's early-stage disadvantage. Therefore, child 2 has a lower human capital than child 1, indicating a negative birth order effect.

Part (ii) of Corollary 1 implies that if family income is large enough, the scale effect of family income can mitigate or eliminate the human capital discrepancy caused by heterogeneous efficiency factors. In other words, as the family income increases, the outcomes of the two children tend to converge, resulting in $\lim_{Y\to\infty} \frac{h_1^*}{h_2^*} = 1$. Figure 1 visualizes this implication. If $a_1 > a_2$, the first-born performs better than the second-born (negative birth order effect), and $\frac{h_1^*}{h_2^*}$ decreases with income and tends to be 1. If $a_1 < a_2$, the first-born performs worse than the second-born child (positive birth order effect), and $\frac{h_1^*}{h_2^*}$ increases with income and tends to be 1. If $a_1 = a_2$, there are no birth order effects, and this has nothing to do with family income.

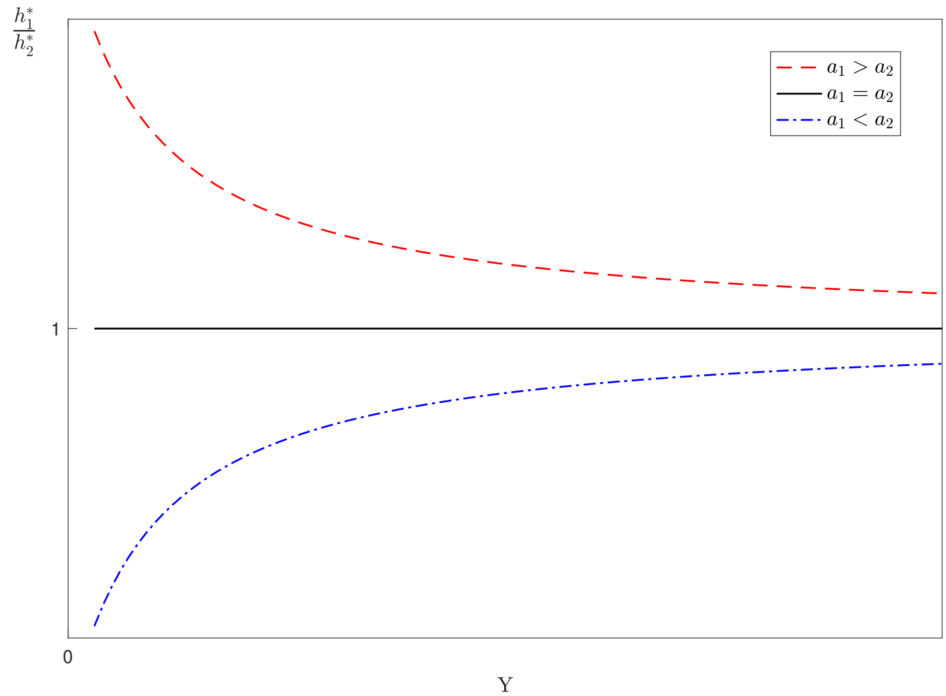


Figure 1. Birth Order Effect, with Equal Concern and Credit Constraint

The One-child Case.—In a one-child family, parents face the following three budget constraints:

$$c_1 + I_{1,1} = Y_1,$$
$$c_2 + I_{1,2} = Y_2,$$
$$c_3 = Y_3.$$

As such, parents' optimization problem becomes:

$$\begin{aligned} \max_{c_1, c_2, I_{1,1}, I_{1,2}} \quad & U_1 = log(c_1) + log(c_2) + log(c_3) + \delta log(h_1) \\ \text{s.t.} \quad & c_1 + I_{1,1} = Y_1, \\ & c_2 + I_{1,2} = Y_2, \\ & c_3 = Y_3, \\ & h_1 = h_{1,0}(a_1 + I_{1,1})(a_2 + I_{1,2}). \end{aligned} \tag{M2}$$

Solving (M2), we derive the following solutions:

$$c_1^* = \frac{Y_1 + a_1}{1+\delta},$$
$$c_2^* = \frac{Y_2 + a_2}{1+\delta},$$
$$I_{1,1}^* = \frac{\delta Y_1 - a_1}{1+\delta},$$
$$I_{1,2}^* = \frac{\delta Y_2 - a_2}{1+\delta}.$$

Using Eq. (3.4), the adult health of the only child is:

$$h_1^* = h_{1,0}(\frac{\delta}{1+\delta})^2(Y_1 + a_1)(Y_2 + a_2).$$

3.1.2 The First Stage: Fertility Decisions

In the first stage, parents decide the family size by comparing the utility of having two children and that of having one child.

Specifically, in a two-child case, by substituting the optimal solutions of consumptions and child investments into Eq. (3.2), we can derive the optimized utility U_2^* given by:

$$\begin{aligned} U_2^* =& log(c_1^*) + log(c_2^*) + log(c_3^*) + \delta[log(h_1^*) + log(h_2^*)] \\ =& (1+\delta)log(Y_1 + a_1) + (1+\delta)log(Y_3 + a_2) + (1+2\delta)log(Y_2 + a_1 + a_2) \\ &+ 4\delta log(\delta) + \delta log h_{1,0} + \delta log h_{2,0} - 2(1+\delta)log(1+\delta) - (1+2\delta)log(1+2\delta). \end{aligned}$$

In a one-child case, by substituting the optimal solutions of consumptions and child investments into Eq. (3.1), we can derive the following optimized utility U_1^*:

$$\begin{aligned} U_1^* =& log(c_1^*) + log(c_2^*) + log(c_3^*) + \delta log(h_1^*) \\ =& (1+\delta)log(Y_1 + a_1) + (1+\delta)log(Y_2 + a_2) + log(Y_3) \\ &+ 2\delta log(\delta) + \delta log h_{1,0} - 2(1+\delta)log(1+\delta). \end{aligned}$$

Formally, we define the utility surplus (S) of having two children relative to one child as follows:

$$S = U_2^* - U_1^* + \eta,$$

where η is an i.i.d. preference shock that follows the standard normal distribution.

Inserting U_1^* and U_2^*, we can solve S. If $S \geq 0$, parents decide to have two children; otherwise, they will have one child.

3.2 Extended model: Introducing Gender Preference and a Fertility Restriction Policy

Next, we extend the basic model by introducing sex preferences and a fertility restriction policy to capture the specific context of China. Similar to the previous model, borrowing and saving are not allowed, which conforms to the common reality in China.[15] For simplicity, family income is assumed to be exogenously given by Y and constant in each period t. This reflects the characteristic of relatively stable life-cycle income in China.[16] We also assume that there is no birth order difference in birth endowment and normalize initial conditions to be 1 (i.e., $h_{1,0} = h_{2,0} = 1$).[17]

Sex preference.—For simplicity, in this study, "sex preference" refers specifically to "pure" sex preference, which is also called "unequal concern" by Behrman and Taubman (1986). This analysis does not consider the "indirect preference," which arises from gender-related price effects.[18] To incorporate pure sex preference in parents' utility function, we allow parents to assign different weights (ω_i, $i = 1, 2$) to children based solely on their gender. In one-child families, ω_1 may vary with a child's gender if parents have a gender preference. In two-child families, ω_1 and ω_2 can be different if parents display gender preference and children have different genders. Formally, we respectively rewrite Eqs. (3.1) and (3.2) as follows:

$$U_1 = log(c_1) + log(c_2) + log(c_3) + \delta\omega_1 log(h_1), \tag{3.1$'$}$$

$$U_2 = log(c_1) + log(c_2) + log(c_3) + \delta[\omega_1 log(h_1) + \omega_2 log(h_2)]. \tag{3.2$'$}$$

To quantify sex preference, without loss of generality, we consider a patrilineal society like China and assume that parents tend to prefer sons.[19] We normalize the preference for girls to 1 and set the preference for boys to be $1 + \phi$, $\phi \in [0, 1]$. The parameter ϕ is exogenously given, captures the preference for sons relative to daughters, and may vary for different parents. If $\phi = 0$, it is equivalent to the case of "no gender preference." The larger ϕ is, the stronger the son prefer-

[15](i) Based on the 2011 China Household Finance Survey (CHFS), about 70% of rural households who need loans face credit constraints. This includes both rejected applicants (40%) and discouraged borrowers (30%). Rejected applicants are those whose loan applications have been rejected by financial institutions. Discouraged applicants are those who need loans but do not apply for loans since they perceive that there is a cost to apply and if they request the credit, they will be refused (Jappelli, 1990). (ii) Rural families in China keep very limited savings. According to data from CFPS 2010–2018, the total annual income of rural families is 26,355 RMB on average. However, their average savings only accounts for 4.5% of the total income (1,440 RMB). Savings in this context is defined as the difference between the total family income and the total family expenditure on consumption, including expenditures on food, daily necessities, home repairs and maintenance, trips and vacations, recreation and entertainment, household furnishings and equipment, child care, durable goods, clothing, education, transportation, utilities, and heating.

[16]As shown in Appendix Table A4, total family income and family income per capita remain constant when mothers are 27–29, 30–32, and 33–35 years old, corresponding to the early stage of child 1 ($t = 1$), the early stage of child 2 ($t = 1$), and the late stage of child 2 ($t = 3$), respectively.

[17]As shown in Appendix Table A5, there is no significant birth order difference in children's birth endowment when family fixed effects are controlled. As noted by Black et al. (2018), ideally, given that siblings randomly inherit half of the genes from each of the parents, there should be no systematic genetic differences among siblings.

[18]"Pure sex preference" and "indirect preference" are two forms of sex preferences, initially differentiated by Ben-Porath and Welch (1976) and Ben-Porath and Welch (1980) as "sex concern" and "price effects," respectively.

[19]The analysis of girl preference is the other way around.

ence is . We then derive the weight for girls and boys $\omega_g = \frac{1}{2+\phi}$ and $\omega_b = \frac{1+\phi}{2+\phi}$, respectively.[20] If child i is a girl, $\omega_i = \omega_g$. If child i is a boy, $\omega_i = \omega_b$.

Sex-selective abortion.—Parents have the option to use the ultrasound equipment to conduct sex-selective abortion based on their gender preference.[21] The parental effort of sex selection, denoted as e, is a function of son preference, ϕ. The stronger the son preference is, the more effort parents will exert for sex selection. To simplify, we assume a linear relationship between effort and preference, that is, $e = \phi$. Additionally, there is a cost associated with gender selection, represented by the price per unit of effort, denoted as p. Therefore, the total gender selection cost is derived as the effort of gender selection times the price of gender selection, ϕp.

The probability of having a boy is expressed as $0.5 + 0.5\phi$. When $\phi = 0$, parents have equal concern for sons and daughters and have no incentive to use sex selection. Thus, the probability of having a boy is 0.5. If $\phi > 0$, parents will make some effort ($e = \phi$) to increase the probability of having a boy beyond 0.5. In the extreme case where $\phi = 1$, parents have the strongest son preference and will put all their effort into practicing gender control to guarantee the birth of a boy.

Fertility restriction policy.—The model abstracts away from exemptions in birth-control regulations in some circumstances and assumes that the policy only allows one birth.[22] Rural residents usually have to pay a one-time fine if they exceed the birth quota (Zhang, 2017). In this model, the lump-sum fine is denoted as g, and is endogenously determined by the enforcement of the fertility policy d and family income Y. Formally, we express g as a function of d and Y, denoted as $g = g(d, Y)$. We impose the following assumptions on the $g()$ function:

Assumption 1. $\dfrac{\partial g(d,Y)}{\partial d} > 0,\ 0 < \dfrac{\partial g(d,Y)}{\partial Y} < 1,\ \dfrac{\partial^2 g(d,Y)}{\partial d \partial Y} > 0.$

The first condition is intuitive, indicating that given the same family income, the more rigorous the policy is, the higher the financial penalty would be. The second condition has two implications. The first inequality ($0 < \frac{\partial g(d,Y)}{\partial Y}$) implies that the fertility fine is strictly increasing in family income. The second inequality ($\frac{\partial g(d,Y)}{\partial Y} < 1$) suggests that a one-unit increase in family income could lead to a less-than-one unit increase in the fine. The second condition is plausible, as fines are usually computed as a particular percentage (usually 10%–20%) of family income (Ebenstein, 2010; Scharping, 2013; Zhang, 2017). The third condition implies that more rigorous enforcement of the fertility policy results in higher penalty rates for parents who earn more

[20]Since $\omega_g + \omega_b = 1$ and $\omega_g/\omega_b = 1/(1+\phi)$, it is straightforward to obtain ω_g and ω_b.

[21]I also develop a model in which parents have son preference but cannot use sex selection technology (see Appendix E.1).

[22]Notably, Gu et al. (2007) review provincial birth control regulations and identify 22 exemptions for allowing a second child. In the empirical analysis in Section 6, we relax the assumption that each couple can only have one child and construct a quantitative measure that considers region-specific birth-control rules.

income than others.

3.2.1 The Second Stage: Investment Decisions

The Two-child Case.—As shown in Table 2, the sex ratio in rural China increases with birth order, implying that parents are more likely to conduct sex-selective abortion for higher-order births. Accordingly, the model assumes that sex selection can only be used for the second-born rather than the first-born child. Considering that sex selection technology affects the probability of having a boy in the second birth, the probability of the first child being a boy remains 0.5, while the probability of the second child being a boy is $0.5 + 0.5\phi$.

In the presence of sex selection cost and penalty rates, the three-period budget constraints can be rewritten as:

$$\begin{aligned} c_1 + I_{1,1} &= Y, \\ c_2 + I_{1,2} + I_{2,1} &= Y - \phi p - g(d, Y), \\ c_3 + I_{2,2} &= Y. \end{aligned} \tag{3.8}$$

Parents' optimization problem is then expressed as:

$$\begin{aligned} \max_{c_1, c_2, I_{1,1}, I_{1,2}, I_{2,1}, I_{2,2}} \quad & U_2 = log(c_1) + log(c_2) + log(c_3) + \delta[\omega_1 log(h_1) + \omega_2 log(h_2)], \\ \text{s.t.} \quad & c_1 + I_{1,1} = Y \\ & c_2 + I_{1,2} + I_{2,1} = Y - \phi p - g(d, Y), \\ & c_3 + I_{2,2} = Y, \\ & h_i = (a_1 + I_{i,1})(a_2 + I_{i,2}), \quad i \in \{1, 2\}. \end{aligned} \tag{M3}$$

By solving this optimization problem, we can derive the solution set $\{c_1^*, c_2^*, c_3^*, I_{1,1}^*, I_{1,2}^*, I_{2,1}^*, I_{2,2}^*\}$. Using Eq. (3.4), we can solve the optimal adult health h_1^* and h_2^*. Based on these results, we establish the following proposition:

Proposition 2. *In the presence of credit constraints, suppose that parents display unequal concern and have constant family income, and there is no birth order difference in birth endowment. Given children's gender, the ratio of adult health in the presence of sex preference is characterized as follows:*

$$\frac{h_1^*}{h_2^*} = \rho_1(\phi) \frac{Y + a_1}{Y + a_2}, \tag{3.9}$$

where $\rho_1(\phi) = (\frac{\omega_1}{\omega_2})^2 \frac{1+\omega_2\delta}{1+\omega_1\delta}$, $\omega_i = \frac{1+\phi}{2+\phi}$ *if child i is a boy, and* $\omega_i = \frac{1}{2+\phi}$ *if child i is a girl (*$i = 1, 2$*).*

Proposition 2 indicates that the birth order effect ($\frac{h_1}{h_2}$) is jointly determined by two components: the relative preference for child 1 and child 2 ($\rho_1(\phi)$) and the relative size of the efficiency factors in early and late stages (a_1 and a_2). Therefore, the birth order effect can be ambiguous even if the relative size of a_1 and a_2 is known. For example, suppose the efficiency factor in the early stage is larger than that in the late stage, then the second term in Eq. (3.9), $\frac{Y+a_1}{Y+a_2}$, is greater than 1. However, if parents prefer child 2 to child 1, then the first term in Eq. (3.7′), $\rho_1(\phi)$, is less than 1. Together with $\frac{Y+a_1}{Y+a_2}$, one can not determine the direction of birth order effect accurately. Apparently, Eq. (3.9) is the general form of Eq. (3.7′). Specifically, when parents place equal weights on children ($\omega_1 = \omega_2$), Eq. (3.9) is simplified to Eq. (3.7′).

Before proceeding to Corollary 2, it is necessary to introduce some notations about gender composition. Let the sequence (τ_1, τ_2) represent child gender composition in a two-child family, where τ_1 and τ_2 denote the gender of child 1 and child 2, respectively, $\tau_i \in \{\text{boy,girl}\}$. There are four possible types of gender composition in a two-child family: (boy, boy), (boy,girl), (girl, boy), and (girl, girl). $P(\tau_1, \tau_2)$ denotes the joint probability of the gender composition (τ_1, τ_2). Furthermore, we define $H(\tau_1, \tau_2)$ as the adult health ratio of child 1 to child 2 ($\frac{h_1}{h_2}$), given gender composition (τ_1, τ_2). Thus, it is natural to deduce the following corollary:

Corollary 2.

$$H(\text{boy}, \text{boy}) = H(\text{girl}, \text{girl}). \tag{3.10}$$

Corollary 2 suggests that the birth order gradient for boys is the same as the birth order gradient for girls.

Gender composition can directly affect parental preference and, hence, resource allocation. Since children's gender is uncertain at the beginning of period 1, we consider the average birth order effects across all families.

Let $E^S(\frac{h_1^*}{h_2^*})$ denote the weighted average of birth order effects, where the superscript S indicates "allowing sex selection." Then $E^S(\frac{h_1^*}{h_2^*})$ is represented as follows:

$$\begin{aligned} E^S(\frac{h_1^*}{h_2^*}) =& P(\text{boy, boy}) \cdot H(\text{boy, boy}) + P(\text{boy, girl}) \cdot H(\text{boy, girl}) \\ &+ P(\text{girl, boy}) \cdot H(\text{girl, boy}) + P(\text{girl, girl}) \cdot H(\text{girl, girl}). \end{aligned} \tag{3.11}$$

Inserting the optimal solution $I_{1,1}^*, I_{1,2}^*, I_{2,1}^*, I_{2,2}^*$, we derive the expected value of $\frac{h_1^*}{h_2^*}$ when sex selection is available (see Appendix E.2):

$$E^S(\frac{h_1^*}{h_2^*}) = \rho_2(\phi)\frac{Y+a_1}{Y+a_2}, \tag{3.12}$$

where $\rho_2(\phi) = \frac{1}{4}\left(2 + (1-\phi)(1+\phi)^2 \frac{2+\phi+\delta}{2+\phi+\delta(1+\phi)} + \frac{1}{1+\phi}\frac{2+\phi+\delta(1+\phi)}{2+\phi+\delta}\right)$. Using Eq. (3.12), we decompose birth order effects into two components: the component related to parental preferences, $\rho_2(\phi)$, and the component related to the efficiency factor in skill formation, $\frac{Y+a_1}{Y+a_2}$. Thus, we can predict how birth order effects change with family income and son preference, as summarized in the following proposition:[23]

Proposition 3. *In the presence of credit constraints, suppose that parents display unequal concern and that sex selection is available.*
(i) $\frac{\partial E^S(\frac{h_1^*}{h_2^*})}{\partial \phi} < 0$. *Therefore, if* $\phi = 0$, $E^S(\frac{h_1^*}{h_2^*}) = \frac{Y+a_1}{Y+a_2}$*; if* $0 < \phi \leq 1$, $E^S(\frac{h_1^*}{h_2^*}) < \frac{Y+a_1}{Y+a_2}$.
(ii) $a_1 > a_2 \iff \frac{\partial E^S(h_1^*/h_2^*)}{\partial Y} < 0$; $a_1 < a_2 \iff \frac{\partial E^S(h_1^*/h_2^*)}{\partial Y} > 0$; $a_1 = a_2 \iff \frac{\partial E^S(h_1^*/h_2^*)}{\partial Y} = 0$.

Part (i) of Proposition 3 states that a stronger son preference ϕ will decrease the weighted average ratio of adult health, $\frac{h_1^*}{h_2^*}$. Specifically, if $E^S(\frac{h_1^*}{h_2^*}) > 1$ (negative birth order effects), a larger ϕ will reduce $E^S(\frac{h_1^*}{h_2^*})$, making it approach 1. Therefore, a higher son preference will mitigate inequality and make the adult health of children converge. If $E^S(\frac{h_1^*}{h_2^*}) < 1$ (positive birth order effects), a larger ϕ will decrease $E^S(\frac{h_1^*}{h_2^*})$, making it far way from 1. As a result, a higher son preference will lead to more prominent sibling inequality, making the later-born much better than the first-born.

Intuitively, the later-born are more likely to be boys if parents are more likely to use sex-selection abortion for higher-order births. Due to son preference, children at a higher birth order will receive more resources if they are more likely to be boys. Therefore, given a negative birth order effect, a stronger son preference mitigates the birth order disparity. By contrast, given a positive birth order effect, a stronger son preference exacerbates the birth order difference.

Part (ii) of Proposition 3 implies that the disparity in human capital between child 1 and child 2 decreases with family income. This finding is similar to Part (ii) of Corollary 1, with the distinction that Proposition 3 examines a weighted average of $\frac{h_1^*}{h_2^*}$.

The One-child Case.—For parents who obey the fertility restriction rule and decide to have only one child, they can choose sex selection technology at $t = 1$ during which the only child is born. This assumption is supported by the stylized fact in Table 2 that the number of boys per 100 women of the one-child families is much higher than the normal range. Therefore, the probabilities of the only child to be a boy and a girl is $P(\text{boy}) = 0.5 + 0.5\phi$ and $P(\text{girl}) = 0.5 - 0.5\phi$, respectively.

If a family has only one child, parents do not have to pay the fertility fine. Compared with the case without sex preference, the additional expenditure that parents may incur is the sex selection cost ϕp. Therefore, the budget constraints are characterized as follows:

$$\begin{aligned} c_1 + I_{1,1} &= Y - \phi p, \\ c_2 + I_{1,2} &= Y, \\ c_3 &= Y. \end{aligned} \tag{3.1.1'}$$

[23]The proof of this proposition is shown in Appendix E.3.

Then, we can express parents' optimization problem as follows:

$$\begin{aligned} \max_{c_1,c_2,I_{1,1},I_{1,2}} \quad & U_1 = log(c_1) + log(c_2) + log(c_3) + \delta\omega_1 log(h_1) \\ \text{s.t.} \quad & c_1 + I_{1,1} = Y - \phi p, \\ & c_2 + I_{1,2} = Y, \\ & c_3 = Y, \\ & h_1 = (a_1 + I_{1,1})(a_2 + I_{1,2}). \end{aligned} \tag{M4}$$

Solving (M4), we derive c_1^*, c_2^*, $I_{1,1}^*$, and $I_{1,2}^*$. Therefore, the adult health of the only child is:

$$h_1^* = \frac{\delta\omega_1(Y - \phi p + a_1)}{1 + \delta\omega_1}\frac{\delta\omega_1(Y + a_2)}{1 + \delta\omega_1}.$$

If child 1 is a girl, $\omega_1 = \frac{1}{2+\phi}$. If child 1 is a boy, $\omega_1 = \frac{1+\phi}{2+\phi}$.

3.2.2 The First Stage: Fertility Decisions

In the presence of sex selection, parents compare the *expected* utility of having two children and the *expected* utility of having one child. Formally, the expected utility surplus (S) of having two children relative to one child is represented by:

$$S = E(U_2^*) - E(U_1^*) + \eta. \tag{3.13}$$ [24]

If $S \geq 0$, parents will plan to have two children; otherwise, they will have one child. Regarding how son preference and the enforcement of the fertility restriction policy affect parents' fertility decisions, we have the following propositions:

Proposition 4. *If* $\frac{\partial^2 g(d,Y)}{\partial d \partial Y}(Y - g(d,Y) - \phi p + a_1 + a_2) - \frac{\partial g(d,Y)}{\partial d}(1 - \frac{\partial g(d,Y)}{\partial Y}) \geq 0$, *then* $\frac{\partial^2 S}{\partial d \partial Y} \leq 0$.

Proposition 5. *If* $(Y - \phi p + a_2)(1 - \frac{\partial g(d,Y)}{\partial Y}) - (Y - g(d,Y) - \phi p + a_1 + a_2) \geq 0$, *then* $\frac{\partial^2 S}{\partial \phi \partial Y} > 0$.

The proofs of Propositions 4 and 5 are shown in Appendixes E.4 and E.5, respectively. Proposition 4 implies given son preference ϕ, under the condition that $\frac{\partial^2 g(d,Y)}{\partial d \partial Y}(Y - g(d,Y) - \phi p + a_1 + a_2) - \frac{\partial g(d,Y)}{\partial d}(1 - \frac{\partial g(d,Y)}{\partial Y}) \geq 0$, a stricter fertility policy results in richer parents being less likely to have two children. Proposition 5 suggests given the intensity of OCP d, under the condition that $(Y - \phi p + a_2)(1 - \frac{\partial g(d,Y)}{\partial Y}) - (Y - g(d,Y) - \phi p + a_1 + a_2) \geq 0$, a stronger son preference leads to richer parents being more likely to have two children.

[24] Let $U_2(\tau_1, \tau_2)$ be the parental utility when children's gender composition is (τ_1, τ_2) in a two-child family. Let $U_1(\tau_1)$ be the parental utility when child gender is τ_1 in a one-child family. $\tau_i \in \{\text{boy}, \text{girl}\}, i = 1, 2$. Then $E(U_2) = P(\text{boy}, \text{boy}) \cdot U_2(\text{boy}, \text{boy}) + P(\text{boy}, \text{girl}) \cdot U_2(\text{boy}, \text{girl}) + P(\text{girl}, \text{boy}) \cdot U_2(\text{girl}, \text{boy}) + P(\text{girl}, \text{girl}) \cdot U_2(\text{girl}, \text{girl})$. $E(U_1) = P(boy) \cdot U_1(\text{boy}) + P(girl) \cdot U_1(\text{girl})$. See Appendix E.4 for more details.

In summary, the extended model that introduces son preference and a fertility restriction policy generates the following four testable predictions, which we will examine in the next few sections:

- Hypothesis 1 (Stage 1, Proposition 4): In regions with a more rigorous fertility restriction policy, richer families are less likely to have two children.
- Hypothesis 2 (Stage 1, Proposition 5): In regions with stronger son preference, richer families are more likely to have two children.
- Hypothesis 3 (Stage 2, Corollary 2): The birth order gradient for boys is the same as (or not significantly different from) that for girls.
- Hypothesis 4 (Stage 2, Proposition 3 part (i)): The stronger son preference is, the smaller birth order effect ($\frac{h_1}{h_2}$).

4 Data and Identification Strategy

4.1 Data Description: CFPS

The major data set used in this study is the CFPS, a nationally representative biennial panel survey project launched by Peking University. The baseline wave of CFPS was conducted in 2010 and interviewed 42,590 individuals, including 33,600 adults and 8990 children, from around 15,000 households in 25 provinces/municipalities/autonomous regions. The CFPS data fit the birth order analysis well for several reasons. First, the CFPS collects exhaustive birth information of each child in each family, regardless of whether the child is currently living in the household. This feature enables a precise ranking of children's birth order. Second, the CFPS contains a wealth of individual-level data on co-residing family members, such as demographics and health. In addition, it includes valuable family-level information, such as family structures and income. The rich data allow us to investigate birth order effects and the underlying mechanisms from different aspects. Third, the longitudinal property of the CFPS can be used to conduct a sensitivity analysis.

This study uses data from the 2010, 2012, 2014, 2016, and 2018 waves of the CFPS. To yield a larger sample, we pool these five waves to construct a pooled cross-sectional data set. In this way, we treat the *same* households (and children) interviewed in *different* waves as *distinct* entities and compare health outcomes among siblings in the same family in the same waves. Given that only children who are currently living in a surveyed household answered their health-related information, we focus on those younger than 18, comprising an initial sample of 69,430 observations.[25] To align with the traditional birth order literature, families with twins or multiple births are excluded, accounting for 2.8% (1,912 observations) of the initial sample.[26] We also exclude families if the birth spacing between any two children is less than eight months due to possible measurement errors. This leads to the removal of 1.1% of the initial sample (731 observations). Due to the strict enforcement of OCP for urban households, we restrict attention to children with agricultural *hukou*, which leaves me with 51,412 observations. Finally, to make a within-family comparison in each wave, each household should have at least two children with non-missing birth, demographic, and health information. Following this process, the final sample comprises 17,355 individual-year observations constructed by linking 7,239 children with 3,933 families.

Table 1. Summary Statistics of the Sample

	N	Mean	Minimal value	Maximal value	Standard Deviation	Within-Family Standard Deviation
Panel A: Child characteristics						
Girl	17,355	.501	0	1	.5	.407
Age of child	17,355	8.312	0	18	4.819	2.687
HFA z-score	15,172	-.879	-6	6	1.9	1.113
Stunted	15,172	.242	0	1	.429	.271
WFA z-score	8,257	-.341	-5.96	4.98	1.526	.843
Underweight	8,257	.126	0	1	.332	.203
Panel B: Household characteristics						
Age of father	7,974	36.074	20	64	5.882	
Age of mother	8,023	34.209	19	58	5.787	
Mean parental schooling years	8,023	7.219	0	17.5	3.315	
At least one parent is minority	6,715	.148	0	1	.355	
Maternal age at first childbirth	7,796	23.161	16	38	2.988	
First-born is boy	8,023	.409	0	1	.492	
Number of children	8,023	2.272	2	7	.606	
Family income per capita (RMB)	6,884	5077.457	402.342	24402.55	3756.247	

Notes: This table provides summary statistics for the analysis sample. The HFA z-score and the stunted index are calculated for children aged 0–17. A child is stunted if his/her HFA is less than or equal to –2. The WFA z-score and the underweight index are calculated for children aged 0–10. A child is underweight if his/her WFA is less than or equal to –2. Family income per capita is trimmed at the 1% level and defined in 2010 RMB. Given that some observations may have missing values for certain characteristics, the sample sizes are not necessarily the same across different variables. (*Data source: CFPS, waves 2010, 2012, 2014, 2016, and 2018.*)

[25] Children aged 18 years or above are more likely to go out to work or study and hence, do not report their health outcomes.

[26] There are two reasons to drop families with twins or multiple births. First, it is hard to define the birth order for these children. Second, families with twins and multiple births could face different constraints or environments than others (Lehmann et al., 2018).

Table 1 presents the descriptive statistics of the pooled cross-sectional data set. On average, the children in the sample are 8 years old. The parents have an average of seven years of schooling, indicating that, on average, they did not complete junior high school. The average maternal age at first childbirth is 23 years old. The multiple-child families in the sample have an average of 2.3 children. The mean net income per capita is about 5,077 RMB (in 2010 RMB).[27]

Table 2. Sex Ratio by Birth Order

	Proportion	Sex Ratio by Birth Order		
	of families	First child	Second child	Third child or above
Panel A: Children with health information				
All families	1	100	128.3	172.9
One-child families	.42	138.2		
Multiple-child families	.58	70.7	128.3	172.9
Panel B: All children				
All families	1	100.6	126.8	163.4
One-child families	.40	139.1		
Multiple-child families	.60	72.2	126.8	163.4
Panel C: Children with health information and from completed-fertility family				
All families	1	100.3	123.7	174.5
One-child families	.22	189.3		
Multiple-child families	.78	68.3	123.7	174.5

Notes: The completed sample in Panel C is defined as children whose mothers are older than 35 years. (*Data source: CFPS, waves 2010, 2012, 2014, 2016, and 2018.*)

Given the traditional son preference in China, it is remarkable that the proportion of girls is about 0.5 in Table 1, which falls within the reasonable range of the population sex ratio in gender-neutral countries.[28] However, if we separate the sample by birth order, the sex ratio in each subgroup is not always balanced. Table 2 reports the sex ratio by birth order using various samples. Panel A uses the sample of all rural children in the CFPS (2010–2018) with health information. Panel B includes the sample of all rural children, regardless of whether they have health information. Panel C focuses on the sample of rural children with health information from approximately completed-fertility families.[29] Based on Table 1, we obtain four stylized facts on the sex ratio in rural China. First, when combining one- and multiple-child families, the sex ratio of the first-born is balanced. Second, the sex ratio of the one-child families is extremely skewed to boys. In the approximate completed-fertility one-child families (Panel C), the sex ratio reaches as high as 189. The skewed sex ratio in one-child families is primarily because that parents who prefer sons but are forced to comply with the OCP are more likely to use technologies such as

[27] According to the National Bureau of Statistics, the mean net income per capita of rural residents is 5,959 RMB in 2010 (`http://www.gov.cn/gzdt/2011-02/28/content_1812697.htm`, accessed on May 11, 2023).

[28] The "population sex ratio" is defined as the total number of males for every 100 females in the population. Coale (1991) reports that the population sex ratio is between 97.9 and 100.3 in gender-neutral countries.

[29] The CFPS does not include information on whether a mother has reached her desired fertility. In our sample, 90% of mothers have delivered a second child by 33, and 95% have delivered a third child by 35 years of age. Thereby, we assume mothers over 35 years have completed fertility.

ultrasound for sex selection. Third, in multiple-child families, the sex ratio of the first-born is around 70 boys per 100 girls. One major reason is that parents are less inclined to have a second child if the first-born is a boy, given the rule of the 1.5 child policy for most rural households. Fourth, the sex ratio increases incredibly with birth order in multiple-child families, suggesting that parents are more likely to selectively abort female fetuses at higher-parity births.

As suggested by the above four facts, children's gender by birth order in China is tightly related to son preference, sex selection, and fertility policy.

4.2 Construction of Health Measurement

Our major health outcome of interest is the HFA z-score for children aged 0–17 years. The HFA z-score is calculated using children's height (in cm), age (in months), and gender, following the WHO Child Growth Standards.[30] The reference group is drawn from six affluent populations across five continents (Brazil, Ghana, India, Norway, Oman, and the US). An HFA z-score of zero represents the 50^{th} percentile of the gender- and age-specific reference population. A negative HFA z-score indicates that a child is not achieving the growth potential at his/her age compared with the corresponding reference population. A lower HFA z-score is correlated to higher morbidity and mortality. We choose the HFA z-score as the main health measurement because it is one of the most commonly used health measurements in the literature and is considered the best cumulative indicator of children's nutrition status (Jayachandran and Pande, 2017). Besides, the HFA z-score is associated with socioeconomic outcomes, such as cognitive ability, education, and labor market outcomes (Strauss and Thomas, 2007). As shown in Table 1, our sample has a mean HFA z-score of -0.88, with a within-family standard deviation of 1.11.

In addition to the HFA, we construct and examine other health anthropometric measurements as part of robustness checks. Firstly, we identify a child as stunted if the HFA z-score is two standard deviations or more below 0. Being stunted indicates a significant deviation from the median HFA of the reference population. Another measurement for children aged 0–10, the weight-for-age z-score (WFA), is calculated similarly to the HFA z-score. Third, we classify a child as underweight if his/her WFA is -2 or below.

Table A1 in the Appendix compares the major features of multiple- and one-child families in rural China. The proportion of girls is significantly lower in one-child families compared with multiple-child ones. On average, children with siblings perform worse in health: they have lower HFA and WFA z-scores and are more likely to be stunted and underweight. Regarding household characteristics, parents with multiple children tend to have an earlier age at childbirth, few schooling years, and lower income than parents with only one child. Overall, this study concentrates on children from relatively poor and less-educated families in rural China.

[30] I compute the HFA z-score and other anthropometric indexes in *Stata* using the *igrowup_restricted* and *who2007* programs for children aged 0–5 and 0–17 years, respectively. For more details about the HFA z-score, see https://www.who.int/tools/child-growth-standards/standards/length-height-for-age.

4.3 Empirical Strategy

We use the family-by-wave fixed effects model to conduct a within-family comparison. Using the pooled cross-sectional data, the main estimation equation is formulated as follows:

$$Y_{iftc} = \alpha_0 + \alpha_1 RelatBirthOrder_{ift} + \boldsymbol{X_{ift}\beta} + \gamma_{ft} + \delta_c + \epsilon_{ifct}, \tag{4.1}$$

where i denotes child, f family, t wave, c birth cohort. Y_{iftc} is the outcome of interest. Since we treat the *same* families in different waves as the *different* ones, we control for the family-by-wave fixed effects (γ_{ft}), which enables to control for family-level heterogeneity in each wave, such as the family size, parents' age, education, income, and ability. $\boldsymbol{X_{ift}}$ is a vector of individual-specific characteristics in wave t, including the child gender, child age (in months) dummies, and maternal age dummies at birth. δ_c is the cohort fixed effects, capturing potential cohort trends in Y_{iftc}. ϵ_{iftc} denotes the standard error clustered at the family-by-wave level.

The key variable of interest, $RelatBirthOrder_{ift}$ is the relative birth order, proposed by Ejrnæs and Pörtner (2004). It is defined as follows:

$$RelatBirthOrder_{ift} = (r_{ift} - 1)/(N_{ft} - 1), \tag{4.2}$$

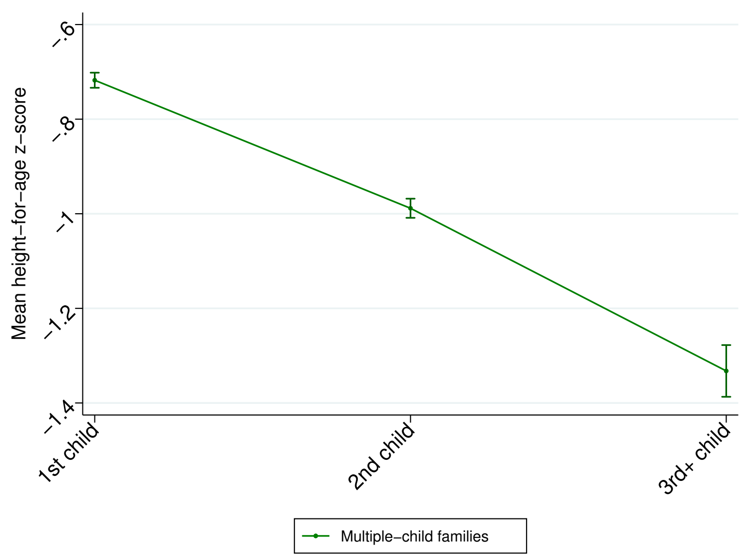
where N_{ft} is the total number of children in the family f in the wave t. r_{ift} is the absolute birth order of child i, taking on the values 1, 2, 3, ..., N_{ft}. The relative birth order monotonically increases with r_{ift}. In particular, it is zero for the first-born and one for the last-born. Intuitively, the coefficient of $RelatBirthOrder_{ift}$, α_1, measures the birth order differences between the first- and the last-born within a family. Compared with the birth order dummies, the relative birth order has two main virtues. On the one hand, it indicates the "relative position" of a child within the family. For example, the relative birth order of the second-born child in a two- and three-child family is 1 and 0.5, respectively. Second, the primary problem of using the birth order dummies is that most variations are driven by larger families (Ejrnæs and Pörtner, 2004). However, using the relative birth order in Eq. (4.2) sufficiently decreases the positive correlation between family size and birth order (from 0.56 with birth order dummies to 0.05 with relative birth order), hence purging family size from birth order.

Notably, if no additional restrictions are imposed, the coefficient of the relative birth order (α_1) in Eq. (4.1) should be considered transitory birth order effects. If the family has not completed fertility, the family size will change, and so will the relative birth order of the non-first-born children. By contrast, if parents have reached their desired fertility and will no longer have another baby, the relative birth order for existing children remains constant. In this case, the coefficient α_1 captures non-transitory birth order effects. In the subsequent analysis, two approaches will be used to estimate non-transitory birth order effects.

To ensure causal inference for birth order effects, the key identifying assumption underlying

Eq. (4.1) is that parents predetermine their family size, or at least the outcomes of existing children do not influence their fertility.[31] However, this assumption may not hold if, for instance, parents follow the "optimal stopping" rule. An optimal stopping behavior predicts that parents would stop having more children if they had a particularly difficult child. This behavior would cause fertility to be endogenous to the skills of existing children, thus leading to selection bias. If optimal stopping behavior is present, we would observe a negative correlation between child health and birth order, even in the absence of causal birth order effects. In the next section, we will examine the upper bound of the potential bias by assuming that all families adopt the optimal stopping rule.

5 Birth Order Effects on Health



Notes: The figure plots the HFA z-score for children aged 0–17 in rural multiple-child families by birth order. The point markers denote the means of the HFA. The whiskers represent the upper and lower 95% confidence intervals for the means. (*Data source: CFPS, waves 2010, 2012, 2014, 2016, and 2018.*)

Figure 2. Child Height by Child's Birth Order

In Figure 2, we plot the mean of HFA z-score by birth order for children from multiple-child families in rural China. Notably, the average HFA z-score is less than zero in each parity, which suggests that rural Chinese children have a disadvantage in nutrition status compared with the WHO reference groups. It also shows that the health outcome decreases with birth order; in other words, there is a negative birth order gradient.

Table 3 examines the negative birth order gradient in the regression using Eq. (4.1). Compared

[31] As suggested by Black et al. (2018), this identifying assumption is implicitly imposed by all other birth order empirical studies.

with the first child, the HFA z-score of the last child is, on average, 0.52 standard deviations smaller (column (1)). In column (2), we use birth order dummies, following a few previous birth order studies (e.g., Black et al. (2005); Lehmann et al. (2018); Jayachandran and Pande (2017)). Compared with firstborns, the HFA z-score of secondborns is, on average, 0.49 standard deviation lower. The disadvantage in HFA z-score intensifies for third-born or higher-order children, with a difference of 0.82 standard deviations lower than that of firstborns.

Table 3. Effect of Birth Order on Child Outcomes

Outcome variables	HFA z-score					WFA z-score	Stunted	Under-weight
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Relative birth order	-0.520***		-0.207***	-0.534***	-0.421***	-0.359***	0.076***	0.055***
	(0.058)		(0.078)	(0.059)	(0.076)	(0.065)	(0.014)	(0.015)
2nd child		-0.489***						
		(0.052)						
3rd+ child		-0.819***						
		(0.089)						
Average of the outcome variable	-0.879	-0.879	-0.848	-0.860	-0.921	-0.341	0.242	0.126
Observations	15,172	15,172	7,295	13,966	7,894	8,257	15,172	8,257
Adj.R^2	0.394	0.395	0.380	0.392	0.424	0.430	0.329	0.298
Family-by-wave FE	✓	✓	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓	✓	✓
Subsample								
Completed-fertility			✓					
1st-born child$<$ 18 years old				✓				
Intact family					✓			

Notes: All regressions control for dummies of child age, child gender, and dummies of maternal age at childbirth. The HFA z-score (for children aged 0–17 years) represents the height-for-age z-score of a child. Stunted is defined as having an HFA z-score< -2. The WFA z-score (for children aged 0–10) represents the weight-for-age z-score of a child. Underweight is defined as having a WFA z-score< -2. Column (3) focuses on children whose mother is older than 35 years. Column (4) focuses on families whose first-born child is not older than 18 years. Column (5) focuses on children whose parents are in their first marriage. Standard errors are clustered at the family-by-wave level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: CFPS, waves 2010, 2012, 2014, 2016, and 2018.*)

Endogeneity Concerns.—As discussed in Section 4.3, an optimal stopping behavior can lead to a spurious correlation between birth order and child health. Borrowing from Black et al. (2018), we now attempt to bound the potential selection bias induced by parents' optimal stopping behavior.[32] We assume that rural families in China have a desired family size of two[33] and that they follow the optimal stopping rule, meaning they would stop having additional children if the first child is problematic. Under the assumption that there is no birth order effect, we randomly draw hypothetical outcomes for "missing" second-born children from the set of realized outcomes of

[32]Employing the US data, Pavan (2016) uses a structural model approach to examine the optimal stopping behavior and finds no such evidence.

[33]According to CFPS 2018, about 80% of rural families have more than one child and more than 75% of the rural multiple-child families have exactly two children.

all first-born children (including those in single-child families and the first-born in multiple-child families).[34] We then incorporate these hypothetical children into the observed sample of first- and second-born children to estimate birth order effects in a family-by-wave fixed-effect model. We repeat this process 1,000 times and obtain average point estimates and standard errors (see Appendix B for more details).

As sensitive checks, we relax the assumption that all parents predetermine to have two children. First, due to biological reasons, the probability of having a child decreases with maternal age. Following Black et al. (2018), we draw the hypothetical second children based on human reproductive probabilities at different ages (Eijkemans et al., 2014). Second, given the OCP and son preference in China, the number of missing second-born children is restricted by both age-specific reproductive probabilities and the gender of the first-born. Third, we run a probit model on a series of family characteristics. This model predicts the probability of having multiple children for each family based on various factors, such as parental education, the gender of the first child, and mother's birth cohort.

Under the assumption of no birth order effects, the relative birth order effects decrease by approximately 50 % for the HFA z-score (Appendix Table A2). This finding implies that the analysis may, to some extent, overstate birth order effects if all families obey the optimal stopping rule. Despite this result, more than half of the estimated birth order effects remain when the "hypothetical" second-born children are simulated. Therefore, a substantial proportion of the negative birth order effects should not be driven by a "bad draw," which is worth probing into.

Non-transitory Relative Birth Order Effects.—We employ two methods to estimate the non-transitory relative birth order effects. We first construct an approximate completed-fertility subsample by restricting mothers to be older than 35 years.[35] By focusing on older mothers who are less likely to have additional children, the family size is close to its final size, and the relative birth order is approximately time-invariant. Column (3) of Table 3 reports the result for this subsample, showing that the relative birth order effect is about –0.2 significant at the 1% level.

[34]Specifically, to ensure sufficient observations in each stratum, we divide families into 16 strata, defined by the interaction between the mother's birth cohort (two classes: in or before 1979 and after 1979), mother's highest educational level (two classes: junior high school or below; senior high school or above), family income (two classes: below median or above median), and maternal age at first childbirth (two classes: at or below 23 and above 23).

[35]See Footnote 29 for the justification.

Table 4. Effect of Birth Order on Child Health
(An Overarching Plan for Resource Allocation)

Outcome variable:	HFA z-score	
	(1)	(2)
Observed relative birth order (2010)	-0.423***	
	(0.154)	
Expected relative birth order (2018)		-0.367**
		(0.156)
Average of the outcome variable	-1.298	-1.298
Proportion of having new children (2010–18)	0.055	0.055
Family-by-wave FE	✓	✓
Cohort FE	✓	✓
Number of clusters	1,147	1,147
Observations	2,445	2,445
Adj.R^2	0.337	0.336

Notes: The table uses a sample in CFPS 2010, that also participate CFPS 2018. All regressions control for dummies of child age, child gender, and dummies of maternal age at childbirth. The observed and expected relative birth orders are defined as $(r-1)/(N^{2010})$ and $(r-1)/(N^{2018})$, respectively. N^{2010} and N^{2018} are the family sizes in 2010 and 2018, respectively. Standard errors are clustered at the family-by-wave level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: CFPS 2010.*)

The second method is to construct the "ex-ante" (or expected) relative birth order. Given that the identification assumption of Eq. (4.1) is that parents make a forward-looking fertility decision, they may invest in existing children following an overarching plan. This means that parents will adjust the relative position of existing children according to the expected relative birth order.[36] Exploiting the panel structure of CFPS, we use a sample in 2010 from our pooled cross-sectional data set and only include children who were also interviewed in 2018.[37] Define N^t as the number of children in a family in wave t. Then the observed and expected relative birth orders are defined as $(r-1)/(N^{2010})$ and $(r-1)/(N^{2018})$, respectively. Given that parents' expected fertility is unavailable in the survey, N^{2018} is approximately treated as the intended or long-run fertility. The results are presented in Table 4. As can be seen, both the observed and expected relative birth order effects are significantly negative. However, the coefficient of the expected relative birth order effect displays a modest decrease in magnitude compared to the observed relative birth order effect. This shrinkage in birth order difference seems reasonable. If parents pursue a forward-looking investment strategy, they will maximize their total discounted life-cycle utility derived from family consumption and child human capital. Parents could possibly gain more

[36] To understand the "observed" and "expected" relative birth order measures, consider the following example. A household currently has two children. Then the "observed" relative birth order for the first- and the second-born child are 0 and 1, respectively. Suppose parents decide to have three children and adopt an overarching intrahousehold resource-allocation plan. In that case, they will invest in the first- and the second-born child as if their relative birth orders are 0 and 0.5, respectively, which are referred to as the "expected" relative birth order.

[37] This leaves us with 2445 children from 1,147 families. About 5.6% of these families have new children between 2010–2018.

utility if health inequality between siblings is smaller.

Alternative Subsamples and Other Health Outcomes.—We next report additional robustness checks in Table 3. By construction, children who are no less than 18 years are excluded from the main sample. In column (4), we limit the sample to families where the eldest children are less than 18 years old, ensuring that existing children in a family are included as far as possible. The estimated relative birth order effect remains largely unchanged, compared with the baseline result in column (1).

Compared to the earlier-born child, a later-born child is more likely to experience the broken marriage of parents during early childhood, which turns out to be a critical stage for human capital development. In column (5), we focus on an intact-family subsample where both father and mother are in their first marriage. The estimated relative birth order effect is -0.42, slightly smaller in magnitude than the baseline estimation. It implies that even if the potential channel of a broken family is cut off, a large fraction of birth order effects remains.

We then turn to consider other health outcomes in Table 3. In column (6), another anthropometric measure, WFA z-score is tested for children aged 0–10 years. The results show that the last-born children have a disadvantage of approximately 0.36 standard deviations in WFA than the first-born child. In columns (7) and (8), we examine being stunted and underweight, respectively, which are important indicators of child malnutrition and, hence, of policy relevance. We predict positive birth order effects since these two indexes are negative health outcomes. The results indicate that the last-born children are about 8% more likely to be stunted and 6% more likely to be underweight, both statistically significant at the 1% level.

Clustering Standard Errors at Various Levels.—In the main specification Eq. (4.1), we assume the same families in different waves are different and cluster the standard errors at the family-by-wave level. We now relax this specification and cluster the standard errors in alternative ways, as reported in Appendix Table A3. In column (1), the standard errors are allowed to be serially correlated within the same family across different years. Clustering the standard errors at the family level results in an estimate of 0.092, which is slightly larger than those clustered at the family-by-wave level (i.e., column (1) in Table 3). In column (2), we allow the standard errors to be correlated within the prefecture where the families live and, hence, the standard errors are clustered at the prefecture level. It is important to note that the observations in column (2) are smaller than those in column (1), so the standard errors in these two columns are not directly comparable. However, the key finding is that the negative birth order effects on child health remain statistically significant regardless of how the standard errors are clustered.

6 Examining the Model: Why Do Birth Order Differences Arise?

6.1 Construction of Quantitative Measures of Son Preference and OCP Enforcement

Before proceeding to test the predictions derived from the theoretical model, it is necessary to introduce how to quantitatively measure son preference and the enforcement of the One-Child Policy (OCP). In this study, we create prefecture-level measurements for son preference and OCP enforcement, respectively.

6.1.1 The Enforcement of OCP

We construct a quantitative indicator of local OCP enforcement intensity, drawing inspiration from the pioneering work of Li and Zhang (2017). Using the China 1982 census, Li and Zhang (2017) develop a prefecture-level measure called the excess fertility rate (EFR), which captures the number of excess births to Han women relative to the "one-child" rule. They then regress EFR on a set of prefecture-level socioeconomic characteristics. The remaining residual after these controls is considered as a proxy measuring the exogenous local policy stringency of OCP. Zhang (2017) use the same approach to estimate the effect of OCP on family outcomes.

Similar to Li and Zhang (2017), we exclude minority women from the sample since they were normally allowed to have two or more children. We also exclude women from Xinjiang and Tibet because these regions had different OCP enforcement and economic conditions than other regions. However, unlike Li and Zhang (2017), we use the China 2000 census, which was conducted in October 2000, to compute the excess fertility for Han women above the *local birth quotas* (which can be greater than one).[38]

The localization of OCP in China began in 1984 and the regulations in local areas stabilized in the 1990s. Each province implemented its own birth control regulations, which varied across rural and urban areas and across regions. For urban residents, they were allowed to have at most one child. For rural residents, there are three types of fertility policies (Gu et al., 2007). The three types of fertility policies are as follows. (1) One-child policy in six provinces: a quota 1, including Beijing, Tianjin, Shanghai, Chongqing, Jiangsu, and Sichuan. (2) 1.5-child policy in 19 provinces: a quota of 1 if the first child is a boy and two otherwise. (3) Two-child policy in four provinces: a quota of 2, including Hainan, Ningxia, Qinghai, and Yunnan.

[38] By contrast, Li and Zhang (2017) use the China 1982 census and restrict the birth quota in all prefectures to be 1.

Table 5. Summary Statistics of Quantitative Measures for OCP Enforcement and Son Preference

	N	Mean	Std.	Min.	Max.
Panel A: The enforcement of OCP					
China 2000 census					
Residual of EFR	316	0.000	0.008	-0.016	0.040
Strict region	316	0.560	0.497	0.000	1.000
CFPS sample					
Residual of EFR	119	0.001	0.008	-0.014	0.040
Strict region	119	0.471	0.501	0.000	1.000
Panel B: Son preference					
China 2000 census					
Residual of sex ratio	307	-0.156	12.396	-31.029	44.396
HSP region	307	0.476	0.500	0.000	1.000
CFPS sample					
Residual of sex ratio	119	0.680	11.176	-21.558	44.396
HSP region	119	0.479	0.502	0.000	1.000

Data sources: China population census 2000; CFPS 2010, 2012, 2014, 2016, and 2018.

Using region-specific and *hukou*-specific birth quotas, we calculate the EFR corresponding to the most recent fertility policies in the years around 2000, during which the majority of childbirth of my sample were affected. Formally, we compute EFR for Han woman i aged 25–44 from prefecture j in 2000 with the following equation:

$$EFR_j^{2000} = \frac{\sum_i (Birth_{ij} \cdot \mathbb{1}_{(NSC_{ij} > Quota_{ij})})}{\sum_i \mathbb{1}_{(NSC_{ij} \geq 1)} - \sum_i (Birth_{ij} \cdot \mathbb{1}_{(NSC_{ij}=1)})}, \tag{6.1}$$

where $Birth_{ij}$ is a dummy indicator for whether a woman gave birth between November 1999 and October 2000, NSC_{ij} represents her number of surviving children by the end of October 2000, and $Quota_{ij}$ denotes birth quota for Han women i in prefecture j. By construction, the nominator in Eq. (6.1) captures the number of excess births in prefecture j by the end of October 2000. The denominator in Eq. (6.1) captures the number of women at a potential risk of violating the OCP in November 1999. We then regress the EFR on a large set of control variables. The control variables contain fertility preferences and socioeconomic characteristics used by Li and Zhang (2017) and Zhang (2017).[39] In addition, we control for the sex ratio of the 1970–1979 cohort. Intuitively, parents with son preference may be motivated to have excess fertility to have sons. Hence, it is necessary to control for the son preference index. One may be concerned that China's "Later,

[39] These control variables include shares of females in different age groups (25–29, 30–34, 35–39, 40–44 years), shares of agricultural *hukou* among adults aged 25–44 years by gender, shares of each education level category among adults aged 25–44 years by gender, shares of households with access to tap water, shares with electric or gas fuel, shares with concrete or brick households, mother's age at first birth, the first child's age, and the average number of children of women aged 45–54 years. To capture fertility preferences before the OCP, the average number of children of women aged 45–54 years is computed using the China 1982 census.

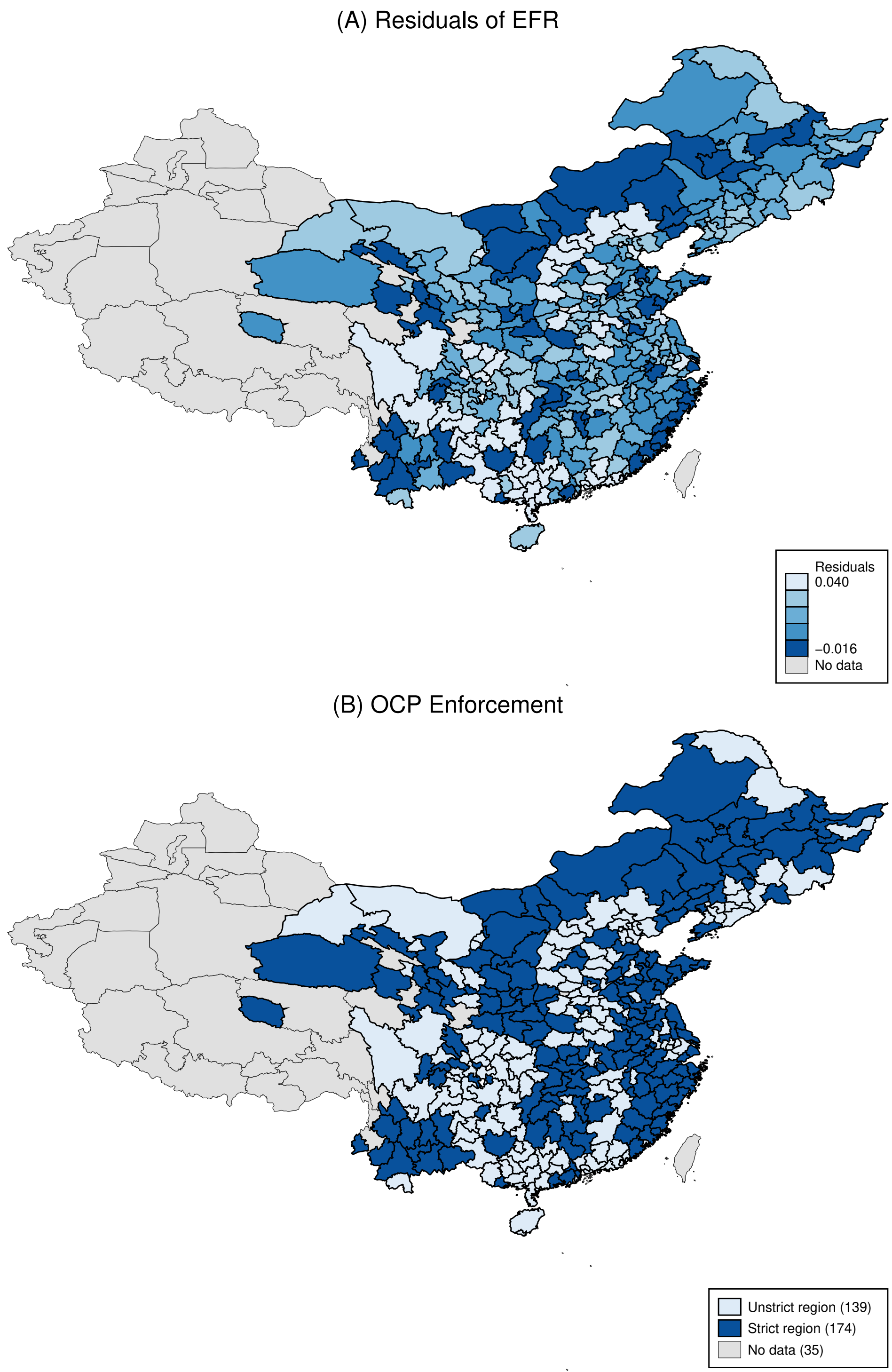
Longer, Fewer" campaign in the 1970s may have led to a contemporaneous increase in the sex ratio. However, Chen and Huang (2018) find that the "Later, Longer, Fewer" campaign has a null effect on the sex ratio. Thus, the sex ratio of the 1970–1979 cohort can be a proxy for son preference before the OCP implementation. By netting out all the controls mentioned above, we obtain the EFR residual, which measures the stringency in the OCP enforcement at the prefecture level. Among the prefectures in the CFPS analysis sample, the EFR residual has a mean of 0.001 and a standard deviation of 0.008, which are quite similar to those of prefectures in the China 2000 census (Panel A of Table 5).

Following Li and Zhang (2017), we define an indicator, "*Strict region*", to measure the stringency of local OCP enforcement. This indicator takes the value of 1 if a prefecture has negative EFR residuals (indicating stricter enforcement) and 0 otherwise. The prefecture-level EFR residuals and "*Strict region*" dummies are visualized in Figure 3.

6.1.2 Son Preference

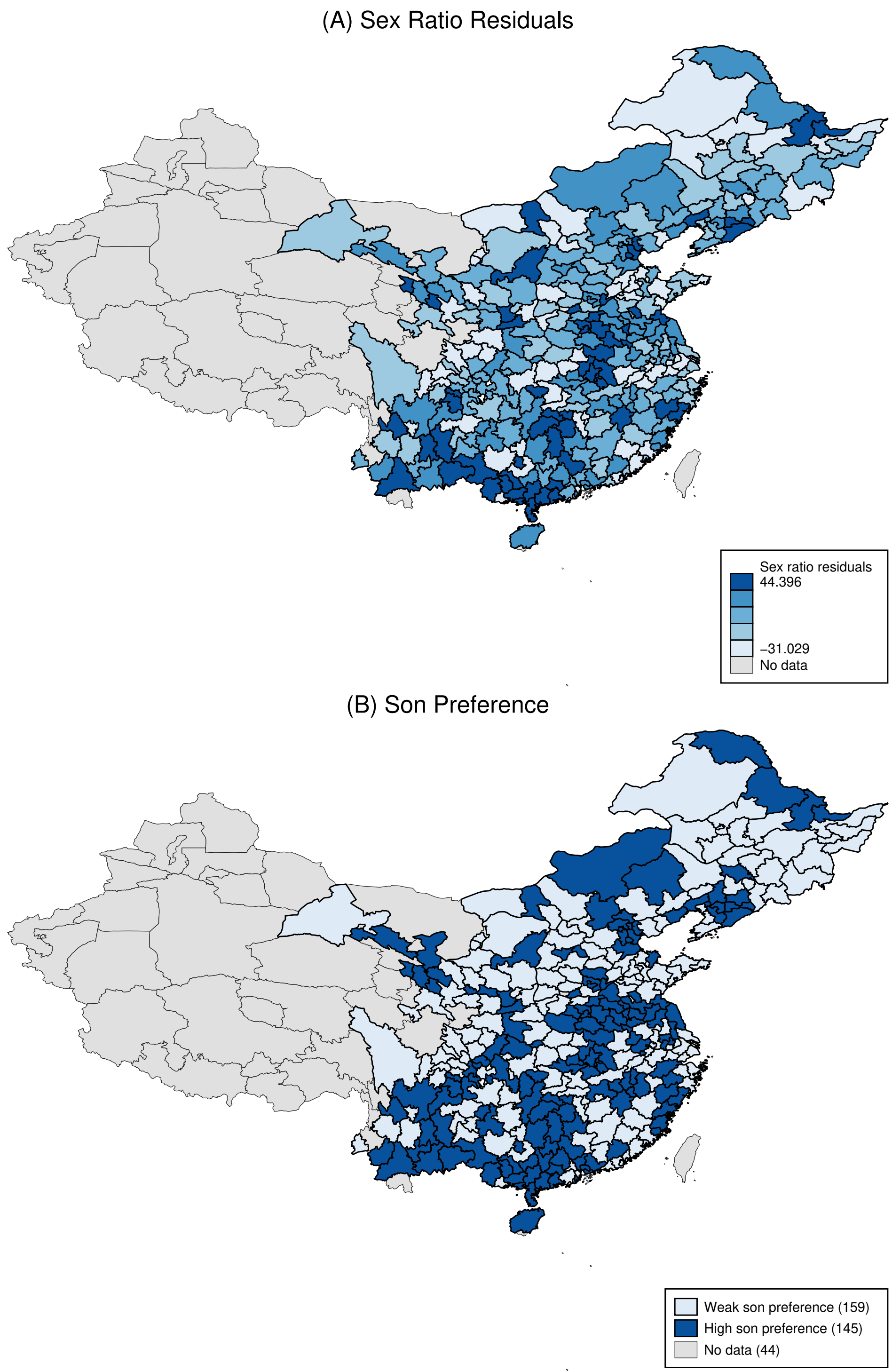
What follows is creating a new measurement to quantify son preference. In a similar spirit of the EFR residual, we first compute the sex ratio (i.e., the ratio of males to females) for the children born to Han women in 1996–2000 using data from the China 2000 census. Note that we keep using the sample of children born to Han women, in order to construct a sample comparable to the EFR analysis. To net out the potential confounders correlated with both sex ratio and son preference, we regress the sex ratio (SR) on a set of prefecture-level fertility and socioeconomic control variables as what we do for obtaining the EFR residuals (see Footnote 39). We additionally control for prefecture-level fertility fines, measured in years of household income, which are drawn from Ebenstein (2010). Controlling for fertility fines is important because regions with higher fines tend to have higher sex ratios, as shown by Ebenstein (2010). However, a higher sex ratio does not necessarily indicate a stronger son preference. Consider two regions with the same preference for sons. Parents who live in the region exposed to a stricter OCP regulation (i.e., with higher fines) will have more incentives to use sex selection to have boys. Hence, the region with more rigorous OCP enforcement can have a higher sex ratio than the other one.

After netting out these control variables, we obtain the residual of sex ratio for each prefecture. The average sex ratio residual in the CFPS analysis sample is 0.97, with a standard deviation of 11.22, similar to that in the China 2000 census (Panel B of Table 5). A prefecture is regarded as a high-son-preference (HSP) region if the sex ratio residual is positive, and as a low-son-preference (LSP) region if the sex ratio residual is negative. The sex ratio residual and the son preference indicator are presented in Figure 4.



Notes: EFR is computed using the data from the China 2000 census. A strict region is a prefecture with a negative EFR residual. A non-strict region is a prefecture with a positive EFR residual. A darker blue color denotes regions with a stricter level of OCP enforcement.

Figure 3. EFR and OCP Enforcement



Notes: The sex ratio is computed for 1996–2000 cohort in the China 2000 census. The high-son-preference region is defined as a prefecture with a positive sex ratio residual. The low-son-preference region is defined as a prefecture with a negative sex ratio residual. A darker blue color denotes regions with higher son preferences.

Figure 4. Sex Ratio and Son Preference

6.2 Results

6.2.1 Results on the First Stage (Fertility Decisions)

We first report the results on testing the predictions for the first stage (i.e., Hypotheses 1–2), which imply that there are selection issues related to son preferences and OCP enforcement.

Fertility Decisions and Son Preference.—The results are reported in Table 6. First, we examine the full rural sample, including one- and multiple-child families. Column (1) of Panel A shows that, on average, families in HSP regions earn less than those in LSP regions, with a difference of approximately 400 RMB. However, in multiple-child families, parents in HSP regions earn 343 RMB more (column (4) of Panel A) and have 0.3 more years of education (column (4) of Panel B). In other words, in HSP regions, positive selection occurs in multiple-child families, that is, parents who earn more income are more likely to violate the fertility policy and have multiple children. These results align with the prediction of Proposition 4.

Table 6. Social Economic Status by Son Preference

	One-child and multiple-child families			Multiple-child families		
	Diff	HSP region	LSP region	Diff	HSP region	LSP region
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Family income						
Family income	-399.877***	5667.593	6067.470	343.219***	5103.636	4760.418
	(64.619)			(120.589)		
Number of families		9,480	9,491		1,887	1,732
Panel B: Parental education						
Parental education	-0.003	7.991	7.994	0.331***	7.815	7.485
	(0.049)			(0.104)		
Number of families		10,990	10,941		2,178	2,021

Notes: The full sample refers to all rural families in CFPS, including one- and multiple-child families. Our analysis sample is restricted to multiple-child rural families, the same as the sample in Table 8. Robust standard errors are shown in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: CFPS, waves 2010, 2012, 2014, 2016, and 2018.*)

Fertility Decisions and OCP Enforcement.—Turning to OCP enforcement (Table 7), we find negative selections in terms of multiple-child families in strict regions. Specifically, in the full sample of rural households (i.e., one- and multiple-child families), those in strict regions earn a higher income by 126 RMB and are not less educated than those in non-strict regions (Panel A). However, in the analysis sample, the multiple-child rural families in strict regions experience a decrease of 0.2 schooling years and earn 241 RMB less than their counterparts in non-strict regions (Panel B). It suggests that with the more stringent enforcement of OCP, poorer and less educated parents are selected to have multiple children.

Table 7. Social Economic Status by OCP Enforcement

	One-child and multiple-child families			Multiple-child families		
	Diff	Strict region	Unstrict region	Diff	Strict region	Unstrict region
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Family income						
Family income	125.721*	5932.818	5807.097	-241.432**	4796.079	5037.511
	(64.721)			(122.715)		
Number of families		9,137	9,834		1,471	2,148
Panel B: Parental education						
Parental education	0.029	8.008	7.978	-0.194*	7.541	7.736
	(0.049)			(0.106)		
Number of families		10,633	11,298		1,716	2,483

Notes: The full sample refers to all rural families in CFPS, including one- and multiple-child families. Our analysis sample is restricted to multiple-child rural families, which is the same as the sample in Table 8. Robust standard errors are shown in parenthesis * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: CFPS, waves 2010, 2012, 2014, 2016, and 2018.*)

6.2.2 Results on the Second Stage (Investment Decisions)

Moving on to the investigation of how birth order effects change with family income and the analysis of predictions for the second stage, the results are presented in Table 8. Column (1) displays the baseline estimations for birth order effects, corresponding to column (1) of Table 3.

Gender-specific Birth Order Gradients.—We start by estimating the gender-specific birth order gradients by narrowing down the sample to families with only boys and those with only girls. As shown in column (2) of Table 8, the birth order gradient of girls is on average –0.64. The coefficient of the interaction between relative birth order and gender is the key of interest, which tests whether the birth order gradient is stronger among girls or boys. The coefficient of the interaction term is close to zero and statistically insignificant, which suggests that boys and girls have a similar birth order gradient. This supports the prediction in Corollary 2 and also accords with the empirical findings in India (Jayachandran and Pande, 2017) and Mexico (Esposito et al., 2020).

How Birth Order Effects Change with Income?—CFPS only asks for respondents' income in the year prior to the survey year. However, income usually fluctuates annually due to labor market conditions and economic situations. Therefore, we compute the average family income from 2010 up to the current year of the survey wave. The calculation is done by using the family income per capita reported in at least two waves of CFPS.[40] In column (3) of Table 8, we interact relative birth

[40]We do not use total family income since it is closely related to the number of people who have a job in a family.

order with the log of income (demeaned by the log of the sample mean). In column (4), relative birth order is interacted with a dummy variable that equals 1 if the mean income is above the median of the sample mean income.[41] The results show that the negative birth order effects on HFA are more substantial in poorer families. Furthermore, we consider birth spacing as an alternative measurement. If a family is closely spaced, parents may not accumulate ample resources before the next child is born, thereby creating a binding constraint and amplifying the negative birth order effects. We test this hypothesis by interacting relative birth order with a family's mean birth spacing (in years). Note that our fixed effects model already captures family-specific factors that may affect average birth spacing. As shown in column (5), the effect of birth order on the HFA z-score is more pronounced in families with closer birth spacing.

Overall, the birth order effect becomes smaller (in magnitude) in richer families. According to Proposition 3 (ii), it suggests that the efficiency factor in the early stage a_1 is larger than that in the later stage a_2.

Birth Order Effects and Son Preference.—We then examine how son preference affects birth order effects on HFA z-score. The sample is restricted to children whose mother is Han women because the proxy of son preference is only constructed for this particular population. In column (6) of Table 8, we use the raw sex ratio to proxy son preference and interact relative birth order with the *High sex ratio* dummy. The *High sex ratio* of a prefecture is equal to 1 if the sex ratio of children born in 1996–2000 is higher than the median across the country. The coefficient of the interaction is about 0.16, statistically significant at the 5% level. In column (7), we use the *HSP region* indicator constructed in Section 6.1 as a more exogenous proxy for son preference. The coefficient of the interaction between relative birth order and the *HSP region* indicator further increases to 0.23, statistically significant at the 1% level. This result shows that the birth order effect in HSP regions is smaller (in magnitude) than that in LSP regions, consistent with Proposition 3 (i).

[41] In columns (3) and (4), we exclude the 2010 sample because it is impossible to calculate mean income for families in 2010 using their previous income reported in at least two waves.

Table 8. How Birth Order Effects Change with Gender, Income, Son Preference, and OCP Enforcement

Outcome variable	HFA *z*-score								
	Baseline	Gender	Family income			Son preference		OCP enforcement	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Relative birth order	-0.520***	-0.639***	-0.552***	-0.619***	-0.599***	-0.497***	-0.505***	-0.357***	-0.329***
	(0.058)	(0.106)	(0.069)	(0.077)	(0.059)	(0.086)	(0.078)	(0.074)	(0.074)
Girl × RBO		0.048							
		(0.101)							
Log(income) × RBO			0.205***						
			(0.056)						
High-income family × RBO				0.150**					
				(0.066)					
Mean birth spacing × RBO					0.094***				
					(0.020)				
High sex ratio × RBO						0.157**			
						(0.071)			
HSP region × RBO							0.232***		
							(0.067)		
High fertility fines × RBO								-0.092	
								(0.077)	
Strict region × RBO									-0.144**
									(0.066)
Average of the outcome variable	-0.879	-0.782	-0.763	-0.763	-0.879	-0.939	-0.939	-0.939	-0.939
Family-by-wave FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Control variabls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	15,172	4,749	9,968	9,968	15,172	8,784	8,784	8,784	8,784
Adj.R^2	0.394	0.407	0.407	0.406	0.396	0.427	0.428	0.426	0.427

Notes: RBO is short for "relative birth order." The sample is rural children aged 0–18 from multiple-child families. The HFA *z*-score and stunted index are calculated for children aged 0–18 years. Income is defined as the average of income per capita (10,000 RMB, trimmed at the 1% level and defined in 2010 RMB) of the family from 2010 to the current year, calculated with at least two waves of family income and defined in 2010 RMB. Log(income) is demeaned by the log of sample mean income. A family is considered rich if its mean income is above the median of the analysis sample. *High sex ratio* is an indicator variable that equals to 1 if the sex ratio of children born in 1996–2000 in the prefecture is higher than the median level across the country. *High fertility fines* is an indicator variable that equals 1 if the fertility fine in the prefecture (drawn from Ebenstein (2010)) is higher than the median level across the country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the family-by-wave level and shown in parentheses. (*Data source: CFPS, waves 2010, 2012, 2014, 2016, and 2018.*)

Birth Order Effects and OCP Enforcement.—Finally, we focus on children whose mothers are Han women and investigate how birth order effects change with the intensity of OCP enforcement. In column (8) of Table 8, we interact the relative birth order with the *High fertility fines* dummy. The *High fertility fines* dummy is equal to 1 if two conditions are met: firstly, the fertility fines in a prefecture are higher than the national median, and secondly, the family is ineligible for multiple-child births. This finding aligns with the concerns raised by Zhang (2017). In particular, the use of fertility fines as an exogenous measure for OCP enforcement can be problematic because the fines set by the local government are based on fertility demand and financial situations. In column (9), we use the quantitative measures, *Strict region*, constructed in Section 6.1. The coefficient of the interaction between relative birth order and *Strict region* is –0.144, statistically significant at the 5% level. It shows that birth order effects are more prominent in strict regions than in non-strict regions, which is consistent with the finding that in strict regions, poor families are more likely to have multiple children (Table 7) and that birth order effects are stronger in poorer families (columns (3)–(5) of Table 8).

7 Conclusion

Children's health and nutrition status play a crucial role in human capital development and benefit the individual throughout life. Child health is not only treated as one of the essential and basic needs for child development, but is also important in acquiring adult health, cognitive skills, educational attainment, labor market outcomes, and socioeconomic status (e.g., Behrman and Rosenzweig, 2004; Case et al., 2005; Black et al., 2007; Black et al., 2015; Parman, 2015).

This study focuses on child health in rural China. We try to understand why birth order effects arise and how birth order effects on child health interact with son preference and the enforcement of OCP. To reveal the mechanism behind birth order effects, we develop an intrahousehold resource allocation model that considers fertility and investment decisions. The model generates a number of predictions on how son preference and the enforcement of OCP affect fertility decisions and birth order effects.

Using a nationally representative data set in China, we find a negative birth order effect on HFA z-score for children under 18 years. Consistent with the implications of the theoretical model, we observe the following main findings. 1) The negative birth order effect on height-for-age (HFA) z-score is lower (in magnitude) in high-income families than in low-income families, which, according to the model's implication, suggests that the early stage of skill formation plays a more important role in human capital. 2) Son preference can affect fertility decisions and birth order effects. In regions with stronger son preference, richer families are more likely to have two children. Birth order effects are less prominent in HSP regions than in LSP regions. 3) The enforcement of OCP can also affect fertility decisions and have an indirect impact on birth order effects. In regions with more strict enforcement of OCP, poorer families are more likely to have two children. The birth order effects in stricter regions are more prominent in less strict regions.

This paper generates important implications for intrahousehold resource allocation by showing how parental fertility decisions and birth order effects interact with the cultural norm of son preferences and the OCP in China. It can also provide important insights for countries that also have gender preferences and population control policies.

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A Complementary Tables

Table A1. Summary Statistics by Child Numbers

	Multiple-child Family	One-child Family	Diff
	(1)	(2)	(2)−(1)
Panel A: Child outcomes			
Girl	0.485	0.418	-0.0667***
	(0.003)	(0.005)	(0.0060)
Age of child	9.470	6.627	-2.8427***
	(0.033)	(0.054)	(0.0624)
HFA *z*-score	-0.860	-0.543	0.3178***
	(0.013)	(0.022)	(0.0250)
Stunted	0.230	0.198	-0.0319***
	(0.003)	(0.004)	(0.0055)
WFA *z*-score	-0.333	0.034	0.3666***
	(0.014)	(0.018)	(0.0228)
Underweight	0.127	0.071	-0.0558***
	(0.003)	(0.003)	(0.0047)
Panel B: Household characteristics			
Age of father	39.235	32.752	-6.4821***
	(0.060)	(0.071)	(0.0936)
Age of mother	37.373	30.631	-6.7426***
	(0.059)	(0.067)	(0.0904)
At least one parent is minority	0.151	0.156	0.0049
	(0.003)	(0.005)	(0.0058)
Mean parental schooling years	6.754	8.775	2.0210***
	(0.028)	(0.032)	(0.0434)
Maternal age at first birth	23.166	24.003	0.8371***
	(0.028)	(0.037)	(0.0456)
Family income (RMB)	5315.937	7048.894	1732.9568***
	(36.554)	(56.075)	(64.0318)

Notes: The sample is rural children aged 0–17 from either one-child families or multiple-child families. The sample of multiple-child families here is not exactly the same as the analysis sample in the main text, since the former may include children who are the only one in the multiple-child family with non-missing characteristics. The HFA z-score and stunted index are calculated for children aged 0–18. The WFA z-score and underweight index are calculated for children aged 0–10. Income variables are trimmed at 1% level and defined in 2010 RMB. Standard deviations are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are shown in parentheses. (*Data source: CFPS, waves 2010, 2012, 2014, 2016, and 2018.*)

Table A2. Simulating "Missing" Second-born Children

	Observed children	Simulating missing second-born children			
		Simulating all missing children	Simulating children likely to be missing		
	(1)	(2)	(3)	(4)	(5)
Relative birth order	-0.542***	-0.235**	-0.248***	-0.307***	-0.268***
	(0.061)	(0.035)	(0.036)	(0.038)	(0.037)
N	12,932	28,546	27,215	21,885	22,931

Notes: The sample is restricted to the first-born and second-born children in all rural families (the explicit restriction is that first-born children in the family should be younger than 18 years old). All regressions control for family-by-wave fixed effects (γ_{ft}), dummies of child age, dummies of childbirth year, child gender, and dummies of maternal age at childbirth. Column (1) shows the birth order effect of being the second-born children in the observed data (i.e., in multiple-child families). In columns (2)–(3), information on "missing" second-born children in one-child families is randomly drawn from the distribution of all first-born children, within a given strata defined by the interaction between mother's birth cohort (2 classes: in or before 1979, after 1979), mother's highest educational level (3 classes: junior high school or below, college or above), family income (2 classes: below or above median), and maternal age at first childbirth (23 or below, above 23). Columns (2)–(5) show the point estimators, the standard deviation of the point estimators, and average sample sizes for 1000 repetitions. Column (3) considers women's age-specific fertility. Column (4) considers the gender of the first-born as well as women's age-specific fertility. Column (5) uses the probit model to predict the probability of having multiple children in one-child families. For more about this table, see the description in Appendix B. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: CFPS, waves 2010, 2012, 2014, 2016, and 2018.*)

Table A3. Cluster Standard Errors at Different Levels

Outcome variables	HFA z-score	
Standard errors clustered by	Family	Prefecture
	(1)	(2)
Relative birth order	-0.520***	-0.513***
	(0.092)	(0.061)
Average of the outcome variable	-0.879	-0.911
Family-by-wave FE	✓	✓
Cohort FE	✓	✓
Observations	15,172	14,300
Adj.R^2	0.394	0.401

Notes: In column (1), the standard errors are clustered at the family level. In column (2), the standard errors are clustered at the prefecture level. The prefecture information is missing for some families, so the sample size in column (2) is smaller than that in column (1). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.(*Data source: CFPS, waves 2010, 2012, 2014, 2016, and 2018.*)

Table A4. Family Income in Periods 1–3

	t=1 (Early stage of child 1)	t=2 (Early stage of child 2)	t=3 (Late stage of child 2)
(Age of mother)	27-29	30-32	33-35
Total family income	31,496.89	31,065.64	27,651.79
Family income per capita	5123.98	5,165.55	5,057.17

Notes: The sample is restricted to rural families with multiple children. Income is adjusted in 2010 RMB. (*Data source: CFPS, waves 2010, 2012, 2014, 2016, and 2018.*)

Table A5. Endowment and Birth Order Effect

	Fetal age	Prematurity	Birth weight	Normal birth weight or not
	(1)	(2)	(3)	(4)
Relative birth order	-0.017	0.008	0.017	-0.012
	(0.016)	(0.007)	(0.015)	(0.010)
Average of the outcome variable	9.320	0.041	3.195	0.909
Family-by-wave FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Maternal age at childbirth	✓	✓	✓	✓
Observations	16,297	16,297	14,127	14,127
Adj.R^2	0.461	0.221	0.469	0.170

Notes: The sample is rural children aged 0–17 from either one-child families or multiple-child families. Prematurity is a dummy variable that equals one if fetal age is less than nine months. Normal birth weight is a dummy variable that equals one if birth weight is between 2.5 kg and 4 kg. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the family-by-wave level and shown in parentheses. (*Data source: CFPS, waves 2010, 2012, 2014, 2016, and 2018.*)

B Endogenous Concerns Induced by "Optimal Stopping Rule"

The main idea of simulating "missing" second-born children is borrowed from Black et al. (2018). If we assume all parents follow the "optimal stopping" rule, we should observe no birth order effects in the simulation. We attempt to find the upper bound of the selection bias induced by the original assumption that fertility is not endogenous to children's realized outcomes. The following steps are taken.

We first randomly draw a hypothetical second-born child for those single-child families. Specifically, families are divided into 16 strata, which is defined by the interaction between the mother's birth cohort (two classes: in or before 1979, after 1979), the mother's highest educational level (two classes: junior high school or below; senior high school or above), family income (two classes: below the median or above median), and maternal age at first childbirth (two classes: at or below 23 and above 23). Each stratum should include sufficient observations (at least 100 observations). For each single-child family, we randomly draw outcomes from the pool of all first-born children (including the one-child and multiple-child families) in their own strata.

Other information needed to draw for the hypothetical children includes gender, child age, and mother's age at childbirth. Likewise, these are drawn from the corresponding strata. Child gender is randomly chosen from the gender of the first-born. We then randomly choose a birth spacing between the first-born and the second-born children in the strata. Using the birth spacing, we can compute child age and maternal age at childbirth.

Then we combine the "real" children (i.e., the first- and second-born children from multiple-children families and the first-born children in one-child families) and the hypothetical children (the second-born children in one-child families) to make up the total sample. We run regressions to estimate birth order effects comparing the first- and the second-born children.

We repeat the above procedure 1000 times and obtain the point estimator of birth order effects and the standard error. The findings are reported in Appendix Table A2. Column (2) presents the baseline results.

We develop a series of sensitive checks by restricting the number of missing children in different ways. First, the possibility of having children may decrease with the mother's age. Following Black et al. (2018), we consider women's age-specific fertility (drawn from Eijkemans et al. (2014)) in column (3). The OCP may also affect parents' fertility decisions. For example, the 1.5 child policy specifies that rural parents can have another child if the first-born is a girl. Indeed, families in China whose first-born children are girls are more likely to have multiple children. We compute the probability of having a second child given the gender of the first-born, using CFPS 2018. Combining this probability with the human productive probability, we then restrict the missing number of children in column (4).

We also run a probit regression to predict the probability of having multiple children.

$$multi\_child_f = b_0 + \boldsymbol{X_f b_1} + \nu_p + \epsilon_f,$$

where $\boldsymbol{X_f}$ is a vector of time-invariant characteristics in family f. It contains a dummy variable that indicates whether the first-born child is a boy, the mean educational years of parents, dummies of maternal age at first childbirth, and dummies of the mother's birth year. ν_p is the province fixed effect. $multi\_child_f$ is a dummy equal to one if the family has more than one child. We first run the probit model for all mothers in CFPS 2018 and obtain the coefficients to predict the probability of having more than one child for single-child families. We then draw the hypothetical second children based on this computed probability and report the average point estimates in column (5).

Comparing the results of observed children (columns (1)) and simulating missing children (columns (2)–(5)), we can see that relative birth order effects drop by around 50% for the HFA z-score.

C A Model Without Credit Constraints

In the absence of credit constraints, parents are allowed to borrow and save. At $t = 1$, they decide how to distribute family income to consumption, child investment, and assets/debts in all three periods. The intertemporal budget constraint is given by:

$$c_1 + c_2 + c_3 + I_{1,1} + I_{2,1} + I_{1,2} + I_{2,2} = \overline{Y}. \tag{C.1}$$

where $\overline{Y}$ denotes exogenous life-time family income. Given that the intertemporal discount factor β is equal to 1, Eq. (C.1) implicitly assumes that the gross interest rate R equals to one. In Appendix D.1, we show that the conclusion in this subsection still holds if R and β are not restricted to be one, as long as the product of R and β is equal to one.

Therefore, in two-child families allowing unrestricted allocations, parents' optimization problem is characterized as:

$$\begin{aligned}
\max_{c_1,c_2,c_3,I_{1,1},I_{1,2},I_{2,1},I_{2,2}} \quad & \mathrm{U}_2 = log(c_1) + log(c_2) + log(c_3) + \delta[log(h_1) + log(h_2)] \\
\text{s.t.} \quad & c_1 + c_2 + c_3 + I_{1,1} + I_{2,1} + I_{1,2} + I_{2,2} = \overline{Y} \\
& h_i = h_{i,0}(a_1 + I_{i,1})(a_2 + I_{i,1}), \quad i \in \{1, 2\}.
\end{aligned} \tag{M5}$$

Taking first order conditions, we can derive the optimal consumption and human capital investment in each period as follows (indexed with *):

$$
\begin{aligned}
c_1^* = c_2^* = c_3^* &= \frac{1}{\lambda} \\
I_{1,1}^* = I_{2,1}^* &= \frac{\delta - \lambda a_1}{\lambda} \\
I_{1,2}^* = I_{2,2}^* &= \frac{\delta - \lambda a_2}{\lambda},
\end{aligned}
$$

where λ is the Lagrangian multiplier of the intertemporal budget constraint. Using Eq. (3.4), the adult health of child 1 and 2 can be solved as follows:

$$
\begin{aligned}
h_1^* &= h_{1,0} \frac{\delta^2}{\lambda^2}. \\
h_2^* &= h_{2,0} \frac{\delta^2}{\lambda^2}.
\end{aligned}
$$

As a result, the ratio of optimal adult health is expressed as:

$$
\frac{h_1^*}{h_2^*} = \frac{h_{1,0}}{h_{2,0}}. \tag{C.2}
$$

This model predicts that in the absence of credit constraints, parents can make intertemporal trade-offs and allocate family resources across different periods, which allows them to smooth consumption and invest in child 1 and child 2 equally in the early and late stages, respectively. Therefore, Eq. (C.2) implies that birth order effects depends on the relative size of birth endowment of child 1 and child 2. If $h_{1,0}$>$h_{2,0}$, child 1 has a better outcome and there are negative birth order effects. If $h_{1,0}$<$h_{2,0}$, child 2 has a better outcome and there are positive birth order effects. If $h_{1,0}$=$h_{2,0}$, two children have the same adult health and no birth order differences.

D Discussion on Some General Cases

In this section, we discuss some general cases by relaxing assumptions in models where parents display equal concern.

D.1 Relaxing the Assumption that the Discount Factor is 1

D.1.1 (1) A Model Without Credit Constraints

In a model without credit constraints, assume the discount factor β belongs to $(0,1]$ and the gross interest rate R is no less than 1. Then parents' optimization problem is expressed as follows:

$$\max_{c_1,c_2,c_3,I_{1,1},I_{1,2},I_{2,1},I_{2,2}} \quad U_2 = log(c_1) + \beta log(c_2) + \beta^2 log(c_3) + \delta[\beta log(h_1) + \beta^2 log(h_2)]$$
$$\text{s.t.} \quad c_1 + \frac{c_2}{R} + \frac{c_3}{R^2} + I_{1,1} + \frac{I_{1,2}+I_{2,1}}{R} + \frac{I_{2,2}}{R^2} = \overline{Y}$$
$$h_i = h_{i,0}(a_1 + I_{i,1})(a_2 + I_{i,2}), \quad i \in \{1,2\}.$$

The optimal investments satisfy the following first-order conditions:

$$I^*_{1,1} = \frac{\delta\beta - \lambda a_1}{\lambda} \tag{D.1a}$$
$$I^*_{1,2} = \frac{\delta\beta R - \lambda a_2}{\lambda} \tag{D.1b}$$
$$I^*_{2,1} = \frac{\delta\beta^2 R - \lambda a_1}{\lambda} \tag{D.1c}$$
$$I^*_{2,2} = \frac{\delta\beta^2 R - \lambda a_2}{\lambda}. \tag{D.1d}$$

where λ is the Lagrangian multiplier of the intertemporal budget constraint. Using Eqs. (D.1a)–(D.1d), we can derive optimal h_1^* and h_2^* and hence

$$\frac{h_1^*}{h_2^*} = \frac{h_{1,0}}{h_{2,0}} \frac{1}{\beta^2 R^2}.$$

If $\beta R = 1$, we have:

$$\frac{h_1^*}{h_2^*} = \frac{h_{1,0}}{h_{2,0}} \tag{D.2a}$$
$$c_1^* = c_2^* = c_3^* = 1/\lambda. \tag{D.2b}$$

As implied by Eqs. (D.2a) and (D.2b), in the absence of credit constraints, as long as $\beta R = 1$, the ratio of children's adult health is equal to the ratio of their birth endowments and the family has smooth consumption.

D.1.2 (2) A Model Ruling Out Saving and Borrowing

In a model with credit constraints, assume that the discount factor β belongs to $(0, 1]$. Parents' optimization problem is expressed as:

$$\begin{aligned}
\max_{c_1,c_2,c_3,I_{1,1},I_{1,2},I_{2,1},I_{2,2}} \quad & U_2 = log(c_1) + \beta log(c_2) + \beta^2 log(c_3) + \delta[\beta log(h_1) + \beta^2 log(h_2)] \\
\text{s.t.} \quad & c_1 + I_{1,1} = Y_1 \\
& c_2 + I_{1,2} + I_{2,1} = Y_2 \\
& c_3 + I_{2,2} = Y_3 \\
& h_i = h_{i,0}(a_1 + I_{i,1})(a_2 + I_{i,2}), \quad i \in \{1, 2\}.
\end{aligned}$$

By solving the first-order conditions, we can derive the ratio of h_1^* to h_2^*:

$$\frac{h_1^*}{h_2^*} = \frac{h_{1,0}}{h_{2,0}} \frac{1+\delta}{1+\delta\beta} \frac{Y_1 + a_1}{Y_3 + a_2}. \tag{D.3}$$

Eq. (D.3) implies that the relative size of h_1^* and h_2^* depends on the value of the discount factor β, the relative size of birth endowments, the relative size of family income in the first and the third periods, and the relative size of the efficiency factors a_1 and a_2.

To discuss birth order effects, consider a case where there is no heterogeneity by birth endowments ($h_{1,0} = h_{2,0}$) and family income is constant ($Y_1 = Y_2 = Y_3 = Y$). Eq. (D.3) can be expressed as follows:

$$\frac{h_1^*}{h_2^*} = \frac{1+\delta}{1+\delta\beta} \frac{Y + a_1}{Y + a_2}.$$

Then the birth order effect is determined by the discount factor β and the relative size of the efficiency factors a_1 and a_2:

$$\begin{cases}
\text{If } a_1 > a_2, \text{ then } \frac{h_1^*}{h_2^*} > 1, \\
\text{If } a_1 = a_2 \text{ and } \beta = 1, \text{ then } \frac{h_1^*}{h_2^*} = 1, \\
\text{If } a_1 = a_2 \text{ and } 0 < \beta < 1, \text{ then } \frac{h_1^*}{h_2^*} > 1, \\
\text{If } a_1 < a_2 \text{ and } \beta = 1, \text{ then } \frac{h_1^*}{h_2^*} < 1, \\
\text{If } a_1 < a_2 \text{ and } \overline{\beta} < \beta < 1, \text{ then } \frac{h_1^*}{h_2^*} < 1, \\
\text{If } a_1 < a_2 \text{ and } \beta = \overline{\beta}, \text{ then } \frac{h_1^*}{h_2^*} = 1, \\
\text{If } a_1 < a_2 \text{ and } 0 < \beta < \overline{\beta}, \text{ then } \frac{h_1^*}{h_2^*} > 1,
\end{cases}$$

where $\overline{\beta}$ is defined as $\frac{Y+a_1}{Y+a_2} + \frac{a_1-a_2}{\delta(Y+a_2)}$. Under the assumption of $a_1 < a_2$ and $\delta(Y + a_1) + a_1 - a_2 > 0$, we have $\overline{\beta} \in (0, 1)$.

D.2 Allowing a More Flexible Function of Skill Formation

Consider a model ruling out saving and borrowing.[42] By allowing both the efficiency factors and investments in early and late stages have different productivity, the skill formation function can be represented as:

$$h_i = h_{i,0}(b_1 + b_3 I_{i,1})(b_2 + b_4 I_{i,1}). \tag{D.4}$$

Then parents' optimization problem is characterized as:

$$\begin{aligned}
\max_{c_1,c_2,I_{1,1},I_{1,2},I_{2,1},I_{2,2}} \quad & \text{U}_2 = log(c_1) + \beta log(c_2) + \beta^2 log(c_3) + \delta[\beta log(h_1) + \beta^2 log(h_2)] \\
\text{s.t.} \quad & c_1 + I_{1,1} = Y \\
& c_2 + I_{1,2} + I_{2,1} = Y \\
& c_3 + I_{2,2} = Y \\
& h_i = h_{i,0}(b_1 + b_3 I_{i,1})(b_2 + b_4 I_{i,1}), \quad i \in \{1,2\}.
\end{aligned} \tag{*}$$

Equivalently, we can write Eq. (D.4) as

$$h_i = h_{i,0} b_3 b_4 (\frac{b_1}{b_3} + I_{i,1})(\frac{b_2}{b_4} + I_{i,1}).$$

If we define $a_1 = \frac{b_1}{b_3}$ and $a_2 = \frac{b_2}{b_4} + I_{i,1}$, then parents' optimization problem can be expressed as:

$$\begin{aligned}
\max_{c_1,c_2,I_{1,1},I_{1,2},I_{2,1},I_{2,2}} \quad & \text{U}_2 = log(c_1) + \beta log(c_2) + \beta^2 log(c_3) + \delta[\beta log(h_1) + \beta^2 log(h_2)] \\
\text{s.t.} \quad & c_1 + I_{1,1} = Y \\
& c_2 + I_{1,2} + I_{2,1} = Y \\
& c_3 + I_{2,2} = Y \\
& h_i = h_{i,0}(a_1 + I_{i,1})(a_2 + I_{i,1}), \quad i \in \{1,2\}.
\end{aligned} \tag{**}$$

It is easy to show that the optimization problems (*) and (**) is equivalent and hence have the same solutions.

E Derivation of Important Expressions and Proof of Propositions

We will next show how to derive some important expressions and how to prove propositions in the extended model in Section 3.2

[42] The proof for models without credit constraints is similar.

E.1 Son Preference without Gender Control

In a model ruling out saving and borrowing, assume that parents display son preference and introduce the fertility restriction policy. Parents have to pay fines if they have an unauthorized birth. Sex selection technology is not available. Therefore, different from Eq. (3.8), there is no gender control cost ϕp in period 2. Parents' optimization problem is expressed as:

$$\begin{aligned}
\max_{c_1,c_2,I_{1,1},I_{1,2},I_{2,1},I_{2,2}} \quad & \mathrm{U}_2 = log(c_1) + log(c_2) + log(c_3) + \delta[\omega_1 log(h_1) + \omega_2 log(h_2)] \\
\text{s.t.} \quad & c_1 + I_{1,1} = Y \\
& c_2 + I_{1,2} + I_{2,1} = Y - g(d, Y) \\
& c_3 + I_{2,2} = Y \\
& h_i = (a_1 + I_{i,1})(a_2 + I_{i,2}), \quad i \in \{1, 2\},
\end{aligned}$$

where $\omega_i = \frac{1+\phi}{2+\phi}$ if child i is a boy, $\omega_i = \frac{1}{2+\phi}$ if child i is a girl, $i = 1, 2$.

We can derive the same expression of $\frac{h_1^*}{h_2^*}$ as the case where sex selection is available. Specifically, we have:

$$\frac{h_1^*}{h_2^*} = \rho_1(\phi)\frac{Y + a_1}{Y + a_2}, \tag{3.9}$$

where $\rho_1(\phi) = (\frac{\omega_1}{\omega_2})^2 \frac{1+\omega_2\delta}{1+\omega_1\delta}$, $\omega_i = \frac{1+\phi}{2+\phi}$ if child i is a boy, $\omega_i = \frac{1}{2+\phi}$ if child i is a girl ($i = 1, 2$).

Following the definition in Section 3.2, we have:

$$\begin{aligned}
H(\text{boy, boy}) &= \frac{Y + a_1}{Y + a_2} \\
H(\text{boy, girl}) &= (1+\phi)^2 \frac{2 + \phi + \delta}{2 + \phi + \delta(1+\phi)} \frac{Y + a_1}{Y + a_2} \\
H(\text{girl, boy}) &= \left[(1+\phi)^2 \frac{2 + \phi + \delta}{2 + \phi + \delta(1+\phi)}\right]^{-1} \frac{Y + a_1}{Y + a_2} \\
H(\text{girl, girl}) &= \frac{Y + a_1}{Y + a_2}.
\end{aligned} \tag{E.1}$$

Since no sex selection technology, the probability of each type of gender composition is the same and equals to 1/4:

$$P(\text{boy, boy}) = P(\text{boy, girl}) = P(\text{girl, boy}) = P(\text{girl, girl}) = \frac{1}{4}.$$

Thus, the expectation of birth order effects $E^N(\frac{h_1}{h_2})$, where N indexed for no sex selection, is expressed as:

$$
\begin{aligned}
E^N(\frac{h_1^*}{h_2^*}) =& P(\text{boy, boy}) \cdot H(\text{boy, boy}) + P(\text{boy, girl}) \cdot H(\text{boy, girl}) \\
&+ P(\text{girl, boy}) \cdot H(\text{girl, boy}) + P(\text{girl, girl}) \cdot H(\text{girl, girl}) \\
=& \rho_3(\phi)\frac{Y+a_1}{Y+a_2},
\end{aligned}
$$

where $\rho_3(\phi) = \frac{1}{4}\left[2 + (1+\phi)^2\frac{2+\phi+\delta}{2+\phi+\delta(1+\phi)} + \left((1+\phi)^2\frac{2+\phi+\delta}{2+\phi+\delta(1+\phi)}\right)^{-1}\right]$. It is easy to show that $\rho_3(\phi)$ is increasing in ϕ.

Therefore, we have:

$$
\begin{cases}
\text{If } \phi = 0, \text{ then } E^N(\frac{h_1^*}{h_2^*}) = \frac{Y+a_1}{Y+a_2} \\
\text{If } 0 < \phi \leq 1, \text{ then } E^N(\frac{h_1^*}{h_2^*}) > \frac{Y+a_1}{Y+a_2}.
\end{cases}
\tag{E.2}
$$

Eq. (E.2) suggests that when parents have son preference ($0 < \phi \leq 1$) without gender control, the expected ratio of h_1^* to h_2^* is always greater than that when parents display equal concern.

E.2 Derivation of Eq. (3.12)

Since no gender selection for the first child, the probability of the first child to be a boy is 0.5 and the probability of the first child to be a girl is 0.5. Since parents with son preference ϕ will use sex selection with an effort ϕ for the second child, the probability of the second child to be a boy is $0.5 + 0.5\phi$, while the probability of the second child to be a girl is $0.5 - 0.5\phi$. Since family size is assumed to be predetermined in the first stage, it is plausible to assume that genders of child 1 and child 2 are independent. Therefore, we have:

$$
\begin{cases}
P(\text{boy, boy}) = 0.5(0.5 + 0.5\phi) \\
P(\text{boy, girl}) = 0.5(0.5 - 0.5\phi) \\
P(\text{girl, boy}) = 0.5(0.5 + 0.5\phi) \\
P(\text{girl, girl}) = 0.5(0.5 - 0.5\phi).
\end{cases}
\tag{E.3}
$$

The expressions of $H(\tau_1, \tau_2)$ are the same as Eq. (E.1). Inserting (E.3) and (E.1), we can derive Eq. (3.12).

E.3 Proof of Proposition 3

(i) Take the derivative of $E^S(\frac{h_1^*}{h_2^*})$ with respect to Y:

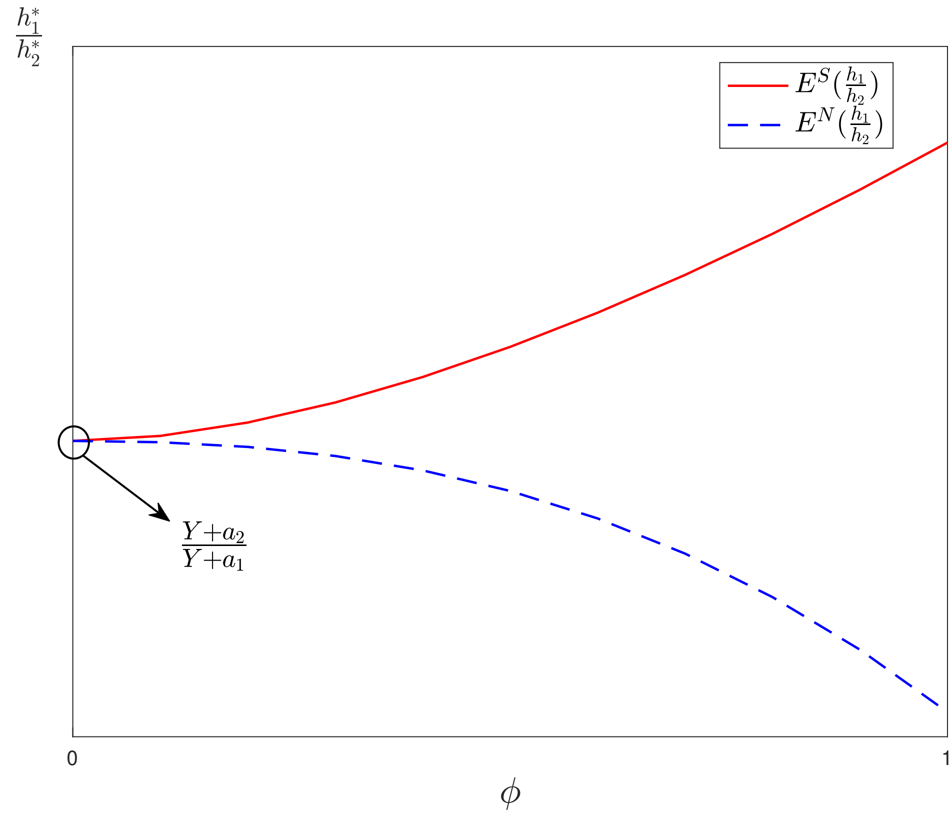
$$\frac{\partial E^S(\frac{h_1^*}{h_2^*})}{\partial Y} = -m(\phi)(a_1 - a_2)\frac{1}{(Y+a_2)^2}.$$

If $a_1 > a_2$, then $\frac{\partial E^S(\frac{h_1^*}{h_2^*})}{\partial Y} < 0$. If $\frac{\partial E^S(\frac{h_1^*}{h_2^*})}{\partial Y} < 0$, then $a_1 > a_2$.
Therefore, $a_1 > a_2 \iff \frac{\partial E^S(h_1^*/h_2^*)}{\partial Y} < 0$.
Likewise, we can show that $a_1 = a_2 \iff \frac{\partial E^S(h_1^*/h_2^*)}{\partial Y} = 0$, $a_1 < a_2 \iff \frac{\partial E^S(h_1^*/h_2^*)}{\partial Y} > 0$.

(ii) Since $\frac{\partial E^S(h_1^*/h_2^*)}{\partial \phi} < 0$, $E^S(h_1^*/h_2^*)$ is decreasing in son preference ϕ. Therefore, we have:

$$\begin{cases} \text{If } \phi = 0, \text{ then } E^S(\frac{h_1^*}{h_2^*}) = \frac{Y+a_1}{Y+a_2} \\ \text{If } 0 < \phi \leq 1, \text{ then } E^S(\frac{h_1^*}{h_2^*}) < \frac{Y+a_1}{Y+a_2}. \end{cases} \tag{E.4}$$

This implies that when parents have son preference ($0 < \phi \leq 1$) with sex selection technology, the expected ratio of h_1^* to h_2^* is always smaller than that when parents display equal concern.



Notes: EFR is computed using the China 2000 census. A strict region is a prefecture with a negative EFR residual. A non-strict region is a prefecture with a positive EFR residual. Darker blue denotes a stricter level of OCP enforcement.

Figure E1. EFR and OCP Enforcement

The interesting results implied in Eqs. (E.2) and (E.4) can be visualized in Figure E1. Given that parents have son preference ($0 < \phi \leq 1$), the ratio of h_1^* to h_2^* is always larger when sex selection technology is not available. The difference between $E^S(\frac{h_1^*}{h_2^*})$ and $E^N(\frac{h_1^*}{h_2^*})$ increases with son preference ϕ.

E.4 Proof of Proposition 4

$$\begin{aligned} S &= E(\mathrm{U}_2^*) - E(\mathrm{U}_1^*) + \eta \\ &= (1 + 1/2\delta)log(Y + a_1) + (1 + 1/2\delta + \frac{\phi^2\delta}{2(2+\phi)})log(Y - g(d, Y) - \phi p + a_1 + a_2) \\ &- (1 + 1/2\delta + \frac{\phi^2\delta}{2(2+\phi)})log(Y - \phi p + a_1) - log(Y) + k(\phi) + \eta \end{aligned} \tag{E.5}$$

where $k(\phi) = \phi/2(1 + \delta\omega_b)log(1 + \delta\omega_b) - \phi/2(1 + \delta\omega_g)log(1 + \delta\omega_g) + \delta\omega_b log(\delta\omega_b) + \delta\omega_g log(\delta\omega_g) - 1/4(1 + \phi)(1 + 2\delta\omega_b)log(1 + 2\delta\omega_b) - 1/4(1 - \phi)(1 + 2\delta\omega_g)log(1 + 2\delta\omega_g) - 1/2(1 + \delta)log(1 + \delta)$.

Therefore, we have:

$$\frac{\partial^2 S}{\partial d \partial Y} = -(1+\delta+\frac{\phi^2\delta}{2(2+\phi)})\frac{\frac{\partial^2 g}{\partial d\partial Y}(Y-g(d,Y)-\phi p+a_1+a_2)-\frac{\partial f}{\partial d}(1-\frac{\partial f}{\partial Y})}{(Y-g(d,Y)-\phi p+a_1+a_2)^2}$$

Given that $\frac{\partial^2 g}{\partial d\partial Y}>0$, $\frac{f}{d}>0$, and $0<\frac{\partial f}{\partial Y}<1$, the sign of $\frac{\partial^2 S}{\partial d\partial Y}$ is uncertain. Under the condition that $(Y-\phi p+a_2)(1-\frac{\partial g(d,Y)}{\partial Y})-(Y-g(d,Y)-\phi p+a_1+a_2)\geq 0$, $\frac{\partial^2 S}{\partial \phi\partial Y}>0$.

E.5 Proof of Proposition 5

Using Eq. (E.5), we can derive

$$\begin{aligned}\frac{\partial^2 S}{\partial \phi\partial Y} =&\frac{\delta\phi(\phi+4)}{2(2+\phi)^2}\frac{(Y-\phi p+a_1)(1-\frac{\partial g}{\partial Y})-(Y-g(d,Y)-\phi p+a_1+a_2)}{(Y-g(d,Y)-\phi p+a_1+a_2)(Y-\phi p+a_1)}\\ &+p\left[\frac{(1+\delta+\frac{\delta\phi^2}{2(2+\phi)})}{(Y-g(d,Y)-\phi p+a_1+a_2)^2}-\frac{1+\delta/2+\frac{\delta\phi^2}{2(2+\phi)}}{(Y-\phi p+a_1)^2}\right]\end{aligned} \tag{E.6}$$

which has an uncertain sign.

Claim: If $(Y-\phi p+a_1)(1-\frac{\partial g(d,Y)}{\partial Y})-(Y-g(d,Y)-\phi p+a_1+a_2)\geq 0$, then $\frac{\partial^2 S}{\partial \phi\partial Y}>0$.

Proof:

If $(Y-\phi p+a_1)(1-\frac{\partial g(d,Y)}{\partial Y})-(Y-g(d,Y)-\phi p+a_1+a_2)\geq 0$, the first term of Eq. (E.6) is positive.

Define $Y' = Y-\phi p+a_1$ and $Y'' = Y-g(d,Y)-\phi p+a_1+a_2$. Then $(Y-\phi p+a_1)(1-\frac{\partial g(d,Y)}{\partial Y})-(Y-g(d,Y)-\phi p+a_1+a_2)\geq 0$ is equivalent to $Y'(1-\frac{\partial g(d,Y)}{\partial Y})-Y''\geq 0$. It is easy to get $\frac{Y''}{Y'}\leq 1-\frac{\partial g(d,Y)}{\partial Y}<1$. Therefore, $Y''<Y'$.

The second term of Eq. (E.6) can be expressed as:

$$p\frac{(Y')^2(1+\delta+\frac{\delta\phi^2}{2(2+\phi)})(1-\frac{g(d,Y)}{\partial Y})-(Y'')^2(1+\delta/2+\frac{\delta\phi^2}{2(2+\phi)})}{(Y')^2(Y'')^2}>0.$$