Deciphering the Upward Spillover Effect of Children's Education on Parental Cognitive Aging: Evidence from the Compulsory Schooling Law in China

Zhuoer Lin[1] Xi Chen[1,2,3*]

[1]Department of Health Policy and Management, Yale School of Public Health

[2]Department of Economics, Yale University

[3]Alzheimer's Disease Research Center, Yale University

ABSTRACT

Cognitive functioning is critical to our life, health and well-being. It has proved challenging to promote cognitive health among older adults to slow down their aging process. This paper provides novel evidence on the spillover effect of increasing children's education on parents' cognitive aging and investigates changes in family caring arrangements that may explain the effect. Using multiple waves of China Health and Retirement Longitudinal Study to model trajectories of cognitive aging, and exploring temporal and geographic variations in the compulsory schooling law enforcement, we show that increases in children's education impose larger effect on reducing level of cognitive deficit among older parents than smoothing their trajectories of cognitive decline. The effect is also larger on crystal intelligence than on fluid intelligence. While both more educated and less educated children benefit parental cognitive health, they demonstrate some within-family coordination. Specifically, more educated children tend to offer older parents more resource-related support, including financial transfer, household appliances and equipment, while less educated children often engage in more time-related support, such as living relatively close to parents, providing informal care and decision-making support, not leaving grandchild care burden to parents. These findings offer insights into leveraging the intergenerational spillover effect of educational policy to delay cognitive aging and related diseases.

1. Introduction

Cognitive functioning plays a pivotal role in our daily lives, as it underpins a myriad of complex and high-stakes decisions that we must make. Enhanced cognitive health has been found to facilitate long-term savings (Smith et al., 2010), diversification of investment portfolios (Korniotis and Kumar, 2011), and a reduction in mistakes when using credit cards or applying for a home equity loans (Agarwal and Mazumder, 2013). Moreover, broader network disruption in the brain is strongly linked to risky financial mistakes in older ages (Samanez-Larkin, 2013). As cognitive aging progresses into more severe states, mild cognitive impairment or dementia can manifest, posing a substantial public health challenge in various parts of the world. Presently, more than 55 million people live with dementia worldwide (Alzheimer's Disease International, 2021). This number is surging, given the global trends of aging populations. More profoundly, dementia exerts a considerable economic burden on afflicted family and societies at large (Winblad et al., 2016), with the global cost estimated to exceed 1.3 trillion USD (Alzheimer's Disease International, 2021).

This study focuses on the upward spillover effect of children's education on older parents, for whom cognitive aging constitutes a major health threat. Few studies have delved into the intergenerational effects of children's education. Recent work has underscored that the educational attainment of offspring can have far-reaching impact on cognition of the older generation, particularly in rapidly aging societies like China, where older adults tend to have lower levels of education and are consequently at greater risk of cognitive decline (Ma 2019). However, our understanding of how children's education may impact the cognitive aging process in parents remains limited. The predominant reliance on cross-sectional or short-term longitudinal studies has hindered the investigation of the cognitive aging process itself (Ma 2019). Furthermore, without a causally designed study, the identified effects are prone to significant bias (Lee 2018).

The process of cognitive aging is influenced by a multitude of biological, social, environmental and physiological factors over the life course (Berkman et al., 2000; Berkman and Glass, 2000; Song and Lin, 2009; Winblad et al., 2016). Education, in particular, has been found to exert a substantial impact on individuals' problem-solving strategies and cognitive capacity (Ardila et al., 2010). Studies have indicated persistent links between educational attainment, cognitive function (Ardila et al., 2010; Meghir et al., 2013; Ostrosky-Solis et al., 1998) and the prevalence of dementia

(Anstey et al., 2010). Nevertheless, findings regarding the relationship between education and various dimensions of cognitive aging remain mixed (Wilson et al. 2004; Arce Rentería et al. 2019). Further research is imperative to explore their causal relationship.

This study enriches the existing literature by pinpointing the causal impact of children's education on cognitive aging *status* and *trajectories* of their parents. Using data from three waves of the China Health and Retirement Longitudinal Study (CHARLS 2011, 2013, 2015), we first decompose the longitudinal measures of cognitive function across multiple waves into two dimensions: the baseline level of cognitive deficit and the rate of cognitive decline. Subsequently, we leverage exogenous variations in timing and program intensity generated by China's Compulsory Schooling Law (CSLs) within an IV/2SLS framework. The results underscore that the increase in children's education resulting from the CSLs exerts a significant protective effect on parents' cognitive reserve and their cognitive aging trajectories. As expected, this effect is more pronounced in terms of crystal intelligence than fluid intelligence, as the latter typically experiences more rapid decline with age.

Meanwhile, this paper provides novel insights into changes in informal family arrangements that may elucidate the upward spillover effect of increasing children's education. While both more and less educated children contribute to the improved cognitive health of their parents, they manifest somewhat distinctive patterns of support within the family that deepen our understanding of sibling coordination in caring for older parents. Specifically, more educated children tend to provide older parents with greater resource-related support, encompassing financial assistance and household amenities, whereas less educated children often engage in more time-related support, such as residing in close proximity to parents, offering informal care, aiding in decision-making, and mitigating the burden of grandchild care on parents. These findings also advance the literature, which has indicated that children's education may impact the health of parents through enhanced financial supports, access to resources, heightened psychological well-being, literacy, cognitive skills, and knowledge of parents (Lee, 2018; Ma, 2019).

In developing nations like China, informal familial support has long been the most important source of help. However, as China rapidly transforms into an aging society, the trend towards smaller households, increased population mobility, and the potential weakening of kinship ties pose a threat to this tradition. Consequently, older parents may find it increasingly challenging to receive coordinated support from their adult children. At this juncture, it becomes imperative to assess the role that such coordinated intergenerational support still plays and to what extent it may function as a part of elderly support to promote healthy aging.

Furthermore, our finding of larger protective effect on parents' cognitive reserve than on their cognitive aging trajectories stresses the importance of distinguishing these two aspects. The rate of cognitive decline often serves as an early indicator of potential cognitive issues, prompting timely diagnosis and treatment, while the level of cognitive deficit largely determines the risk of being classified as cognitively impaired or even demented. Present cognitive assessments, a crucial component of dementia diagnosis, hinge on achieving a certain threshold of cognitive reserve (Winblad et al., 2016). However, individuals with lower educational attainment are more vulnerable to biases in cognitive assessment, presenting a greater challenges for dementia diagnosis, as they tend to perform worse and closer to the diagnostic threshold for dementia than those with higher cognitive skills (Huang and Zhou, 2013; Schmand et al., 1995; Stern et al., 1992; Gaugler et al., 2013; Contador et al., 2017; Arce Rentería et al., 2019). These misclassifications often lead to severe mental distress (Winblad et al., 2016), an elevated risk of suicide (Erlangsen et al., 2008), and substantial healthcare costs (Winblad et al., 2016). Our findings suggest that an increase in children's education can serve as a buffer against these risks and associated societal burdens.

Finally, these findings offer insights into harnessing the intergenerational spillover effect of educational policy to delay cognitive aging and related diseases. While literacy programs have been introduced to reduce illiteracy rates among the elderly (Arce Rentería et al., 2019), the conventional cognitive interventions for older parents may be costly and can be complemented by educational policies targeted at children, which indirectly enhance the cognitive abilities of older adults. In this context, our finding of the significant impact of children's education on parental cognitive aging presents an alternative policy avenue that warrants cost-effectiveness assessments.

The remainder of the paper is organized as follows. Section 2 introduces the Compulsory Schooling Law in China and outlines the identification strategy. Section 3 provides an overview of the data and our primary variables of interest. Section 4 specifies the model used to decompose the longitudinal cognitive measurements and presents details regarding the study sample. Section 5 presents the estimation results alongside various robustness checks and discusses the mechanisms. Section 6 offers concluding remarks and a discussion of the findings.

2. Institutional Background and Identification Strategy

2.1. The Compulsory Schooling Law in China

Since the 1980s, China has embarked on an extensive reform of its education system, driven by the goal of decentralizing free basic education and implementing nationwide nine-year compulsory education (Ming, 1986). On July 1, 1986, the Compulsory Schooling Law (CSL) was enacted, marking a pivotal moment in this educational transformation. This law extended the period of compulsory education from six years (primary school) to nine years (junior high school) across the entire country. It mandated that all children commence their education at age 6 and receive nine-year compulsory education, free of charge. Typically, a child completed this formal education by the age of 15. Consequently, the CSL mainly affected children aged 15 or younger when it came into effect (Cui et al., 2019).

Following the initiation of the reform by the central government, provincial authorities formulated comprehensive plans to advance compulsory education within their respective regions. The provisioning and financing of compulsory education were predominantly overseen by local governments. Due to variations in economic and educational resources across provinces, the enforcement of CSLs varied in terms of timing and effectiveness (Cui et al., 2019). Economically prosperous areas, such as Beijing, Zhejiang, Jiangxi, aimed to achieve universal junior secondary education by 1990 and were among the first to enforce the law (Ma, 2019; Ming, 1986). Table A1 provides information on the timing of the implementation, the year it became effective, and the birth cohort it initially impacted in each province. To address potential endogeneity issues associated with policy rollout, this study controls for province-specific fixed effects and province-cohort-specific trends, accounting for the disparities arising from provincial differences in economic and development conditions (Rosenzweig and Wolpin, 1986).

In China, the academic year commences from September and extends to the following July. Consequently, if provinces initiated the reform before September, the law's effective year is considered the same year. However, if provinces initiated the reform in or after September, it is considered the following year (Cui et al. 2019). Figure 1 provides a geographical representation of the effective years of CSLs across various provinces.

[Figure 1 about here]

2.2. Identification Strategy: Instrumental Variable (IV) Approach

In this study, we aim to quantify the causal impact of children's education on their parents' cognitive outcomes, considering both the highest-educated children and the lowest-educated children within each family. In empirical terms, if children's education is uncorrelated with omitted factors in the error term, we can directly estimate the causal effects of children's education on parents' cognitive outcomes using linear regression (OLS). The model can be expressed as follows:

$$Y_i = \beta_0 + \beta_1 ChildEdu_{ipk} + \beta_3 X_i + \lambda_p + \theta_k + Trend_{pk} + \omega_t + u_i \tag{1}$$

In this equation, Y_i represents the cognitive outcomes of individual i. $ChildEdu_{ipk}$ denotes the education level of individual i's child born in province p in year k. The parameter of interest is β_1, which captures the effect of children's education on parents' cognitive outcomes. The vector X_i comprises observed characteristics of the individual, the child's characteristics, and regional factors such as the regional average educational level before the enforcement of CSLs. The λ_p terms are province fixed effects, which account for all time-invariant differences across provinces, while θ_k represents birth cohort fixed effects, addressing unobserved heterogeneity across cohorts. Additionally, $Trend_{pk}$ accounts for province-cohort-specific trends; and ω_t are survey wave fixed effects, accommodating heterogeneity in cognitive measurements across different waves.

However, the OLS approach may yield biased estimates of β_1 because the error term u_i could include unobserved omitted variables that are correlated with both parental outcomes and children's education. To tackle this endogeneity issue related to education, we adopt an Instrumental Variables (IV) approach by exploiting the temporal and geographical variations in the CSLs in China. These variations offer exogenous sources of changes in children's education (Duflo, 2001; Kemptner et al., 2011; Lundborg and Majlesi, 2018). Following the approaches of Huang (2015) and Ma (2019), we utilize two instruments that respectively capture within-cohort and across-cohort variations in the timing of law enforcement, as well as program intensity and law effectiveness across provinces and regions. Ma (2019) demonstrates that the effects of compulsory education increase almost linearly with the years of exposure, with more pronounced effects in regions with lower educational levels.

The first instrument Exp_{ipk} is defined as a linear trend function of law exposure ranging from 0 (individuals aged 16 and above at law enforcement) to 1 (for those age 6 and below at law enforcement). Formally, it takes the following form,

$$Exp_{ipk} = \begin{cases} 0, & if\ Age\_Cohort_{ip} > 15; \\ \dfrac{(15 - Age\_Cohort_{ip}) + 1}{10}, & if\ \ 6 \leq Age\_Cohort_{ip} \leq 15; \\ 1, & if\ Age\_Cohort_{ip} < 6 \end{cases}$$

In this equation, Age_Cohort_{ip} represents the age of the child cohort i when the CSLs came into effect in province p. The first affected cohort in province p was aged 15 when the law took effect, and the fully affected cohorts were aged 6 or below when the law took effect. As shown in Figure 2, the effects of CSLs increase linearly with the years of exposure, and stabilize for cohorts fully exposed to the policy, confirming the suitability of the linear design of the exposure variable.

[Figure 2 about here]

The second instrument captures the program intensity across different areas, defined as,

$$ExpPreLaw_{ipk} = Exp_{ipk} \times PreLaw_{iph}$$

where $PreLaw_{iph}$ represents the average years of schooling for cohorts born five years or less before the first eligible cohorts, stratified by urban or rural status, in the province of birth[1]. The interaction term of the law exposure Exp_{ipk} with the regional average years of schooling $PreLaw_{iph}$ accounts for the variation in the effects of CSLs across regions with high and low educational levels. Previous work has shown that, with the same law exposure, children in areas with lower educational attainment experience greater educational gains compared to those in regions with higher educational levels (Duflo, 2001; Huang, 2015; Ma, 2019).

Within the IV/2SLS framework, we first estimate the first-stage equation, modeling the impact of CSL exposure on children's education as follows,

$$ChildEdu_{ipk} = \gamma_0 + \gamma_1 Exp_{ipk} + \gamma_2 ExpPreLaw_{ipk} + \gamma_3 X_i + \lambda_p + \theta_k + Trend_{pk} + \omega_t + \epsilon_{ipk} \tag{2}$$

Subsequently, we estimate the second-stage equation,

$$Y_i = \beta_0 + \beta_1 \widehat{ChildEdu}_{ipk} + \beta_3 X_i + \lambda_p + \theta_k + Trend_{pk} + \omega_t + u_i \tag{3}$$

where $\widehat{ChildEdu}_{ipk}$ represents the fitted value of a child's years of schooling obtained from the first-stage regression. The IV estimate of β_1 identifies the local average treatment effects of children's schooling on parents' cognitive outcomes for those children whose education was positively influenced by the CSLs (Angrist and Imbens, 1995; Imbens and Angrist, 1994). We estimate these effects separately for the highest-educated and the lowest-educated children within each family. Additionally, to shed light on the underlying mechanism, we assess the effects of children's education on the support parents receive and make intra-family comparisons. Standard errors are clustered at the household level to account for correlations within clusters.

[1] The regional average years of schooling for CSLs illegible cohorts are calculated using the population census of the people's republic of China.

3. Data and Variables

3.1 Data Sources

In this study, we draw upon data from three waves (2011, 2013, 2015) of China Health and Retirement Longitudinal Study (CHARLS), a nationally representative survey of the Chinese middle-aged and older population aged 45 and above (Zhao et al., 2013a, 2013b). As a sister study of Health and Retirement Study (HRS) in the United States, CHARLS offers comprehensive and comparable information on various aspects, including basic demographics, family information, health and functioning, health care and insurance, employment, and the household finances in China. The national baseline survey, conducted in 2011/2012, involved 17,708 participants from 10,257 households across 150 counties spanning 28 Chinese provinces (Zhao et al., 2016). Two waves of follow-up surveys were conducted in 2013 and 2015, respectively. Our analytical sample is confined to individuals aged 45 and above, with families consisting of at least two children, to examine within-family heterogeneity.

3.2 Education and Birth information of Children

Children's education is quantified in terms of completed years of formal schooling, ranging from 0 (no formal schooling) to 22 (completion of a doctoral degree). Within each family, we identify both the highest-educated children (Ma, 2019; Zimmer et al., 2007) and the lowest-educated children, matching them respectively with their parents to explore how the effects of children's education may differ based on varying levels of human capital[2].

Children's date of birth and province of birth are used to measure exposure to CSLs. As the survey did not inquire about the history of children's residence and migration, it is challenging to precisely determine where children were subject to the CSLs. Following Ma (2019), we use the province of

[2] In the baseline survey of CHARLS, data on co-residing children and non-co-residing children were collected separately through different modules. Some information about co-residing children's information was redundantly recorded across these modules without clear and definitive identifiers. This situation introduced the possibility of misinformation and data duplication when merging multiple data modules. Fortunately, this data limitation was addressed in Wave 2, where all information about children was consolidated in a single module. To ensure the accuracy of children's information, we use data from Wave 2 to construct the essential variables related to children.

birth as a proxy for the location of exposure, including only children for whom identifiable birthplace information is available.[3]

3.3 Covariates

This study controls for the sociodemographic characteristics of older parents, children's characteristics, and the regional factors. For parents, we account for age, gender, education, rural/urban hukou status (household registration), marital status, the number of dependent and independent children, the number of chronic diseases, working status and log per capita annual income. Children's characteristics encompass age, gender, marital status, working status and their living arrangement with parents before the age of 16[4]. Regional characteristics include place of residence (rural/urban), provincial per capita GDP, the number of hospital beds and doctors per 10,000 population in the child's birth year, and the average years of schooling among cohorts born five years or less before the first eligible cohort affected by CSL in children's province of birth, stratified by rural and urban status[5]. The latter captures the regional variations in the educational levels before the enforcement of CSLs (Ma, 2019).

To account for the time-invariant heterogeneity across provinces and control for unobserved factors that uniformly varied across cohorts, we introduce birth-province fixed effects and the birth-cohort fixed effects. Additionally, to address potential province-cohort-specific unobservables correlated with the timing of reform or cohort-specific trends in years of schooling, we include province-specific linear trends of birth cohorts.

3.4 Cognitive Assessment of Older Parents

---

[3] In CHARLS survey, the primary respondents from each family were queried about whether their particular child was born in the same province and county as their current residence. Approximately 94% of the sample confirmed that their children were born in their current place of residence. However, for those respondents whose children were born in a different location, they were subsequently asked to provide details about the place of birth. Unfortunately, the coding of these birthplaces is classified as confidential and cannot be identified. Consequently, we exclude children with unmatchable birthplaces and those with missing birthplace information from our analysis.

[4] To be consistent, we use data from the Wave 2 to construct these variables; and the results are fairly robust to the alternative control of baseline characteristics.

[5] The provincial per capita GDP, number of hospital beds and doctors per 10,000 population in child's birth year are obtained from National Bureau of Statistics of China. The average years of schooling of illegible cohorts are calculated using the data from the population census of China (National Bureau of Statistics of China, 2012).

Cognitive function is evaluated using five cognitive tests in the CHARLS surveys, including immediate word recall, delayed word recall, the serial 7's test (involving successive subtractions of 7 from 100), orientation tests (assessing the ability to correctly report the current date and day of the week) and picture re-drawing. These tests assess individuals' short-term and long-term memory, mathematical abilities, and orientation to one's surroundings (Ofstedal et al., 2005; Xu et al., 2015). Prior research using the Health and Retirement Study (HRS) in the U.S. has shown that a composite score derived from all five tests is associated with defining cognitive impairment (Langa et al., 2008), which has significant clinical implications (Borenstein and Mortimer, 2016). Therefore, in this paper, we initially determine individuals' cognitive status using a composite score (ranging from 0 to 30), with higher scores indicating better cognitive abilities. Subsequently, to assess cognitive deficit and facilitate modeling of the rate of change, we reverse-code the composite cognitive scale (0-30), with higher scores indicating more pronounced cognitive deficits (Xu et al., 2015). For each individual, we calculate both the average cognitive status and average cognitive deficit (reverse-coded) based on all available measurements (a minimum of two waves).

4. Cognitive Trajectories and Sample Selection

4.1 Model of Change: Linear Mixed-effect Model

Given the longitudinal nature of the CHARLS study, it is valuable to explore both the time-related constancy and changing trends in cognitive function. As individuals' cognitive function is assessed multiple times across different waves, we can identify the trajectories of change over repeated measurements. In life course research, the linear mixed-effects growth model (LMM) is regarded as a fundamental modeling technique. It enables the estimation of individual health outcome development while accounting for the correlations among repeated measures within a subject (Burton-Jeangros et al., 2015; Laird and Ware, 1982). A growing body of literature has used the linear mixed-effects model to investigate the longitudinal trajectory of cognitive decline (Hall et al., 2000; Hout et al., 2015; Wilson et al., 2011).

In this study, the linear growth model employed is presented as follows:

$$Cog_{it} = \pi_{0i} + \pi_{1i} Time_{it} + \epsilon_{it}$$

$$\pi_{0i} = \alpha_{01} + \alpha_{02}X_i + \mu_{0i} \tag{4}$$
$$\pi_{1i} = \alpha_{11} + \alpha_{12}X_i + \mu_{1i}$$

where Cog_{it} represents the composite score of cognitive deficits measured for individual i at time t. π_{0i} and π_{1i} represent the growth parameters, which stand for the intercept and slope for individual i, respectively. X_i is the covariate matrix controlling for observed characteristics that may influence these two growth parameters, including baseline age, gender, and education level (Wilson et al., 2011). In the linear mixed-effects model, two types of parameters are distinguished: the central values, which are common for a group of individuals with given characteristics ($\alpha_{01} + \alpha_{02}X_i$ and $\alpha_{11} + \alpha_{12}X_i$), called fixed effects, and individual deviations from these central values (μ_{0i} and μ_{1i}), called random effects (Burton-Jeangros et al., 2015). The fixed intercept $\alpha_{01} + \alpha_{02}X_i$ and fixed slope $\alpha_{11} + \alpha_{12}X_i$ are directly estimated by the model, while the best linear unbiased predictions of the random intercept μ_{0i} and random slope μ_{1i} are generated subsequently.

For each individual i, we obtain an intercept value π_{0i}, which defines the predicted cognitive deficit score at baseline (i.e., $time = 0$); and a slope value π_{1i}, which represents the predicted change in cognitive score per year. These individual intercept and slope values capture two distinct aspects of aging trajectories (Belsky et al., 2015), and serve as key outcomes in our analysis.

4.2 Sample Selection and Descriptive Statistics

We restrict the sample to the respondents aged 45 and older at the baseline survey, with the highest-educated children or the lowest-educated children born between 1956 and 1991, ensuring that the children were likely to have completed their education without being too old to have living parents (Huang, 2015; Ma, 2019). For modelling purposes, we further restrict the sample to respondents with at least two waves of cognitive measurements and complete background information.

Table 1 presents the summary statistics of parents. The average years of schooling for parents are 4.36. Approximately 52% of parents are female and 84% are married. The average age of parents at the baseline survey is 61, with around 84% having rural hukou. On average, parents have approximately 3.1 children. The average cognitive function score is 12.7 across all measured waves, with an average of 2.7 waves of cognitive measures.

[Table 1 about here]

Table 2 displays the characteristics of the highest-educated and lowest-educated children within a family. The highest-educated children have on average 9.7 years of schooling. Approximately 41% of the children are female, with an average age of 32. In contrast, the lowest-educated children have on average 6.8 years of schooling, with over 51% being female.

[Table 2 about here]

5. Results

5.1 First Stage Estimates

Table 3 presents the results of the first stage estimation for the IV analyses. The strength of identification is robust when both instruments are incorporated. The F statistics, as determined by the Kleibergen-Paap Wald rk test using two instruments, stand at 12.03 for the highest-educated children and 12.84 for the lowest-educated children, surpassing the weak identification threshold (i.e., 10). Moreover, both the exposure to compulsory education and its interaction term are statistically significant at the 1% level. The negative effect of the interaction term suggests that children born in lower schooling area benefit more from the policy. Overall, the average increase in education induced by CSLs is slightly higher for highest-educated children compared to the lowest-educated children (i.e., 1.24 vs 0.87 years).

[Table 3 about here]

5.2 Effects of Children's Education on Cognitive Deficit: Baseline Levels versus Trajectories

Table 4 reports the effects of children's years of schooling on parents' average cognitive deficit scores based on repeated measurements from all three waves (2011, 2013, 2015). Using the average cognitive scale (0-30), both the OLS and IV estimates are highly significant. The effects of the highest-educated children seem slightly more pronounced than those of the lowest-educated children.

[Table 4 about here]

To examine the effects of children's education on cognitive aging trajectories, the longitudinal cognitive measurements are further decomposed into two dimensions: the baseline level of cognitive deficit and the rate of decline. The effects of children's education are estimated respectively for these two cognitive aging outcomes.

Table 5 and 6 present the estimates of children's education on the baseline level of cognitive deficit and the rate of decline. Years of schooling for both the highest- and lowest-educated children are negatively and significantly associated with the baseline level of cognitive deficit, particularly for the highest-educated children. Based on IV estimates, a one-year increase in children's schooling results in a 0.64 point or 0.18 standard deviation (SD) reduction in cognitive deficit score for the highest-educated children, and a 0.55 point or 0.15 SD reduction for the lowest-educated children. This finding aligns with the results for average cognitive function, underscoring the protective effect of children's education on parents' cognitive well-being.

[Table 5 about here]

On the other hand, both the OLS and IV estimates indicate a significant causal effect of children's education on the rate of cognitive decline. We show that a one-year increase in children's education significantly decelerates parents' rate of cognitive decline, reducing it by approximately 0.07 SD per year for both the highest-educated and the lowest-educated children. The standardized effects on the rate of decline are smaller than those on parents' baseline level of cognitive deficit.

[Table 6 about here]

5.3 Mechanisms: Effects of Children's Education on Resource-related Support, Time-related Support and Comprehensive Support to Parents

Children's education can benefit parental health through various pathways. We hypothesize that, owing to their differing time and budget constraints, children with varying levels of human capital within a family may strategically coordinate to support their parents. Specifically, higher-educated children may provide more economic or resource-related support due to their better socioeconomic conditions; while lower-educated children may allocate more time to caring for their parents given their lower opportunity costs. To examine this hypothesis, we estimate the effects of children's education on their resource-related support, time-related support to parents, and compare between the highest-educated children and lowest-educated children within a family.

We find that increasing children's education has large and significant beneficial effects on time-related supports. These effects are particularly pronounced among lowest-educated children but not among highest-educated children (Figure 3). Notably, increased education among the lowest-educated children may encourage them to provide better care and support to their parents, including more anticipated informal care and assistance, as well as greater decision-making support, such as pension enrollment. Besides, increased education among lowest-educated children can also alleviate the excessive burden of grandchild care that they may otherwise impose on their parents.

Regarding resource-related support, increasing education among both the highest-educated children and lowest-educated children can improve parents' access to resources. However, a one-year increase in children's schooling among the highest-educated children may lead to greater financial transfers and net transfers received by parents from their children, while also reducing parents' transfers to their children compared to the effects observed among the lowest-educated children. These findings support our hypothesis of strategic caring arrangements and coordination among children within a family.

[Figure 3 about here]

Additionally, Figure 4 presents the results of other factors that may potentially link children's education and parental cognitive aging, involving both time and economic support, i.e., comprehensive supports. The findings are mixed, with small differences across children: the lowest-educated children tend to live closer to their parents, while the highest-educated children tend to influence more extensive use of health supplements by their parents.

[Figure 4 about here]

5.4 Robustness Checks

Several concerns regarding the validity of the results are addressed. One potential issue is the effects of children's education on parental survival, which may alter the composition of the sample to some extent. This concern is mitigated by our IV estimates presented in Table 7, which indicate that increases in children's years of schooling have no significant effect on parents' composition.

[Table 7 about here]

Another concern pertains to the confounding effects of other public policies, such as one-child policy implemented after 1978, and the new cooperative medical scheme and urban resident basic medical insurance introduced in the early 2000s. We assess the robustness of the results by controlling for the average penalty rate for an unauthorized births in each province during the year of a child's birth, which measures the differential strictness across provinces and time (Ebenstein, 2010). Table 8 Panel A reveals that the estimates are qualitatively the same as the main findings, and the inclusion of the one-child policy has minimal impact on the results. For the two social insurance programs, given the new cooperative medical schemes and urban resident medical schemes were established after 2003 and quickly rolled out over the country, the effects of these policy changes are unlikely to vary with children's exposure to CSLs (Fan et al., 2011; Ma, 2019).

To explore the sensitivity of the results to a more restricted sample, Table 8 Panel B presents the findings for models using children aged 25 or younger at the time of CSLs enforcement. The estimated effects of children's years of education are qualitatively unchanged. Moreover, we test an alternative strategy to adjust for the correlation and heteroscedasticity in standard errors. As the education policies are primarily implemented at the provincial level, and may exhibit some variation across birth cohorts, we cluster the standard errors at the province-year level. The main results remain fairly robust, as shown in Table 8 Panel C.

[Table 8 about here]

Furthermore, the interpretation of the results may be challenged, as the composite cognitive measure employed in this study could obscure the heterogeneous effects of different cognitive domains. Therefore, we re-estimate the linear mixed-effects models using mental intactness (ranging from 0 to 10) and episodic memory (ranging from 0 to 20) as outcomes, aiming to identify the causal effects of children's education on parents' cognitive aging following the same procedure. The main findings are qualitatively consistent. The IV results in Table 9 suggest that children's education significantly affect parents' baseline level of cognitive deficit as well as the rate of change, either for mental intactness (Panel A) or for episodic memory (Panel B). The effects are more pronounced on crystal intelligence (i.e., mental intactness) than on fluid intelligence (i.e., episodic memory). Additionally, in our primary analysis, we used cognitive tests from 2011 to 2015 to model the cognitive trajectory, as the cognitive assessment protocol underwent changes after 2018, resulting in impaired comparability between the 2011-2015 waves to the 2018 wave. Nevertheless, to assess the robustness of the results to trajectory modeling and the inclusion of more waves of cognitive data, we re-estimate the cognitive trajectory based on a 20-point composite score derived from cognitive tests[6] with relatively high comparability across 2011-2018. The estimates in Panel C indicate the robustness of our findings.

[Table 9 about here]

Overall, the results presented above highlight the robustness of our findings to sample selection, model specifications, and outcome measures.

[6] The 20-point cognitive scale comprises two components: immediate word recall (scored on a scale of 0-10) and mental intactness (scored on a scale of 0-10). Notably, there was a difference in the administration of the word recall test between the waves of data collection. In the 2011-2015 waves, the word recall list was read to the respondents once. However, in the 2018 wave, the word list was read to the respondents three times; once before the immediate word recall test and twice after the immediate word recall test. Consequently, this led to a significantly higher average score for delayed word recall in the 2018 wave as compared to the scores in the 2011-2015 waves.

6. Conclusion and Discussion

While adult children's education has been found to affect parents' cognitive abilities, little is known about if this is driven by changes in cognitive status or cognitive trajectories of older parents, and to what extent children may coordinate their caregiving for parents. This paper first extends the existing literature by identifying and differentiating the level effect and the incremental effect of children's education on parents' cognitive aging. Utilizing a linear mixed-effects model, we disaggregate the multi-wave cognitive assessments into two distinct dimensions: the baseline level of cognitive deficit and the rate of cognitive decline. This study then examines if more educated and less educated children may engage differently with caregiving for parents. To obtain the causal estimates for these investigations, we harness the 1986 Compulsory Education Law in China, leveraging temporal and geographical variations in its enforcement to construct instrumental variables.

The IV estimation results reveal that children's education significantly reduces the baseline level of cognitive deficit. Specifically, a one-year increase in children's education leads to roughly a 0.17 SD decrease in the level of cognitive deficit, aligning closely with the previous estimates (Ma, 2019). Furthermore, we find that children's years of schooling have a notable causal impact on the rate of cognitive change, albeit to a lesser extent than on cognitive deficit level. This finding corroborates previous research on individuals' own education and their rate of cognitive change (Manly et al., 2005, 2003; Zahodne et al., 2015). While prior work has indicated associations between children's education and cognitive trajectories of their parents (Lee, 2018), our analysis explicitly disentangles the level and incremental effects. Additionally, the bias of correlational evidence may be nonnegligible. In our study, both OLS and IV estimates indicate that parents with better-educated children experience slower cognitive decline, underscoring the causal link between children's education and parental cognitive trajectories. Additionally, we demonstrate that, while both more educated and less educated children contribute positively to their parents' cognitive health, they engage in somewhat different forms of support within the family. More educated children tend to provide greater resource-related support, while less educated children are more involved in time-related support.

These findings carry several implications. First, they suggest that children's education have both level effects and incremental effects on parental cognitive health. Previous work has shown that parents benefit from their children's education through increased financial transfers, improved access to resources and sanitation, and higher perceived life satisfaction (Lee, 2018; Ma, 2019). Hence, children may exert a persistent and long-term influence on parental cognitive aging. Second, these findings reveal that children's education may benefit parents' cognitive health through diverse pathways, dependent on the relative human capital within a family. Thus, family arrangements and coordination could play a role in elderly support, contributing to healthy aging. Moreover, low health awareness presents significant challenges, especially in populations with low levels of education. These findings imply that more education for children may have great potential in promoting disease diagnosis, including cognitive impairment assessments, given the substantial illiteracy rate among Chinese older adults (approximately 40% older adults have received no formal education)[7]. In addition to receiving higher quality of care, the spillover effects of children's education may enhance their parents' cognitive skills, potentially shifting them away from the diagnostic threshold and reducing their risk of misdiagnosing dementia and the associated costs of disease misclassification. Finally, the modest differences in the form of caregiving between highest- versus lowest-educated children suggest an increasingly limited scope of intra-family division of informal elder care, especially given the trends of rapid population aging and lower birth rate globally.

Nevertheless, some limitations should be noted. First, although cognition was assessed longitudinally, only three waves of comparable cognitive test data were available in CHARLS. The modeling and estimation of individual trajectories may be limited by the short duration of follow-up. Longer-term cognitive assessments might provide additional insights into the rate of change. Second, the cognitive tests used in CHARLS are not the most suitable measures for clinical diagnosis. Other cognitive assessments, such as the Mini-Mental State Examination (MMSE) and the Alzheimer's Disease Assessment Scale-Cogntive (ADAS-Cog), could offer more clinically relevant insights into cognitive impairment and dementia (Winblad et al., 2016). Third, this study does not investigate the heterogeneity in the effects of children's education on parental cognitive aging. Parents with varying educational levels, socioeconomic statuses, and gender may derive

[7] Estimated from CHARLS longitudinal surveys

different benefits from their children's education. However, due to sample size limitations, it is challenging to conduct subsample analyses. Future research with larger datasets should explore such heterogeneity, as it can shed more light on potential pathways of effects. Additionally, as we lack an objective measure of parents' literacy, this study does not explicitly examine the potential effects of children's education on parents' literacy and related skills. Further investigation is warranted to explore this effect, given that an individual's literacy significantly predicts their cognitive performance (Arce Rentería et al., 2019; Contador et al., 2017).

In conclusion, this study offers novel insights into the level effect and incremental effect of children's education on parental cognitive aging. The revealed protective effects of children's education on parental cognition trajectories underscores the intergenerational benefits of offspring education, particularly concerning cognitive performance in old age and disease diagnosis. Our findings illuminate the multifaceted ways in which children's education can enhance parental cognitive health and highlight the importance of family arrangements and coordination in promoting healthy aging.

References

Agarwal, S., Mazumder, B., 2013. Cognitive abilities and household financial decision making. American Economic Journal: Applied Economics 5, 193–207. https://doi.org/10.1257/app.5.1.193

Alzheimer's Disease International, 2021. World Alzheimer Report 2021: Journey through the diagnosis of dementia. Alzheimer's Disease International, London.

Alzheimer's Disease International, 2019. World Alzheimer Report 2019: Attitudes to dementia. Alzheimer's Disease International, London.

Angrist, J.D., Imbens, G.W., 1995. Two-stage least squares estimation of average causal effects in models with variable treatment intensity. Journal of the American statistical Association 90, 431–442.

Anstey, K.J., Burns, R.A., Birrell, C.L., Steel, D., Kiely, K.M., Luszcz, M.A., 2010. Estimates of probable dementia prevalence from population-based surveys compared with dementia prevalence estimates based on meta-analyses. BMC neurology 10, 62.

Arce Rentería, M., Vonk, J.M.J., Felix, G., Avila, J.F., Zahodne, L.B., Dalchand, E., Frazer, K.M., Martinez, M.N., Shouel, H.L., Manly, J.J., 2019. Illiteracy, dementia risk, and cognitive trajectories among older adults with low education. Neurology 93, e2247–e2256. https://doi.org/10.1212/WNL.0000000000008587

Ardila, A., Bertolucci, P.H., Braga, L.W., Castro-Caldas, A., Judd, T., Kosmidis, M.H., Matute, E., Nitrini, R., Ostrosky-Solis, F., Rosselli, M., 2010. Illiteracy: the neuropsychology of cognition without reading. Archives of clinical neuropsychology 25, 689–712.

Belsky, D.W., Caspi, A., Houts, R., Cohen, H.J., Corcoran, D.L., Danese, A., Harrington, H., Israel, S., Levine, M.E., Schaefer, J.D., Sugden, K., Williams, B., Yashin, A.I., Poulton, R., Moffitt, T.E., 2015. Quantification of biological aging in young adults. Proceedings of the National Academy of Sciences 112, E4104–E4110. https://doi.org/10.1073/pnas.1506264112

Borenstein, A.R., Mortimer, J.A., 2016. Clinical Appearance, Progression, and Classification, in: Alzheimer's Disease. Elsevier, pp. 7–23. https://doi.org/10.1016/B978-0-12-804538-1.00002-X

Burton-Jeangros, C., Cullati, S., Sacker, A., Blane, D. (Eds.), 2015. A Life Course Perspective on Health Trajectories and Transitions, Life Course Research and Social Policies. Springer International Publishing, Cham. https://doi.org/10.1007/978-3-319-20484-0

Contador, I., del Ser, T., Llamas, S., Villarejo, A., Benito-León, J., Bermejo-Pareja, F., 2017. Impact of literacy and years of education on the diagnosis of dementia: A population-based study. Journal of Clinical and Experimental Neuropsychology 39, 112–119. https://doi.org/10.1080/13803395.2016.1204992

Cui, Y., Liu, H., Zhao, L., 2019. Mother's education and child development: Evidence from the compulsory school reform in China. Journal of Comparative Economics 47, 669–692. https://doi.org/10.1016/j.jce.2019.04.001

Duflo, E., 2001. Schooling and labor market consequences of school construction in Indonesia: Evidence from an unusual policy experiment. American economic review 91, 795–813.

Ebenstein, A., 2010. The "missing girls" of China and the unintended consequences of the one child policy. Journal of Human Resources 45, 87–115.

Erlangsen, A., Zarit, S.H., Conwell, Y., 2008. Hospital-diagnosed dementia and suicide: a longitudinal study using prospective, nationwide register data. The American journal of geriatric psychiatry 16, 220–228.

Fan, S., Kanbur, R., Zhang, X., 2011. China's regional disparities: Experience and policy. Review of Development Finance 1, 47–56.

Hall, C.B., Lipton, R.B., Sliwinski, M., Stewart, W.F., 2000. A change point model for estimating the onset of cognitive decline in preclinical Alzheimer's disease. Statistics in Medicine 19, 1555–1566. https://doi.org/10.1002/(SICI)1097-0258(20000615/30)19:11/12<1555::AID-SIM445>3.0.CO;2-3

Hout, A. van den, Fox, J.-P., Muniz-Terrera, G., 2015. Longitudinal mixed-effects models for latent cognitive function. Statistical Modelling: An International Journal 15, 366–387. https://doi.org/10.1177/1471082X14555607

Huang, W., 2015. Understanding the effects of education on health: evidence from China.

Imbens, G.W., Angrist, J.D., 1994. Identification and Estimation of Local Average Treatment Effects. Econometrica 62, 467–475. https://doi.org/10.2307/2951620

Kemptner, D., Jürges, H., Reinhold, S., 2011. Changes in compulsory schooling and the causal effect of education on health: Evidence from Germany. Journal of Health Economics 30, 340–354.

Korniotis, G.M., Kumar, A., 2011. Do older investors make better investment decisions? The Review of Economics and Statistics 93, 244–265.

Laird, N.M., Ware, J.H., 1982. Random-Effects Models for Longitudinal Data. Biometrics 38, 963–974. https://doi.org/10.2307/2529876

Langa, K.M., Larson, E.B., Karlawish, J.H., Cutler, D.M., Kabeto, M.U., Kim, S.Y., Rosen, A.B., 2008. Trends in the prevalence and mortality of cognitive impairment in the United States: Is there evidence of a compression of cognitive morbidity? Alzheimer's & Dementia 4, 134–144. https://doi.org/10.1016/j.jalz.2008.01.001

Lee, Y., 2018. Adult children's educational attainment and the cognitive trajectories of older parents in South Korea. Social Science & Medicine 209, 76–85. https://doi.org/10.1016/j.socscimed.2018.05.026

Lundborg, P., Majlesi, K., 2018. Intergenerational transmission of human capital: Is it a one-way street? Journal of health economics 57, 206–220.

Ma, M., 2019. Does children's education matter for parents' health and cognition? Evidence from China. Journal of Health Economics 66, 222–240. https://doi.org/10.1016/j.jhealeco.2019.06.004

Manly, J.J., Schupf, N., Tang, M.-X., Stern, Y., 2005. Cognitive decline and literacy among ethnically diverse elders. Journal of geriatric psychiatry and neurology 18, 213–217.

Manly, J.J., Touradji, P., Tang, M.-X., Stern, Y., 2003. Literacy and memory decline among ethnically diverse elders. Journal of clinical and experimental neuropsychology 25, 680–690.

Meghir, C., Palme, M., Simeonova, E., 2013. Education, cognition and health: Evidence from a social experiment (No. 0898–2937). National Bureau of Economic Research.

Ming, C.K., 1986. China's recent education reform: the beginning of an overhaul. Comparative Education 22, 255–269.

National Bureau of Statistics of China, 2012. Tabulation on the 2010 population census of the People's Republic of China.

Ofstedal, M.B., Fisher, G.G., Herzog, A.R., Wallace, R., Weir, D., Langa, K., 2005. HRS/AHEAD documentation report: Documentation of cognitive functioning measures in the Health and Retirement Study. Michigan: Survey Research Center, University of Michigan.

Ostrosky-Solis, F., Ardila, A., Rosselli, M., Lopez-Arango, G., Uriel-Mendoza, V., 1998. Neuropsychological test performance in illiterate subjects. Archives of Clinical Neuropsychology 13, 645–660.

Rosenzweig, M.R., Wolpin, K.I., 1986. Evaluating the effects of optimally distributed public programs: Child health and family planning interventions. The American Economic Review 76, 470–482.

Samanez-Larkin, G.R., 2013. Financial decision making and the aging brain. APS observer 26, 30.

Smith, J.P., McArdle, J.J., Willis, R., 2010. Financial decision making and cognition in a family context. The Economic Journal 120, F363–F380. https://doi.org/10.1111/j.1468-0297.2010.02394.x

Wilson, R.S., Leurgans, S.E., Boyle, P.A., Bennett, D.A., 2011. Cognitive Decline in Prodromal Alzheimer Disease and Mild Cognitive Impairment. Archives of Neurology 68, 351–356. https://doi.org/10.1001/archneurol.2011.31

Wilson, R.S., Li, Y., Aggarwal, N., Barnes, L., McCann, J., Gilley, D., Evans, D., 2004. Education and the course of cognitive decline in Alzheimer disease. Neurology 63, 1198–1202.

Winblad, B., Amouyel, P., Andrieu, S., Ballard, C., Brayne, C., Brodaty, H., Cedazo-Minguez, A., Dubois, B., Edvardsson, D., Feldman, H., Fratiglioni, L., Frisoni, G.B., Gauthier, S., Georges, J., Graff, C., Iqbal, K., Jessen, F., Johansson, G., Jönsson, L., Kivipelto, M., Knapp, M., Mangialasche, F., Melis, R., Nordberg, A., Rikkert, M.O., Qiu, C., Sakmar, T.P., Scheltens, P., Schneider, L.S., Sperling, R., Tjernberg, L.O., Waldemar, G., Wimo, A., Zetterberg, H., 2016. Defeating Alzheimer's disease and other dementias: a priority for European science and society. The Lancet Neurology 15, 455–532. https://doi.org/10.1016/S1474-4422(16)00062-4

Xu, X., Liang, J., Bennett, J.M., Botoseneanu, A., Allore, H.G., 2015. Socioeconomic Stratification and Multidimensional Health Trajectories: Evidence of Convergence in Later Old Age. The Journals of Gerontology Series B: Psychological Sciences and Social Sciences 70, 661–671. https://doi.org/10.1093/geronb/gbu095

Zahodne, L.B., Stern, Y., Manly, J.J., 2015. Differing effects of education on cognitive decline in diverse elders with low versus high educational attainment. Neuropsychology 29, 649.

Zhao, Y., Crimmins, E.M., Hu, P., Shen, Y., Smith, J.P., Strauss, J., Wang, Y., Zhang, Y., 2016. Prevalence, diagnosis, and management of diabetes mellitus among older Chinese: results from the China Health and Retirement Longitudinal Study. International Journal of Public Health 61, 347–356. https://doi.org/10.1007/s00038-015-0780-x

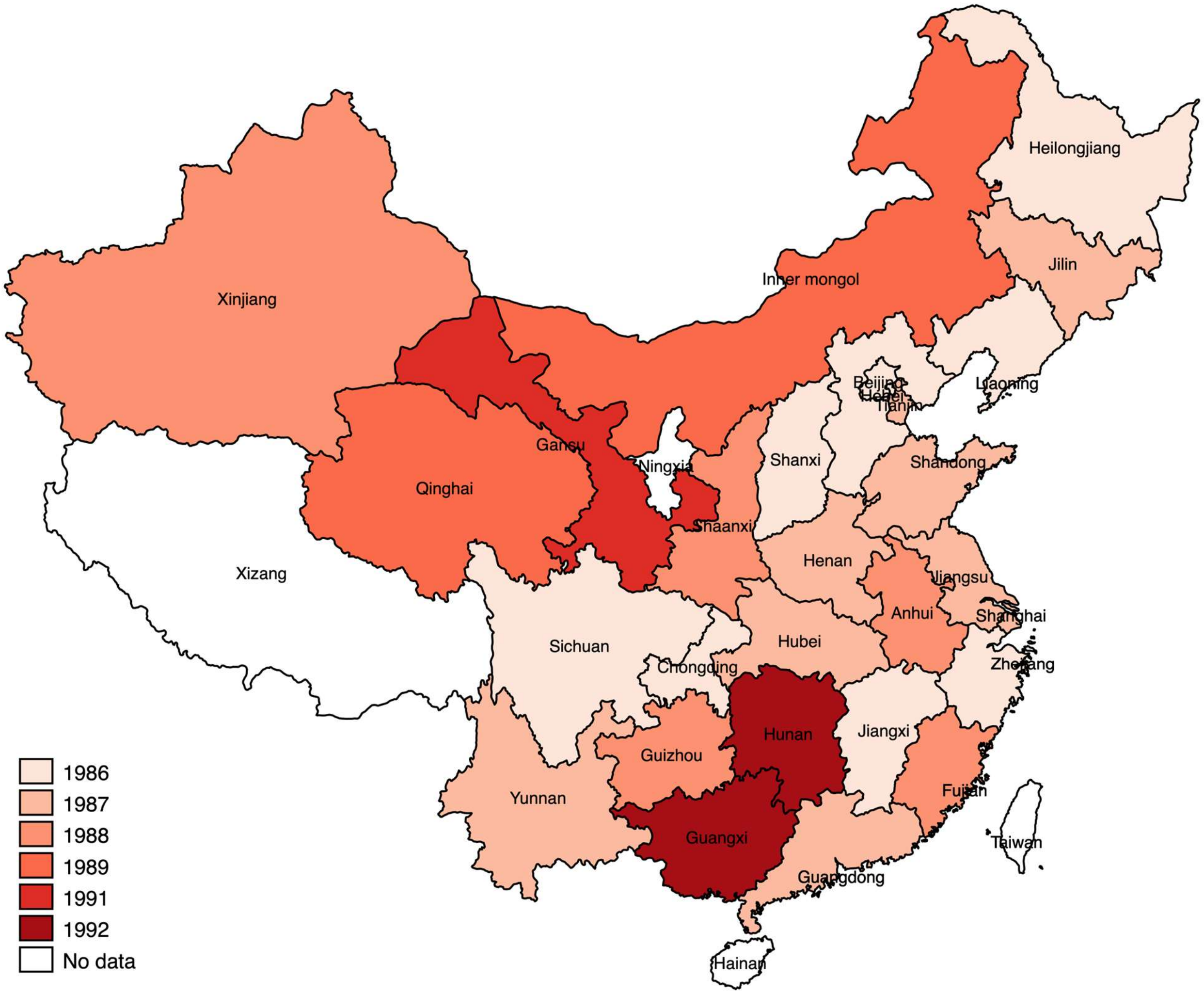
Zhao, Y., Park, A., Strauss, J., Giles, J., Mao, S., Crimmins, E., Yin, X., 2013a. Challenges of population aging in China: Evidence from the national baseline survey of the China Health and Retirement Longitudinal Study (CHARLS). National baseline survey report, Beijing: National School of Development, Peking University.

Zhao, Y., Strauss, J., Yang, G., Giles, J., Hu, P., Hu, Y., Lei, X., Park, A., Smith, J.P., Wang, Y., 2013b. China health and retirement longitudinal study–2011–2012 national baseline users' guide. Beijing: National School of Development, Peking University 1–56.

Zimmer, Z., Martin, L.G., Ofstedal, M.B., Chuang, Y.-L., 2007. Education of adult children and mortality of their elderly parents in Taiwan. Demography 44, 289–305.

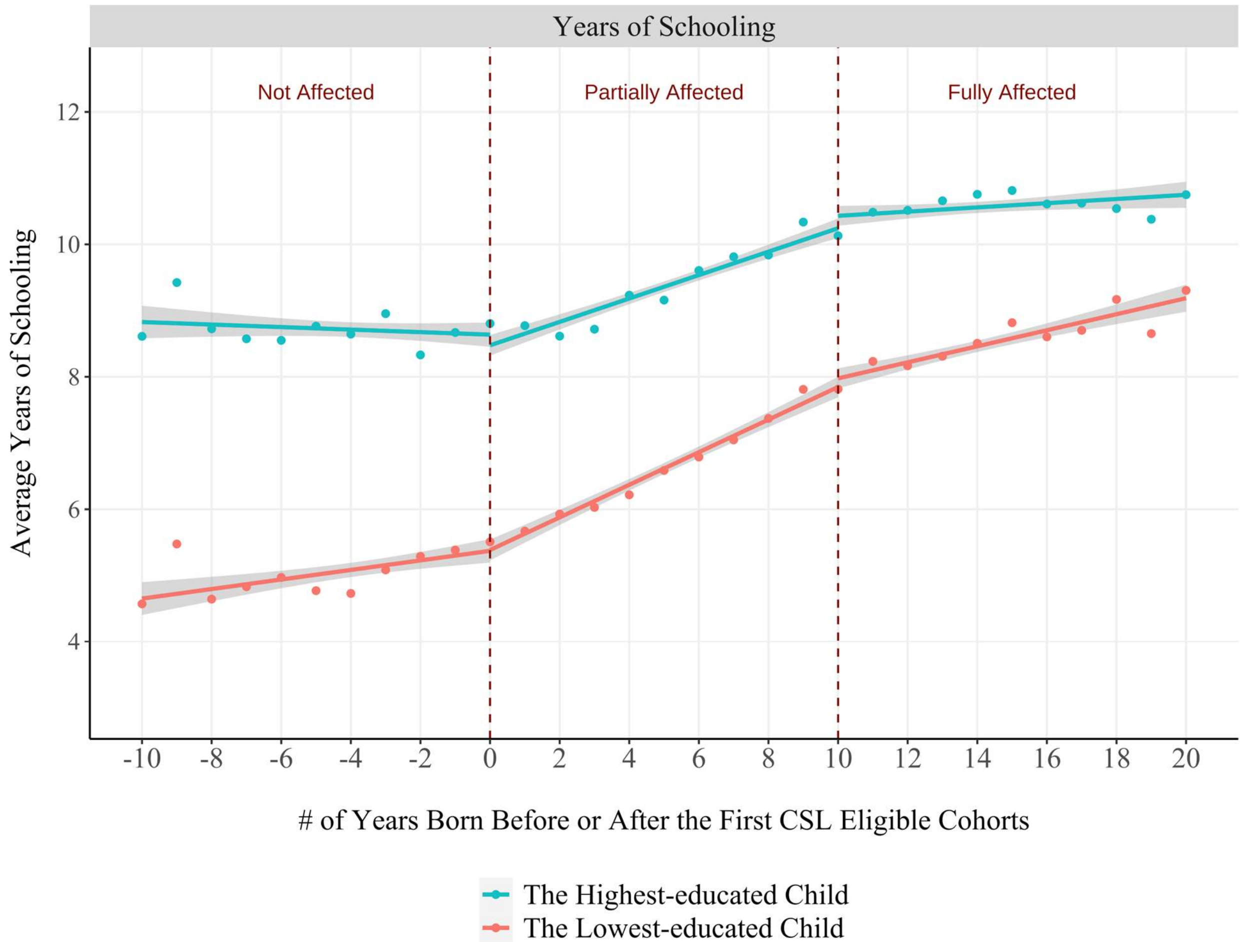
Figures and Tables

Figure 1. Compulsory Schooling Law (CSLs) effective year at province level.



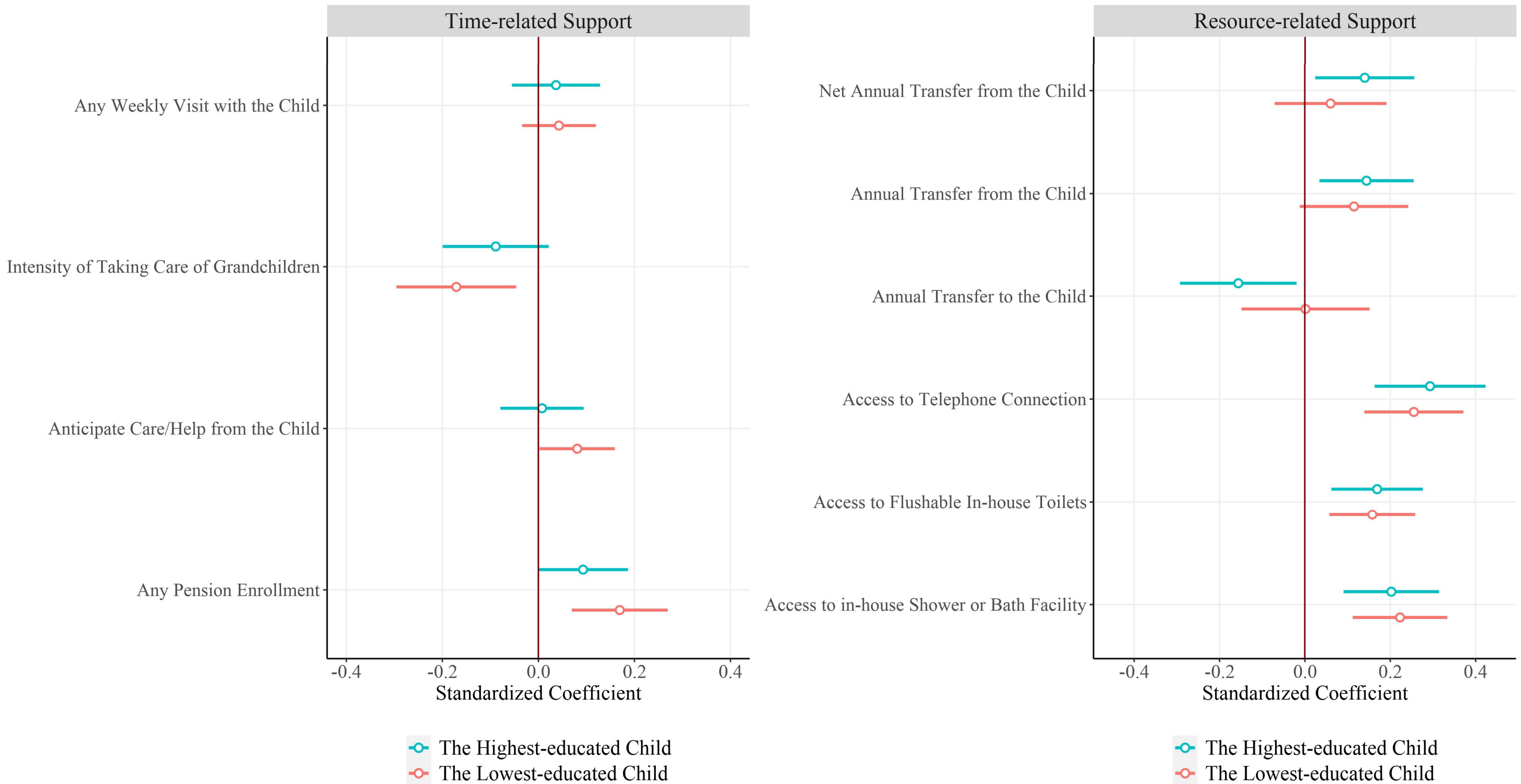
Notes: The data are retrieved from Cui et al., 2019 and China's National People's Congress and Chinese Laws and Regulations Information Database. Law effective year is the actual time that students are affected by Compulsory Schooling Law, depending on whether law initiation time is before or after the beginning (i.e., September) of a new academic year.

Figure 2. Effects of compulsory schooling law on the years of schooling of the highest and the lowest-educated child.



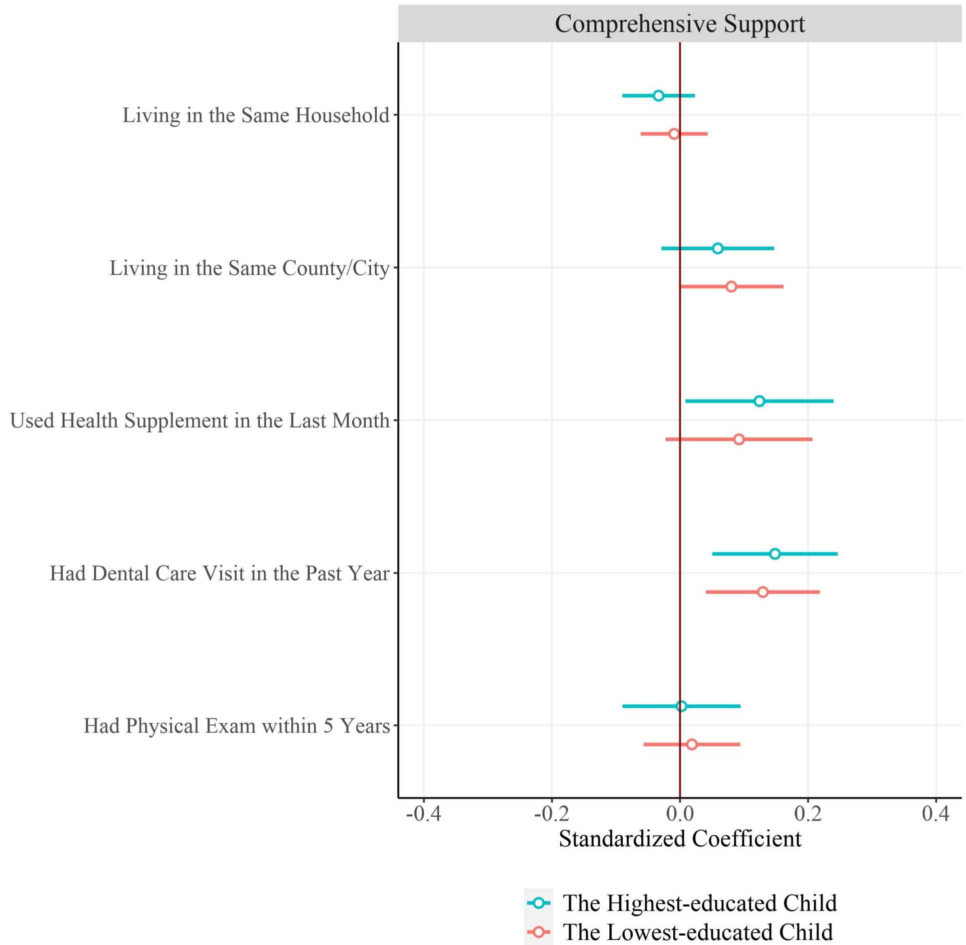
Notes: First eligible cohorts are the cohorts of age 15 when the compulsory schooling law (CSL) took effect in each province, who are marginally affected by CSL. Children born prior to the first eligible cohort (i.e., $X < 0$) are not affected by CSL; children born between the first eligible cohort and the fully eligible cohorts (i.e., $0 \leq X \leq 9$) are partially affected by CSL; and children born after the fully eligible cohorts (i.e., $X \geq 10$) are fully affected by CSL.

Figure 3. Effects of Children's Education on Time and Resource-related Support



Notes: Plotted points represent the standardized ("beta") coefficients of the IV models that regress time and resource-related supports parents receive on children's education. 90% confidence intervals are constructed based on clustered standard errors at the household level. All models control for the sociodemographic characteristics of respondent (i.e., age, gender, education, rural/urban hukou status, marital status, number of dependent and independent children, number of chronic diseases, working status and log per capita annual income), child characteristics (i.e., age, gender, marital status, working status and living arrangement before 16), regional characteristics, child's birth cohort fixed effects, province fixed effect, survey year fixed effect, and birth province specific cohort trends.

Figure 4. Effects of Children's Education on Comprehensive Support



Notes: Plotted points represent the standardized ("beta") coefficients of the IV models that regress comprehensive (i.e., time + resource) supports parents receive on children's education. 90% confidence intervals are constructed based on clustered standard errors at the household level. All models control for the sociodemographic characteristics of respondent (i.e., age, gender, education, rural/urban hukou status, marital status, number of dependent and independent children, number of chronic diseases, working status and log per capita annual income), child characteristics (i.e., age, gender, marital status, working status and living arrangement before 16), regional characteristics, child's birth cohort fixed effects, province fixed effect, survey year fixed effect, and birth province specific cohort trends.

Table 1. Descriptive statistics of parents and regional characteristics

Characteristics	Mean	SD	N
Demographic characteristics of parents			
Age	60.695	8.649	9428
Female	0.522	0.500	9428
Years of schooling	4.364	4.485	9428
Rural	0.839	0.367	9428
Married	0.840	0.367	9428
Number of children	3.066	1.241	9428
Number of chronic diseases	6.806	5.569	9428
Log income	3.874	4.107	9428
Working, agricultural	0.211	0.408	9428
Working, non-agricultural	0.470	0.499	9428
Cognition			
Average mental intactness (0-10) of all measured waves	6.103	2.571	9428
Average episodic memory (0-20) of all measured waves	6.571	2.847	9428
Average cognitive scale (0-30) of all measured waves	12.695	4.742	9428
Total measured waves	2.716	0.451	9428
Other mechanism variables			
Pension enrollment	0.813	0.390	9354
Access to telephone connection	0.397	0.489	9417
Access to in-house flushable toilet	0.391	0.488	9394
Access to in-house shower or bath facility	0.459	0.498	9414
Used health supplement in the last month	0.056	0.230	9400
Had dental care visit in the past year	0.170	0.376	9416
Had physical exam in the past 5 years	0.644	0.479	8057

Notes: SD=Standard Deviation.

Table 2. Descriptive statistics of the highest-educated children and of the lowest-educated children

	(1)	(2)	(3)	(4)	(5)
	The Highest-Educated Children		The Lowest-Educated Children		*p*-value
	Mean (SD)	N	Mean (SD)	N	
Years of schooling	9.74 (3.87)	13948	6.80 (4.25)	14837	<0.001
Age	32.11 (7.78)	13948	32.82 (7.86)	14837	<0.001
Female	0.414 (0.492)	13948	0.518 (0.500)	14837	<0.001
Married	0.829 (0.376)	13948	0.858 (0.349)	14837	<0.001
Working	0.893 (0.309)	13948	0.876 (0.330)	14837	<0.001
Living with parents before age 16	0.972 (0.164)	13948	0.975 (0.156)	14837	0.127
Had weekly visit to parents	0.482 (0.500)	13238	0.488 (0.500)	14246	0.353
Parent's # of hours taking care of the grandchildren	570.6 (1581.2)	11064	512.3 (1492.5)	12149	0.004
Parent anticipated care/help from the child	0.567 (0.496)	13007	0.546 (0.498)	13860	<0.001
Net annual transfer from the child to parents	577.5 (1121.6)	10139	467.9 (998.8)	11070	<0.001
Annual transfer from the child to parents	1228.5 (1926.8)	10436	1013.0 (1652.9)	11347	<0.001
Annual transfer from parents to the child	252.9 (1154.4)	10679	235.1 (1096.0)	11561	0.238
Living in the same household with parent	0.244 (0.430)	13835	0.231 (0.422)	14742	0.010
Living in the same city/county with parent	0.709 (0.454)	13835	0.760 (0.427)	14742	<0.001

Notes: P-values are calculated based on Chi-square test for categorical variables, and t test for continuous variables.

Table 3. First stage results for years of education of the highest-educated children and the lowest-educated children

Variables	(1) Years of Education of the Highest-educated Children	(2) Years of Education of the Lowest-educated Children
Exposure to compulsory education (0-1)	4.937***	5.101***
	(1.007)	(1.023)
Exposure x PreLawEdu	-0.454***	-0.522***
	(0.106)	(0.109)
Observations	13,948	14,837
Average Increase in Education	1.242	0.868
F statistic for weak identification	12.03	12.84

Notes: Standard errors in parentheses are robust and clustered at household level. All models control for the sociodemographic characteristics of respondent (i.e., age, gender, education, rural/urban hukou status, marital status, number of dependent and independent children, number of chronic diseases, working status and log per capita annual income), child characteristics (i.e., age, gender, marital status, working status and living arrangement before 16), regional characteristics, child's birth cohort fixed effects, province fixed effect, survey year fixed effect, and birth province specific cohort trends. Statistical significance: ***p<0.01, **p<0.05, *p<0.10.

Table 4. Effects of children's education on cognitive deficit score (three waves pooled)

	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Variables	Cognitive Deficit Score (Pooled)			
Education of the highest-educated child	-0.142***	-0.966***		
	(0.014)	(0.271)		
Education of the lowest-educated child			-0.136***	-0.823***
			(0.014)	(0.242)
Own years of education	-0.412***	-0.239***	-0.409***	-0.237***
	(0.012)	(0.059)	(0.012)	(0.062)
Observations	37,849	37,849	40,315	40,315
p value of LM statistic (under id)		<0.001		<0.001
F statistic for weak identification		11.825		12.843
p value of Anderson-Rubin F statistic		<0.001		<0.001
Standardized effect (in SDs)		-0.179		-0.151
Outcome Mean		17.320		17.398

Notes: Standard errors in parentheses are robust and clustered at household level. All models control for the sociodemographic characteristics of respondent (i.e., age, gender, education, rural/urban hukou status, marital status, number of dependent and independent children, number of chronic diseases, working status and log per capita annual income), child characteristics (i.e., age, gender, marital status, working status and living arrangement before 16), regional characteristics, child's birth cohort fixed effects, province fixed effect, survey year fixed effect, and birth province specific cohort trends. Statistical significance: ***p<0.01, **p<0.05, *p<0.10.

Table 5. Effects of children's education on parents' level of cognitive deficit

	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Variables	Level of Cognitive Deficit (Intercept)			
Education of the highest-educated child	-0.094***	-0.635***		
	(0.009)	(0.178)		
Education of the lowest-educated child			-0.091***	-0.549***
			(0.009)	(0.162)
Own years of education	-0.420***	-0.305***	-0.419***	-0.304***
	(0.008)	(0.039)	(0.008)	(0.042)
Observations	13,948	13,948	14,837	14,837
p value of LM statistic (under id)		<0.001		<0.001
F statistic for weak identification		12.034		12.845
p value of Anderson-Rubin F statistic		<0.001		<0.001
Standardized effect (in SDs)		-0.175		-0.151
Outcome Mean		16.762		16.833

Notes: Standard errors in parentheses are robust and clustered at household level. All models control for the sociodemographic characteristics of respondent (i.e., age, gender, education, rural/urban hukou status, marital status, number of dependent and independent children, number of chronic diseases, working status and log per capita annual income), child characteristics (i.e., age, gender, marital status, working status and living arrangement before 16), regional characteristics, child's birth cohort fixed effects, province fixed effect, survey year fixed effect, and birth province specific cohort trends. Statistical significance: ***p<0.01, **p<0.05, *p<0.10.

Table 6. Effects of children's education on parents' rate of cognitive decline

	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Variables	Rate of Cognitive Decline (Slope)			
Education of the highest-educated child	-0.003***	-0.013**		
	(0.000)	(0.005)		
Education of the lowest-educated child			-0.003***	-0.013**
			(0.000)	(0.005)
Own years of education	-0.016***	-0.014***	-0.016***	-0.013***
	(0.000)	(0.001)	(0.000)	(0.001)
Observations	13,948	13,948	14,837	14,837
p value of LM statistic (under id)		<0.001		<0.001
F statistic for weak identification		12.034		12.845
p value of Anderson-Rubin F statistic		0.019		0.027
Standardized effect (in SDs)		-0.068		-0.064
Outcome Mean		0.300		0.306

Notes: Standard errors in parentheses are robust and clustered at household level. All models control for the sociodemographic characteristics of respondent (i.e., age, gender, education, rural/urban hukou status, marital status, number of dependent and independent children, number of chronic diseases, working status and log per capita annual income), child characteristics (i.e., age, gender, marital status, working status and living arrangement before 16), regional characteristics, child's birth cohort fixed effects, province fixed effect, survey year fixed effect, and birth province specific cohort trends. Statistical significance: ***p<0.01, **p<0.05, *p<0.10.

Table 7. Effects of children's education on parental survival

	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Variables		Both Parents Alive (0/1)		
Education of the highest-educated child	0.002***	0.001		
	(0.001)	(0.008)		
Education of the lowest-educated child			0.003***	-0.004
			(0.001)	(0.007)
Own years of education	0.000	0.000	-0.000	0.002
	(0.001)	(0.002)	(0.001)	(0.002)
Observations	13,140	13,140	13,992	13,992
p value of LM statistic (under id)		<0.001		<0.001
F statistic for weak identification		11.226		15.030
p value of Anderson-Rubin F statistic		0.720		0.778
Standardized effect (in SDs)		0.005		-0.014
Outcome Mean		0.902		0.903

Notes: Standard errors in parentheses are robust and clustered at household level. All models control for the sociodemographic characteristics of respondent (i.e., age, gender, education, rural/urban hukou status, marital status, number of dependent and independent children, number of chronic diseases, working status and log per capita annual income), child characteristics (i.e., age, gender, marital status, working status and living arrangement before 16), regional characteristics, child's birth cohort fixed effects, province fixed effect, survey year fixed effect, and birth province specific cohort trends. Statistical significance: ***p<0.01, **p<0.05, *p<0.10.

Table 8. Robustness to sample selection and model specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Variables	Level of Cognitive Deficit (Intercept)				Rate of Cognitive Decline (Slope)			
Panel A: Controlling for one-child policy								
Education of the highest-educated child	-0.094***	-0.635***			-0.003***	-0.013**		
	(0.009)	(0.177)			(0.000)	(0.005)		
Education of the lowest-educated child			-0.091***	-0.547***			-0.003***	-0.013**
			(0.009)	(0.161)			(0.000)	(0.005)
Observations	13,948	13,948	14,837	14,837	13,948	13,948	14,837	14,837
F statistic for weak identification		12.162		12.917		12.162		12.917
Standardized effect (in SDs)		-0.175		-0.150		-0.068		-0.064
Panel B: Restricted sample (children age 0-25 years old at the time of CSLs)								
Education of the highest-educated child	-0.099***	-0.574***			-0.003***	-0.010*		
	(0.010)	(0.173)			(0.000)	(0.005)		
Education of the lowest-educated child			-0.094***	-0.542***			-0.003***	-0.012**
			(0.010)	(0.182)			(0.000)	(0.005)
Observations	11,794	11,794	12,783	12,783	11,794	11,794	12,783	12,783
F statistic for weak identification		10.888		9.680		10.888		9.680
Standardized Effect		-0.175		-0.151		-0.055		-0.062
Panel C: Clustering standard errors at province-year level								
Education of the highest-educated child	-0.094***	-0.635***			-0.003***	-0.013***		
	(0.007)	(0.146)			(0.000)	(0.004)		
Education of the lowest-educated child			-0.091***	-0.549***			-0.003***	-0.013***
			(0.007)	(0.119)			(0.000)	(0.004)
Observations	13,948	13,948	14,837	14,837	13,948	13,948	14,837	14,837
F statistic for weak identification		14.949		17.745		14.949		17.745
Standardized effect (in SDs)		-0.175		-0.151		-0.068		-0.064

Notes: All models control for the sociodemographic characteristics of respondent (i.e., age, gender, education, rural/urban hukou status, marital status, number of dependent and independent children, number of chronic diseases, working status and log per capita annual income), child characteristics (i.e., age, gender, marital status, working status and living arrangement before 16), regional characteristics, child's birth cohort fixed effects, province fixed effect, survey year fixed effect, and birth province specific cohort trends. In Panel A and B, the standard errors in parentheses are robust and clustered at household level. Statistical significance: ***p<0.01, **p<0.05, *p<0.10.

Table 9. Robustness to different measures of cognitive outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Variables	Level of Cognitive Deficit (Intercept)				Rate of Cognitive Decline (Slope)			
Panel A: Mental Intactness (0-10)								
Education of the highest-educated child	-0.060***	-0.345***			-0.001***	-0.003**		
	(0.005)	(0.094)			(0.000)	(0.002)		
Education of the lowest-educated child			-0.056***	-0.308***			-0.001***	-0.003**
			(0.005)	(0.085)			(0.000)	(0.001)
Observations	14,329	14,329	15,239	15,239	14,329	14,329	15,239	15,239
F statistic for weak identification		11.781		13.085		11.781		13.085
Standardized effect (in SDs)		-0.166		-0.147		-0.067		-0.062
Panel B: Episodic Memory (0-20)								
Education of the highest-educated child	-0.031***	-0.228***			-0.001***	-0.006**		
	(0.005)	(0.084)			(0.000)	(0.003)		
Education of the lowest-educated child			-0.030***	-0.192**			-0.001***	-0.005**
			(0.005)	(0.078)			(0.000)	(0.002)
Observations	14,276	14,276	15,185	15,185	14,276	14,276	15,185	15,185
F statistic for weak identification		12.027		13.274		12.027		13.274
Standardized Effect		-0.123		-0.103		-0.046		-0.039
Panel C: Global Cognitive Score for 2011-2018 (0-20)								
Education of the highest-educated child	-0.085***	-0.494***			-0.001***	-0.003**		
	(0.007)	(0.134)			(0.000)	(0.002)		
Education of the lowest-educated child			-0.083***	-0.451***			-0.001***	-0.004***
			(0.007)	(0.124)			(0.000)	(0.002)
Observations	13,980	13,980	14,866	14,866	13,980	13,980	14,866	14,866
F statistic for weak identification		12.161		13.079		12.161		13.079
Standardized effect (in SDs)		-0.172		-0.156		-0.043		-0.054

Notes: All models control for the sociodemographic characteristics of respondent (i.e., age, gender, education, rural/urban hukou status, marital status, number of dependent and independent children, number of chronic diseases, working status and log per capita annual income), child characteristics (i.e., age, gender, marital status, working status and living arrangement before 16), regional characteristics, child's birth cohort fixed effects, province fixed effect, survey year fixed effect, and birth province specific cohort trends. Standard errors in parentheses are robust and clustered at household level. Statistical significance: ***p<0.01, **p<0.05, *p<0.10.

Appendix

Table A1. Compulsory schooling laws by provinces

Province	Law initiation time	Law effective year	First eligible birth cohort
Zhejiang	Sep-85	1986	1971
Jiangxi	Feb-86	1986	1971
Beijing	Jul-86	1986	1971
Hebei	Jul-86	1986	1971
Shanxi	Jul-86	1986	1971
Liaoning	Jul-86	1986	1971
Heilongjiang	Jul-86	1986	1971
Chongqing	Jul-86	1986	1971
Sichuan	Jul-86	1986	1971
Jiangsu	Sep-86	1987	1972
Shanghai	Sep-86	1987	1972
Shandong	Sep-86	1987	1972
Henan	Oct-86	1987	1972
Guangdong	Oct-86	1987	1972
Yunnan	Oct-86	1987	1972
Tianjin	Nov-86	1987	1972
Jilin	Feb-87	1987	1972
Hubei	Mar-87	1987	1972
Shaanxi	Sep-87	1988	1973
Anhui	Sep-87	1988	1973
Guizhou	Jan-88	1988	1973
Xinjiang	May-88	1988	1973
Fujian	Aug-88	1988	1973
Inner Mongolia	Sep-88	1989	1974
Qinghai	Oct-88	1989	1974
Gansu	Sep-90	1991	1976
Hunan	Sep-91	1992	1977
Guangxi	Sep-91	1992	1977

Notes: The data are retrieved from Cui et al., 2019 and China's National People's Congress and Chinese Laws and Regulations Information Database. Law effective year is the actual time that students are truly affected by Compulsory Schooling Law, depending on whether law initiation time is before or after the beginning (i.e., September) of a new academic year.