ROCKWOOL Foundation Berlin
Institute for the Economy and the Future of Work (RFBerlin)

DISCUSSION PAPER SERIES 034/26

Unintended Consequences of China's Double Reduction Policy: Its Immediate and Intergenerational Impacts

Xin Liu, Xin Meng, Guangqian Pan, Guochang Zhao

www.rfberlin.com JANUARY 2026

Unintended Consequences of China's Double Reduction Policy: Its Immediate and Intergenerational Impacts

Authors

Xin Liu, Xin Meng, Guangqian Pan, Guochang Zhao

Reference

JEL Codes: I21, I24, J22, J24, D04, D13

Keywords: Education Policy, Private Tutoring, Academic Outcome, Intergenerational Inequality, Parent Outcome

Recommended Citation: Xin Liu, Xin Meng, Guangqian Pan, Guochang Zhao (2026): Unintended Consequences of China's Double Reduction Policy: Its Immediate and Intergenerational Impacts. RFBerlin Discussion Paper No. 034/26

Access

Disclaimer

Imprint

RFBerlin
ROCKWOOL Foundation Berlin –
Institute for the Economy
and the Future of Work

Gormannstrasse 22, 10119 Berlin
Tel: +49 (0) 151 143 444 67
E-mail: info@rfberlin.com
Web: www.rfberlin.com

Unintended Consequences of China's Double Reduction Policy: Its Immediate and Intergenerational Impacts*

Xin Liu† Xin Meng‡ Guangqian Pan§ Guochang Zhao¶

January 19, 2026

Abstract

This paper evaluates the unintended consequences of China's 2021 "Double Reduction" policy, which aimed to ease students' academic burden by limiting homework and private tutoring. Using a tailored household survey, a constructed policy enforcement index, and a difference-in-differences design, we find that the policy increased private tutoring enrollment, household tutoring expenditures, and parental time spent on helping children with schoolwork. These effects disproportionately harmed low-income families, resulting in worse academic outcomes. Our findings suggest that the policy's effects run counter to its intended goals and may exacerbate educational inequality.

Keywords: Education Policy, Private Tutoring, Academic Outcome, Intergenerational Inequality, Parent Outcome

JEL Classification Code: I21, I24, J22, J24, D04, D13

1 Introduction

Parental investment in children's education is a key channel through which intergenerational transmission of income and wealth occurs (Guryan et al., 2008). In societies where education yields high returns, rational parents would invest heavily in their offsprings' education, due both to their altruistic motives and/or concerns for their own old-age care. In some societies where education itself is a status symbol, education is sought after as a private investment even when its financial returns are not particularly attractive (Kim et al., 2024). Governments, on the other hand, invest in education

*We would like to thank conference participants at the AASLE 2024 annual meeting and the NBER Chinese Economy Working Group Meeting in Boston, March 2025; as well as seminar participants at the RSE, Australian National University; Remin University, University of Macau and University of Sydney.

†Research School of Finance, Actuarial Studies and Statistics, Australian National University, email: xin.liu@anu.edu.au

‡Research School of Economics, Australian National University, e-mail: xin.meng@anu.edu.au

§Business School, The University of Sydney, e-mail: guangqian.pan@sydney.edu.au

¶Research Institute of Economics and Management, Southwestern University of Finance and Economics, e-mail: guochangzhao@swufe.edu.cn

because it has strong positive externalities. At the same time, due to the crucial role that education plays in the intergenerational transmission of income, wealth, or status, governments that prioritise equality may also seek to limit private educational investment. Thus, the interaction between public and private educational investments plays a critical role in shaping long-term economic mobility (Genicot and Ray, 2017; Kim et al., 2024).

Like other East Asian societies, China has seen a significant increase in returns to education over the past 40 years (Zhang et al., 2005; Appleton et al., 2005; Yang, 2005; Meng, 2012; Huang et al., 2022). Combined with its traditional Confucian reverence for education and intellectuals, the society has become a place with fierce competitions among schools, students, and parents with regard to students' educational efforts and achievements (Kim et al., 2024).[1] To enhance children's educational performance, schools and parents exert increasing pressure on students to work harder, assign them more and more homework, and enrol them in extensive private tutoring, which deprives them of leisure time or time to take responsibility for household chores. Two inevitable consequences have emerged: household spending on private tutoring has skyrocketed (Zhou et al., 2023) and mental health and physical health issues among teenagers are becoming increasingly prevalent (Hou and Chen, 2021; Dong et al., 2023). These developments may potentially exacerbate future income inequality among the next generation, as more resourceful parents find new ways to boost their children's competitiveness, and deprive society of a healthy and knowledgeable workforce (Zhang and Xie, 2016; Zhang and Bray, 2018; Guo and Qu, 2022).

To mitigate these undesirable consequences, the Chinese government, as has been the case in some other East Asian countries,[2] had embarked on a continued effort to reduce students' excessive homework burden. Starting as early as 1988, various government agencies have made numerous announcements and implemented a range of policies to reduce students' educational burden. Despite these efforts, the pressure on students appeared to increase year after year. By 2019, after decades of policy interventions, China had developed one of the largest and fastest-growing K-12 private tutoring industries, with a market value between 200 and 300 billion USD, which is equivalent to nearly half of that year's total public spending on education in China (Deloitte, 2019).[3] Studies evaluating the impact of the Chinese government's policies in curbing the unchecked increase in educational burdens generally suggest that these efforts have been ineffective. If anything, the measurable trend of students' burden and spending on private tutoring kept increasing (For the most recent literature, see Yang,

[1] Of course, this phenomenon is not unique to the East Asian society. Increasingly studies in the U.S. have reported how meritocracy has dominated their education system, which feeds income inequality, and dismantles the middle class (Markovits, 2019; Sandel, 2020; Wai et al., 2024; David, 2024).

[2] To reduce students' educational burden and parental educational spending, the South Korean government has adopted many policies since the 1960s (Kim, 2004). In 2006, the South Korean government introduced a curfew that prevents private tutoring organisations from operating after 8:00 p.m. (Choi and Choi, 2016). Similarly, the Japanese government implemented a policy to reduce curriculum coverage and decrease students' time spent at school (Goodman, 2003).

[3] The data on China's public education spending for 2019 are obtained from Ministry of Education of the People's Republic of China and National Bureau of Statistics of China (2020)

2019; Xiang, 2019; Chen and Zhang, 2020; Zhou et al., 2023; Qian and Chen, 2024).[4] A key reason cited for the failure of earlier policies was their vagueness and the challenges associated with monitoring them (Chen and Zhang, 2020).

In July 2021, amid the Covid-19 pandemic, China launched a new campaign known as the "Double Reduction" (DR) policy. This initiative aimed to both reduce students' excessive school homework burden and regulate after-school private tutoring. The broader goals of the DR policy were to promote balanced development for students, control household education expenditures, and relieve parents from the extra time spend into their children's education. Ultimately, the policy was designed to reduce intergenerational education and income inequality (Zang, 2022).

The policy measures introduced this time were notably detailed. For example, the policy regulates the amount of homework teachers are allowed to assign for each grade level. On the private tutoring side, the policy banned for-profit operations, restricted the hours and days tutoring institutions could operate, and significantly reduced the incentives for these institutions to remain in business. Contrary to the previously implemented policies, the DR policy specifies and quantifies the restrictions, allowing various levels of government to more effectively monitor its implementation.

The announcement of the DR policy sent shock waves through society. According to the *Financial Times*, on the day the policy was introduced, the value of Chinese education stocks plummeted by nearly 60% (Agnew et al., 2021). Households also responded almost immediately. As the DR policy restricted institutional tutoring and the homework load, parents reacted by switching to individualised private tutoring (Hale, 2023). This can be seen in Figure 1, in which we use the Baidu (China's leading search engine) search frequency to show that while interest in institutional tutoring slightly tapered off following the introduction of the DR policy, interest regarding individualised tutoring surged significantly.

In this paper, we use a newly conducted online survey tailored to investigate whether the DR policy achieved its intended objectives. The survey collected a rich array of education- and parenting-related information. In addition, leveraging the detailed nature of the DR policy we create a measure that tracks how policy enforcement varied over time and across regions. This measure is based on the number of government documents or news articles that contain any of the keywords identified as indicators of DR policy enforcement in each city for each year.[5] Using a difference-in-differences (DID) approach with individual-level fixed effects, we examine whether the DR policy reduced students' educational burden as measured by participation in private tutoring, household spending on private tutoring, and parental time spent on their children's education.[6] We also investigate the impact of the

[4] For a detailed review of this line of literature on the evaluation of the earlier policies related to the reduction of students' burden in the Chinese language, see Chen and Zhang (2020); Zhou et al. (2023).

[5] The specific keywords we used to construct this measure will be discussed in "The Survey and Data" section.

[6] There is a large body of literature that examines the determinants and consequences of private tutoring as a major parental investment (Dang, 2007; Jung and Lee, 2010; Ryu and Kang, 2013; Jheng, 2015; Zhao, 2015; Zheng et al., 2020; Wiseman, 2021; Kang, 2023).

DR policy on children's academic achievement, as well as mothers' labour market outcomes. Finally, we explore the impact of the policy on potential intergenerational inequality by examining differences in private tutoring spending and academic outcomes among children from households with varying income levels.

Our results show that the DR policy did not reduce, but instead increased, the likelihood of children being enrolled in private tutoring, primarily through increasing in individualised tutoring rather than large-scale institutional classes. The policy led to increases in both academic- and arts/physical education (PE)-related tutoring. In addition, the DR policy increased households' private tutoring spending, though children's educational performance, on average, remained unaffected. Parental investment can take forms beyond monetary investment. We show that the DR policy induced an increase in parental time spent helping with their children's schoolwork, a form of parental investment especially effective in early childhood (Yum, 2022). We also show that the policy increased mothers' labour market participation. These results suggest that anxious parents, facing uncertainty, took strategic actions in response to the introduction of the DR policy to boost their children's future competitiveness. Since the most enforceable aspects of the DR policy involve limiting excessive homework and institutional private tutoring, parents turned to the less enforceable parts of the policy by increasing the use of individualised tutoring and increasing their own effort to offset potential disadvantages from the reduction in school educational efforts.[7]

However, these average impacts of the DR policy were not uniformly experienced across all households. Further investigation reveals that the increase in children's private tutoring and tutoring spending occurred primarily among households in the second income quartile and above, with the effect becoming stronger as household income rises. Households in the bottom income quartile did not increase their use of private tutoring or increase spending on their children, resulting in a decline in their children's educational performance. Interestingly, the low-income households spent much more time helping with their children's schoolwork to compensate for their inability to enrol their children in private tutoring. In addition, mothers from low-income households also increased their labour supply (both labour force participation and full-time work), presumably to help pay for the future need to increase spending on their children's education, such as private tutoring, even though they were currently unable to.

If we consider that households in the bottom two income quartiles all aspire to improve their children's future economic prospects, second-quartile households appear able to compensate for higher education costs by working more, ensuring their children's educational performance does not decline. In contrast, first-quartile households, despite also working more, lack the financial means to do so. Instead, they invest more of their leisure time in helping their children with homework, yet their

[7] Although previous research has shown that private tutoring in China positively affects academic performance (Guo et al. (2020)), under the DR policy, the surge in tutoring seems to have acted as a counterbalance to the reduction in schoolwork.

children's educational performance still suffers. These findings suggest that there may be a long-term intergenerational consequences of the DR policy: if children's current educational performance can be translated into their future income, the impact of the DR policy will exacerbate income inequality in the next generation and hinder the government's desire to reduce future income inequality.

Our paper contributes to the growing body of literature evaluating the DR policy. However, due to the lack of micro-survey data, most existing literature on evaluating the DR policy has relied on Internet search frequency data to indirectly infer the policy's impacts on the demand for institutionalised private tutoring and its substitution effects (Liu et al., 2022; Zhao et al., 2024).[8] We are the first to use data from a specially designed household survey to directly examine the behavioural implications of the DR policy on outcomes for both children and their mothers. Chen et al. (2025) employed existing data from the China Household Financial Survey (CHFS) to examine household education spending. However, their DID identification strategy relies on grades and time fixed effects, implicitly assuming uniform policy implementation across regions and over time, which is inconsistent with the staggered and heterogeneous rollout of the DR policy across regions. In contrast, our identification strategy explicitly exploits cross-city variation in enforcement intensity and implementation timing.[9]

In addition, unlike most existing studies on the DR policy, which primarily rely on the timing of the policy implementation to identify the average treatment effect, we construct a measure of policy enforcement intensity to examine the heterogeneity of treatment effects across regions and over time. The nonlinear relationship between enforcement intensity and policy outcomes offers new insights into the dynamics of policy implementation as well as potential strategic responses from households.

Furthermore, existing literature on the impact of the DR policy or similar policies introduced in various regions predominantly focuses on average effects (Choi and Choi, 2016; Zhou et al., 2023; Liu et al., 2022; Dai, 2023; Zhao et al., 2024). Our study contributes to this body of work by examining the policy impact across different income groups. Previous literature (Becker and Tomes, 1979; Tomes, 1981; Becker and Tomes, 1986; Mulder et al., 2009; Black and Devereux, 2011; Jang and Yum, 2024) has highlighted the importance of education and human capital in the intergenerational transmission of wealth and income. The DR policy intended to equalise the educational support children receive from schools and families to promote more equal educational outcomes. Our paper is the first to empirically demonstrate that, in practice, the DR policy led to rising education costs and an even more unequal distribution of private educational resources. These unintended disparities, combined with China's longstanding social preference for high educational achievement, could exacerbate intergenerational income inequality and result in long-term social losses.

[8]Another branch of the research focuses on the policy's impact on the education industry itself: its growth and employment (Dai, 2023; Huang et al., 2024).

[9]As a robustness analysis, we also deployed an alternative data source from a nationally representative biannual household survey — China Family Panel Studies (CFPS). A detailed comparison between our survey and CFPS is also provided in Appendix.

Finally, this paper is related to a broad literature on policy designs and their unintended adverse consequences. Previous studies have found that policies designed for one purpose often ignore their general equilibrium impact on other aspects of the market or societies (see, e.g., Johnston, 2021; Timpe, 2024). While the DR policy may initially seem to have achieved its intended goals – schools did reduce students' homework, and many private tutoring institutions were shut down – but its broader objectives were ultimately undermined. To compensate for the reduction in homework, households, on average, increased their children's enrolment in private, individualised tutoring, resulting in higher tutoring costs. This disproportionately affected children from poorer households, limiting their access to private tutoring as a substitute for school-assigned homework and ultimately leading to a decline in their academic performance. In a society with a deep-rooted emphasis on education and intense market competition, the demand for education is inelastic. In such circumstances, policy designs that fail to account for potential household reactions inevitably lead to unintended consequences.

The remainder of the paper is organised as follows. The next section outlines the institutional background of China's education system, its evolution, and the details of the DR policy. Section 3 describes our survey and the data used in the paper. Section 4 details the model specification and validates our identification strategy. Section 5 presents the results, and the concluding remarks are discussed in the last section.

2 Background

China has had a long history of respect for education. In the seventh century B.C., one of the early Chinese philosophers, Guan Zhong, stated, "For a one-year plan, nothing surpasses planting grains; For a ten-year plan, nothing surpasses planting trees; For a lifetime plan, nothing surpasses educating people. A single planting yields a single harvest with grain; A single planting yields tenfold harvests with trees; A single planting yields a hundredfold harvests with people." This sentiment might be considered one of the earliest discussions of "human capital" in history.

Throughout history, Chinese philosophers and rulers have engrained its society with aspirations for education and to be educated. They have placed a high value on education as a means for moral development and societal improvement. They established the civil servant examination system (the *Keju* system) to select rulers and managers of society, allowing any member of the society to rise to the top through education. As Mencius famously stated, "Those who labour with their minds govern others; those who labor with their strength are governed by others." Over the past thousands of years, these teachings have made Chinese society aspire to become the educated and intellectuals (Watkins, 2000). Legends, such as the one about Mencius' mother moving house three times to help her son focus on education (Known as "Meng Mu San Qian"), more than two millennia ago, and numerous stories of "Tiger Mothers" in the twenty-first century, all highlight how deeply Chinese society values and aspires to academic excellence (Schuman, 2015; Yen and Wu, 2015).

This cultural belief forms the foundation of learning and teaching in China. Coupled with the deeply status-conscious nature of Chinese society and the growing demand for educated professionals in the job market following China's economic reforms, it has fueled intensifying competition among schools, students, and parents. The pressure to secure better class rankings and excel in high-stakes school entrance exams has become a central focus of this race for academic success (Guo and Qu, 2022). In a 2012 PISA survey, the OECD identified that among 62 countries and regions, including 15-year-old students in Shanghai, Chinese students, on average, spent the longest hours doing homework, around 14 hours weekly (OECD, 2014). Zhao et al. (2024) uses a nationally representative survey, the China Education Panel Survey (CEPS) and finds that in 2013-14 academic year, Chinese students in grades 7 and 9 spent an average of 2.13 hours each weekday and another 2-3 hours each weekend day doing homework. Furthermore, parents also enrol children into additional private tutoring. The demand for the private tutoring has surged dramatically over the past decade, and the industry sustained an annual growth rate exceeding 10% from the early 2010s through to 2018, ultimately expanding to a $100 billion (US) market size by 2019 (Deloitte, 2019; McMorrow et al., 2021).

The persistent pressure placed by families and society on children to excel academically, which begins when children are young, has led to significant adverse effects on their mental and physical health (Hou and Chen, 2021; Dong et al., 2023; Zhao et al., 2024). Further, the intense educational competition has not only driven up family education costs but has also exacerbated educational inequality and potential intergenerational income disparities (Zhang and Xie, 2016; Zhang and Bray, 2018; Guo and Qu, 2022).

Over the years, the Chinese government has made relentless efforts to mitigate the extremely high academic expectations and pressure placed on children by parents and society. Initiatives have included administrative mandates for schools to reduce homework hours and in-school time, but they met with limited success (Yang, 2019; Xiang, 2019; Chen and Zhang, 2020; Zhou et al., 2023; Qian and Chen, 2024). The most recent major reform before the Double Reduction policy was the "Thirty Education Burden Reduction Policies" in late 2018 and 2019. While the policies outlined a framework to regulate both in-school and after-school education practices, their effect was limited due partly to the narrow scope and partly due to the Covid-19 pandemic that emerged in late 2019.[10] Despite these policies, China's K-12 after-school education market still grew by 17% between 2017 and 2018 (Deloitte, 2019).

2.1 The Double Reduction Policy

[10]The pandemic led to widespread school closures, and online learning and private tutoring became essential tools to substitute face-to-face teaching and maintain continuity of education.

2.1.1 Policy restrictions

By early 2021, Covid lockdowns were largely over. The Chinese government picked up the momentum from its 2018–19 reform and introduced the "Double Reduction" policy on July 24, 2021. Formally titled "The Notification about Further Reducing Students' Homework Burden and Their After-School Private Tutoring Burden for the Compulsory Schooling Age," the policy aims to reduce both homework and after-school private tutoring, hence the term "Double Reduction". The policy primarily targets children enroled in compulsory education, that is, grades 1 to 9 (Qian and Chen (2024)).[11]

Two main reforms regarding homework reduction were introduced. First, the policy stipulates that students in grades 1 and 2 should not be assigned any homework. For grades 3 to 6, homework should not exceed one hour per day, and for grades 7 to 9, it should not exceed 90 minutes daily. Second, the policy urges schools to provide more after-class activities to students to meet their education needs. For example, teachers are encouraged to assist students with their homework on campus. If possible, students, especially primary school students, should be able to finish all their homework on-campus under teachers' assistance. It also asks schools to encourage students to attend other after-class activities on campus, such as science education, art training, physical exercises, and physical work activities. The policy requires these after-class activities to extend the school hours until parents finish their work so to reduce the parental child-care burden. For junior high schools, the on-campus training can be in the evenings.

To reduce after-school academic tutoring, the most prominent restriction targets after-school K-12 academic tutoring institutions. From an operational perspective, the DR policy prohibits issuance of licenses for these institutions and requires existing institutions serving the compulsory schooling ages to convert from for-profit to not-for-profit institutions. Furthermore, the policy bans private tutoring activities on weekends, and school- and public-holidays, and restricts weekday in-person tutoring to before 8:30 p.m.. Tutoring institutions are also prohibited from assigning homework to students. Local authorities are to monitor the content of private tutoring materials, and advertisements for tutoring institutions were banned.

From a financial perspective, the policy prevents tutoring institutions from obtaining funding from financial markets.[12] Subsequently, initial public offerings (IPOs) for companies in the sector, whether onshore or offshore, are forbidden. Tutoring institutions are restricted from charging fees on an annual basis; instead, they may charge a maximum of three months' worth of tutoring fees or 5,000 RMB.

[11] In China pre-college education consists of three stages: primary school (grades 1–6), junior high school (grades 7–9), and senior high school (grades 10–12). Primary and junior high school are classified as compulsory education.

[12] Consequently, publicly traded institutions were forced to exit the regulated market in response to the regulatory development. For instance, TAL Education, one of the industry leaders, traded on the New York Stock Exchange, ceased offering after-school tutoring services on academic subjects for students in grades 1–9 in mainland China as of December 31, 2021. Subsequently, the company suffered a 76.8% net revenue decline in the following financial year, which the company claims "was mainly driven by the cessation of the K-9 Academic AST Services in the mainland of China by the end of December 2021".(TAL Education Group, 2024)

Moreover, regulators are authorized to monitor the institutions' bank accounts to detect any violations.

The effects on private tutoring institutions were immediate. On the day the policy was announced, the share prices of the leading publicly listed private tutoring companies dropped by 60%. Analysts forecast that the size of China's tutoring market would collapse by 76%, to $24 billion (McMorrow et al. (2021)). Dai (2023) finds an immediate negative impact of the "Double Reduction" policy on the stock prices of education companies in China. Online job postings in the sector also plummeted by 89% within four months (Huang et al., 2024). One year after the introduction of the policy, the number of registered tutoring institutions declined by more than 90%, and the average fee dropped by 40% for the remaining institutions. All the remaining institutions have been converted into not-for-profit entities (Ministry of Education of the People's Republic of China, 2022).

2.1.2 Policy exemptions

Subject matter: The goal of the DR policy is to reduce students' ***academic tutoring*** burden; ***non-academic tutoring*** is generally exempted from the restrictions (Ministry of Education of the People's Republic of China, 2021a). Specifically, the "academic subjects" include morality and law, Chinese, history, geography, mathematics, foreign languages (including English, Japanese, and Russian), physics, chemistry, and biology. In contrast, "non-academic" subjects include physical education, arts, music, painting, and general practical activities (including information technology, life-skills, and other hands-on learning).

Age groups: The main purpose of the DR policy was to reduce educational burdens for children in compulsory education (Grades 1 to 9). The policy enacted only minimal restrictions for students in senior high school (Grades 10-12). Table 1 highlights the key differences between policies for students in compulsory education and senior high school. Notably, there is no restriction on the amount of homework that senior high schools can assign to their students (Ministry of Education of the People's Republic of China, 2021b). In addition, most restrictions imposed on after-school academic tutoring institutions for compulsory education students are not applicable to senior high school students (Ministry of Education of the People's Republic of China (2021b)). For example, tutoring institutions for senior high students can remain as for-profit organisations. As of March 2025, there are still more than 6,000 senior high after-school tutoring institutions, of which more than 2,000 are for-profit organisations (Ministry of Education of the People's Republic of China, 2025). Overall, private tutoring institutions serving senior high school students were less affected by the Double Reduction policy compared to those serving compulsory education age groups.

2.1.3 Policy enforcement

Like many policies implemented in China, the DR policy, despite being introduced nationwide, relied heavily on local governments for enforcement. Since July 2021, different provinces and cities have employed various tools to monitor compliance among schools, business registration authorities, and private tutoring institutions.[13] Moreover, the intensity of enforcement efforts also varied over the three-year period from the policy's introduction to the time of the survey used in this study (2021-2023). For example, during the three year period we study local officials were originally took the DR policy very seriously, but as time went on and the initial shock of the policy wore off, some local officials became less vigilant in enforcing the policy. That is probabily why in early 2024 the central government had to issue another notice to local governments to step up enforcement of the DR policy and calling for unwavering and vigorous enforcement (Ministry of Education of the People's Republic of China, 2024).

One of the main differences between the DR policy and many previously implemented policies in reducing student burden is to make the policy more specific and easier to monitor. As such, regional governments in the post implementation period adopted many concrete monitoring measures. Enforcement measures included official supervision, formal inspections, undercover visits, public disclosure of institutions that violated policy requirements, and denouncement of noncompliant institutions. We use these enforcement measures to gauge the strength of regional policy enforcement and how it changed overtime in our subsequent analyses.

2.2 Other relevant events

The DR policy was introduced in the second half of 2021, and our data covers 2019–2023. During the period, two other events occurred that may also affect household behaviour regarding educational investment as well as local governments' DR policy enforcement.

One of these events was the Covid-19 pandemic that began in the early 2020 and lasted until the end of 2022. The severity of the disease outbreak varied across regions and over time, leading to differing local government responses. During the initial stage of the Covid, Wuhan and its surrounding areas experienced a complete lockdown, while most other regions in China were less affected. As the virus spread more widely, more regions were affected. Effective public health responses, such as contact tracing, broad-based testing, mask-wearing, isolated lockdowns, and school closures, eventually curbed the initial spread of the disease. By early 2021, China was largely open. However, in 2022, the emergence of the Omicron variant rendered previous responses less effective, and the country faced renewed lockdowns until the end of 2022.[14] Inevitably, these various lockdowns and school closures affected how local governments and households responded in the education sector, which in turn, might have affected their reactions to the DR policy. A study by Deng et al. (2022) reveals that there was an increase in the education gap between the rich and the poor during the Covid-19 lockdown

[13]For instance, in TAL's 2024 annual report, it highlights the potential concerns on heterogeneous implementation as "local authorities in different regions may adopt different interpretation and implementation measures".

[14]Studies have shown that the lockdown policies during Covid-19 negatively impacted the labour market in China (Zeng et al., 2022; Gong et al., 2024).

periods.

Another event relevant to our study is the "Education Streaming" policy. China's upper secondary education comprises two streams: the academic (senior high schools (SH)) and the technical streams (vocational schools (VS)). At the dawn of China's economic reform era, upper secondary education was predominantly academic. For instance, in 1980, more than 85% of upper secondary students were enroled in the academic stream. In 1983, the government set a goal to achieve parity between the two streams by 1990 to address the shortage of skilled workers during China's rapid industrialisation (Wang and Guo, 2019). This goal was achieved by 1985, and the share of the VS enrolment peaked at approximately 65% in 1995–1996. However, a significant shift occurred in 1998, when the VS share again declined sharply. This change was driven by several factors. First, the government ended job assignments for VS graduates. Second, the large-scale higher education expansion in 1999 increased enrolments at SHs. Third, many vocational schools were upgraded to vocational colleges (Wang and Guo, 2019; Yu, 2019). In the first two decades of this century, the central government issued two policies aimed, again, at increasing VS enrolment, both with little success.

In 2019, a new policy, titled the "National Vocational Education Reform Implementation Plan" was introduced to rebalance VS and SH education. This plan mandated that each region allocate a fixed share of its junior high school graduates to enrol in the academic stream of senior high schools. We refer to this policy as the "Education Streaming" policy. Local governments determine the fixed share based on their capacity and market demand. The introduction of this policy generated widespread media interest and public anxiety (Jiang, 2024). It can be argued that the strength of the "Education Streaming" policy's implementation could be correlated with local governments' efforts to implement the DR policy. At the same time, the households' reaction to the two policies may have reinforced each other.

3 The Survey and the Data

3.1 The survey

In October 2023, we conducted an online household survey entitled, "Double Reduction and Household Education Decision Survey," using the survey platform Wenjuanxing (www.wjx.com). Wenjuanxing is a leading service provider in China for creating and distributing online questionnaires. It offers free tools for questionnaire designing and charges a fee for collecting online surveys and providing a sampling service. As of 2023, the platform boasted over 6.2 million registered members, which serves as the sampling pool. Their sample pool maintains a gender balance of 48% male and 52% female, with the primary age groups being 20–30 (41.3% of the total sample) and 30–40 (32.5% of the total sample). Geographically, while the sample pool covers individuals from all provinces in China, it disproportionately contains respondents from developed regions like Guangdong, Beijing, and Shanghai.

Our survey specifically targets mothers of children in grades 1 through 12 and has a sample size of around 10,000. Because in general online surveys are more likely to attract more-educated urban dwellers and surveys of our type are more likely to attract mothers with children in primary schools,[15] to strike a balance, we set two sampling requirements: First, at least 50% of the sampled mothers should have an education level at or below senior high school; second, at least 40% of the children should be attending junior high school or higher.

In September 2023, we initiated three rounds of pilot surveys, each consisting of a sample of 200 respondents, to refine the questionnaire and detect potential sampling imbalances. After this validation process, the formal survey began in October 2023 and lasted approximately two months. The final sample consists of 10,120 valid responses.[16]

Figure A1 in Appendix A compares the sample geographic distribution with the aggregate population distribution data for the year 2022 (National Bureau of Statistics, 2023). It shows that the provincial share of our sample is roughly consistent with the provincial share of the population. To the extent that our sample does not fully reflect the population distribution, we adjust our results using the population weight generated from the 2020 Population Census.

To gauge the representativeness of our sample concerning the age of children, the education level of mothers, and household income distribution we compare our sample distribution with two different data sources. First, we use the 2022 CFPS, which is a panel survey of nationally representative households. As the DR policy predominantly affects children in urban setting and our survey also mainly captures this population group, we use the sample of CFPS children, who are currently living in cities, aged 6 to 18 and enrolled in primary to senior high school. Despite the 2022 wave of the CFPS survey comprises over 10,000 households and over 37,000 individuals, the number of observations that satisfy our sample selection criteria is less than 2000 individuals. Figure A2 in Appendix A shows that relative to the CFPS 2022 relevant sample, our survey over-sampled, for both genders, children of 7- and 13-year of age. Regarding the mother's education level, our sample mothers have a higher level of education than the CFPS sample. Of the mothers of children age 6–15 in the CFPS sample, 87% have a senior high or lower education level, while our sample only has 63% of mothers with an education level at or below the senior high school.

However, there is a sign that the CFPS survey may also have some biases in their sample of 2018 to 2022.[17] To see this we use the National Bureau of Statistics (NBS) annual data on urban household

[15]We observed this pattern during our three rounds of pilot surveys.

[16]There were also 4,201 responses deemed invalid. A response is deemed as invalid if it has at least one of following issues: 1. incomplete survey; 2. inconsistency in responses; 3. failed random attention test; 4. response time too short; 5. inconsistent log-in; 6. abnormal IP address.

[17]This could be due to the panel nature of the survey. The CFPS began its first wave survey in 2010 and has followed most original households over a decade. In general panel surveys would decline in their representativeness as time goes on.

per capita income distribution (by quintile) from the Statistical Yearbooks for the year 2018 to 2023 as the benchmark, and compare the distribution using our sample and that of the CFPS sample. The results of the comparison are shown in Figure A3 in Appendix A. Panel A compares our sample's income distribution with the NBS data, and Panel B compares the CFPS sample with the NBS data. Overall, our data closely match the NBS distribution, though there is some bias at the top quintile (see Panel A). The 2023 data are an exception, with nearly all quintiles in our sample being somewhat higher than that in the NBS data.[18] The CFPS sample (Panel B), however, is everywhere below the NBS distribution by a large margin, especially for the years 2020 and 2022. With the sample per capita income below the national average, we assume that the CFPS mothers' education distribution would also below the national urban average.

Our survey collects, retrospectively, information from 2019 to 2023, relating to children's private tutoring experiences, spending on private tutoring, children's academic ranking within their respective classes, as well as the time parents spent assisting their children with school homework. In addition, we asked the respondents to report basic demographic information for parents and children, parental labour market involvement, and income. Finally, we also assess their parenting style.[19]

3.2 Sample and summary statistics

Our main sample includes children who were enrolled in grades 1–9 (aged 6–15) for each of the five years between 2019 and 2023.[20] Table 2 reports the summary statistics for key variables used in the paper that relate to parents. Panel A presents some basic parental characteristics. On average, mothers in our main sample (grades 1–9) are around 36 years of age, while their husbands are about one year older. Parents of children in senior high school, are, understandably, older. Around 35% of mothers and 51% of fathers in the main sample have at least a college degree and these proportions are similar for parents with senior high school children. Of the mothers, 96% are in their first marriage; the rate for parents with older kids is much lower, at 92%.

Panel B of Table 2 reports variables that changed over time. We observe, for our main sample,

[18]This may be due to the fact that for years 2018-2022 we asked for the annual income, but an average monthly income for 2023 because our survey was conducted in October that year. We then multiplied the monthly figure by 12. This could exaggerate the annual figure.

[19]We follow Doepke and Zilibotti (2017) to categorize mothers' parental styles by ranking a list of ten qualities that they value for their children. The ten qualities are: independence, hard work, feeling of responsibility, imagination, tolerance and respect for others, thrift and saving money, determination and perseverance, religious faith, unselfishness, and obedience. We label as authoritarian any mother who lists obedience among the top five desired qualities. We further label as authoritative any mother who (i) is not authoritarian, and (ii) mentions hard work among the top five values. Finally, we label as permissive any mother who (i) is neither authoritarian nor authoritative, and (ii) lists either independence or imagination (or both) among the top five values.

[20]Later we also use children who were enrolled in senior high school (grades 10-12, aged 16–18) as an attempt to assess the parallel pre-trend assumption. Note that even though mothers were instructed to report the eldest of their children aged 6–18, some with more than one child reported an eldest child who was over 18 in 2023. As a result, in 2019 and 2020 we have a small number of observations who were already in grades 10–12. These observations are excluded from our main estimation. Although these entries reflect reporting errors, they inadvertently provide useful control observations for our parallel-trend analysis.

that both mothers' labour force participation and their full-time employment increased between 2019 and 2023, especially since 2021. In addition, the average income for both parents has increased significantly. This general trend is also observed for the sample of parents whose children enrolled in senior high schools, although the sample size for this group, especially in the early years, is very small. Furthermore, for the main sample, the data show that parental time spent helping children with their homework increased sharply. Note that the question regarding parental time spent helping with children's schoolwork is an ordinal categorical variable ranging from 0 to 4. The categories are defined as follows: 0 corresponds to zero hours; 1 represents less than 5 hours per week; 2 indicates 5-10 hours; 3 signifies 11-20 hours; and 4 denotes over 20 hours per week. To facilitate interpretation, we convert these categories into hours (0, 3, 8, 15, and 23, respectively). Average time spent by parents with homework assistance rises monotonically from about 9 hours per week in 2019 to over 10 hours in 2023, a pattern not observed for older children.

Table 3 summarises some important outcome variables for children. For the main sample (grades 1–9), participation in private tutoring increased significantly. However, for the senior high school sample, the increase is less pronounced. Conditional on participating in private tutoring, the majority used institutionalised private tutoring services, and this general trend has remained consistent over time.

3.3 The policy intensity measure

To measure regional variation in the enforcement of the DR policy, we explore the monitoring methods used by various levels of government for the policy enforcement. Using these methods as keywords, we searched each prefecture-level city's official website and relevant online news articles during three periods: July 24, 2021 to December 31, 2021; January 1, 2022 to December 31, 2022; and January 1, 2023 to December 31, 2023. We focused on the frequency of five keywords: 1) DR undercover visits, 2) DR blacklist, 3) DR inspections, 4) DR violations, and 5) DR public disclosures. Each official publication or news article that contained any of the five keywords was assigned a value of 1, and these values were subsequently summed to form the measure of policy enforcement intensity. The constructed policy intensity variable is shown in Figure 2. There is a large variations in the number of documents that contained these keywords across cities and over the three periods.

We use both official websites and news articles for two main reasons. First, local governments' official websites typically publish only formal government documents. For any given policy, there are usually only one or a few local policy documents released at the outset of implementation. This limited number is unlikely to capture either cross-city variation in enforcement effort or changes in enforcement over time. Second, enforcement efforts must be publicly known in order to have an effect. News articles help disseminate information and inform the local population about the actions taken by the government. In particular, keywords such as "DR blacklist," "DR violations," and "DR public disclosures" are intended to shame policy violators. The number of documents and articles with these keywords can therefore capture the extent to which information about enforcement is being spread. In the sensitivity analysis we also test using only government document to capture the enforcement intensity.

3.4 Variables measuring Covid-19 severity

To account for the impact of the pandemic on government and household behavior, we include measures that capture regional Covid-19 conditions. During the Covid period, China's regional health commissions provided daily updates to the public on their website on local and imported new cases, cumulative cases, number of recoveries, and deaths, and they occasionally detailed travel histories of confirmed cases. We downloaded mainly the daily case number data and generated two variables to be included in our estimation: the annual average of the daily new cases and the standard deviation (SD) of the daily new cases for each year.

Our dataset covers the period from January 21, 2020, to December 21, 2022, for 344 prefectural regions.[21] On average, the annual daily number of new cases is 5.1, with a SD of 17.3. However, as shown in Figure 3, the primary disruption occurred in 2022.

3.5 Education Streaming

To accurately measure the Education Streaming policy across different regions, we employ the ratio of senior high school enrolments to junior high school graduates as the key metric. Most of these data are sourced from the Comprehensive Statistical Yearbooks of China. When the yearbook data are unavailable, we supplement them with reported values from local media outlets. Data points from around 63 cities in 195 city-year cells are obtained from this latter source. We use a city's academic streaming ratio in the previous year $t-1$ to proxy parents' expectations of their children's exposure to the education streaming policy in year t. Figure 4 presents the distribution of the academic streaming ratio during the period 2018–2022, which shows that the mean ratio remains stable but becomes a little less dispersed in 2021 and 2022.

4 Model Specification and Identification Strategy

Our purpose is to examine the impact of the implementation of the DR policy on household behaviours, specifically in relation to children's participation in private tutoring, spending on private tutoring, children's academic performance, mothers' labour market responses, and parental time spent assisting

[21]To construct our variables, we first matched city names in the Covid-19 data with a list of prefectural cities in our dataset. For each year from 2020 to 2022, we calculated new cases by summing daily new case numbers over the year to generate the annual average of the daily number, the standard deviation (SD) of the daily number, as well as the maximum daily number.

their children with homework. In a standard DID setting, the two-way-fixed-effects (TWFE) model typically requires only the city and year fixed effects. However, since we have a panel dataset, we estimate a more restrictive model using *individual* rather than *city* fixed effects. This approach can improve our identification, particularly when policy impacts vary across individuals, and enhance the precision of our estimates. In the case of children's academic performance, which is measured by within-class ranking, adding individual fixed effects also resolves the potential issue of comparability of within-class ranking across different schools in a city. The model is specified as follows:

$$Y_{ijt} = \alpha_0 + \alpha_1 DRP_{jt} + \alpha_2^{'} X_{ijt}^{c} + \alpha_3^{'} W_{ijt}^{p} + \alpha_4^{'} C_{jt} + \eta_i + \delta_t + \epsilon_{ijt}, \tag{1}$$

where Y_{ijt} is a vector of outcome variables for child/mother i in city j at year t. DRP is the DR policy intensity variable, which measures the frequency of the appearance of the five DR enforcement-intensity-related keywords in the cities' official documents or news articles for each of the three years after the implementation of the policy. X_{ijt}^{c} is a vector of the child's control variables (age, gender). W_{ijt}^{p} is a vector of parental controls (marital status, father's education, log of household income (log of father's income in the case of mother's labour market responses), and parenting style. C_{jt} is a vector of city-level time-varying variables capturing the pandemic situation (average daily number of cases and the standard deviation of the daily cases for the year), as well as the Education Streaming policy for city j in year t. η_i and δ_t are individual and time fixed effects, while ϵ_{ijt} is the random error term.

Note that in Equation (1), DRP is a continuous variable that ranges from 0 to 1200, while α_1 is the estimated average causal effect of the DR policy. However, the magnitude of α_1 is hard to interpret and the assumption that it measures the average effect is also very strong, suggesting that in such a wide range of policy intensities the effect is linear. To enable an easy interpretation of the magnitude of the policy effect and also to capture the potential nonlinearity of the policy impact, we divide DRP into six equally distanced bins (G), and the lowest frequency is used as the omitted category. Thus, Equation (1) becomes the following:

$$Y_{ijt} = \alpha_0 + \sum_{g=2}^{6} \gamma_g GDRP_{gjt} + \alpha_2^{'} X_{ijt}^{c} + \alpha_3^{'} W_{ijt}^{p} + \alpha_4^{'} C_{jt} + \eta_i + \delta_t + \epsilon_{ijt}, \tag{2}$$

where $GDRP$ is five dummy variables that equal one if the city's policy intensity frequency falls into the g group, zero otherwise.

The α_1 and γ_g estimated from the above models should capture the causal effect of the DR policy, under the assumption that cities with and without intensive policy implementation would have behaved similarly in the absence of the DR policy. This is a strong assumption that requires a pre-trend analysis. To test this, a counterfactual group is required. In our case, however, as the policy was implemented nationwide in China at around the same time, there is no ideal counterfactual group available.

Instead, we adopt two less ideal alternatives. First, we define households from cities that had the lowest level of policy enforcement as our counterfactual group (frequency = 1 to 200). Figure 5 shows the density distribution of the DR policy-related keywords. The two vertical dotted lines represent the median (137) and the mean (233) frequencies in the distribution. Our choice of 200 as the cutoff is between the median and mean values. Later in the robustness section, we will test the sensitivities of our results to the choice of this cutoff.

Our second alternative is defined based on the design of the DR policy. As discussed in Section 2, the DR policy primarily targeted junior high and lower students, with no restrictions on either homework or private tutoring services for senior high school students. For this reason, senior high school students would serve as a good counterfactual. Unfortunately, our survey covers children enrolled in grades 1–12 in 2023 and only a limited number of the students in the sample were in senior high school in the pre-DR policy period (around 85 observations). Thus, it is also not perfect. However, if both of these imperfect alternative counterfactuals yield consistent findings, our conclusions will be more robust and credible.

To test the parallel pre-trend, we estimate the following model:

$$Y_{ijt} = \alpha_0 + \sum_{t=2020}^{2023} \beta_t T_t * P^{treated} + \alpha_2^{'} X_{ijt}^{c} + \alpha_3^{'} W_{ijt}^{p} + \alpha_4^{'} C_{jt} + \eta_i + \delta_t + \epsilon_{ijt}, \tag{3}$$

where T is a vector of year dummy variables with 2019 being the omitted category, and $P^{treated}$ is the dummy variable for the treated group (either cities with a high density of policy frequency or those enroled in the primary and junior high schools). We estimate Equation (2) using the primary and junior high school sample when the low policy density is used as the control group and using the full sample when the senior high school students are the control group. We test the pre-trend using three of our main outcome variables, namely, whether the individual participated in private tutoring, whether the tutoring was conducted in an institutional or individual manner, and spending on private tutoring. As 2019 and 2020 are the pre-DR policy years, we expect $\beta_{2020} = 0$ while for other years $\beta \neq 0$.

Figures 6 and 7 present the coefficients β when using the low policy density and the senior high school students as the counterfactuals, respectively. In the first instance (Figure 6), for all three outcome variables, we observe that individuals from both high and low policy density cities seem to behave similarly during the two pre-DR years (2019 and 2020). Changes began to emerge from 2021 as the policy was introduced in the second half of the year. By 2022 and 2023, households in cities with higher policy density exhibited significantly different behaviours compared to those in cities with low policy density. Figure 7 shows similar patterns for the tutoring participation and spending outcome variables, but not for the type of tutoring received.

5 Results

5.1 Effects on children's outcomes

Table 4 presents the results from estimating Equations (1) and (2) with private tutoring outcomes. Panel A of Table 4 shows the average impact using the continuous policy variable. The results from this panel indicate that students from cities that have more-intense policy enforcement are more likely to participate in after-school private tutoring, and, conditional on participation, the increase in private tutoring is mainly driven by a rise in individualised rather than institutionalised or school-conducted tutoring.[22] These results are quite intuitive. As shown in Figure 1, the introduction of the DR policy significantly heightened parental anxiety, leading to a spike in searches for individualised tutoring, while search activities for institutional or school-conducted tutoring show only a slight reduction.

To understand the magnitudes of the effects on participation and on engaging in individualised tutoring, we move to Panel B of Table 4. Here, the variable "policy" is measured using dummy variables for six bins with equal frequency distances, with the first bin (1–200) serving as the omitted category. The coefficients for the remaining five bins indicate the size of the DR policy impact relative to the first bin. It is important to note that if the omitted bin relative to the pre-treatment period also has a positive effect, the estimated effects relative to the omitted bin would be underestimates of the actual effects.

The results shown in Panel B indicate that the coefficients for all the bins are positive and largely statistically significant, suggesting that, relative to households in cities with the lowest DR policy enforcement efforts, households in cities with higher enforcement efforts are more likely to participate in private tutoring. The magnitudes of the effects, ranging from 2 to 6.6 percentage points, initially increase with the intensity of the policy implementation, and then, as the intensity further increases, the effect reduces to 3 percentage points. This pattern suggests a possible strategic interaction among households, tutoring providers, and the government. As policy enforcement intensifies, households may become increasingly anxious about their children's education, leading to higher enrolment in private tutoring. However, if government enforcement becomes too stringent, participation in private tutoring might be constrained by supply-side limitations.

The effect on participation in the individualised tutoring exhibits a similar nonlinear pattern. The strength of the policy enforcement increases individualised tutoring by between 1.4 and 5.6 percentage

[22] A question naturally arises as to why there is a near zero impact of policy enforcement on institutionalised private tutoring. After all, the policy targeted the institutional providers and should have significantly reduced the supply of the institutions. Our data, however, are unable to answer this question. Nevertheless, using the Places of Interests (POI) data from Gaode map (one of the most popular Chinese map apps) we summarised the number of private tutoring institutions across different years. The results are presented in Figure A4 in Appendix A. The trend presented in the figure does not show much of a reduction in the number of institutions during the DR period.

points. In this case though, the supply-side constraints are less significant due to the difficulty of monitoring behaviours of the individualised providers. This might explain why the reduction in the size of the effect is less pronounced when policy enforcement intensifies.

As discussed in the Section 2, the DR policy mainly targets academic-related private tutoring. In Table 5, we examine the size of the effect of the policy intensity on academic-related versus Art/PE tutoring. The results from Equation (1) (left two columns) indicate that both types of tutoring are positively affected by the policy, but the magnitude of the effect is about twice as large for the academic-related tutoring compared to Art/PE tutoring. Columns (3) and (4) of Table 5 further suggest that the effect of the policy implementation intensity on academic tutoring follows a similar pattern to the overall private tutoring participation, while the effect on Art/PE tutoring is considerably smaller.

Finally, we examine the impact of the DR policy on household spending on private tutoring and on children's educational outcomes. The measure of educational outcomes is derived from parental reports. In the survey, parents were asked to report their children's academic ranking within their own class for each of the five years from 2019 to 2023. Note that because our estimation uses individual FE model, this within-class ranking does not suffer from across region/school/class comparability problems. Table 6 presents the estimated results. We find that, on average, there is no impact of the DR policy on children's educational performance ranking. However, the policy does have a positive and significant effect on spending. Households in cities with higher levels of policy enforcement spend between 18% and 62% more on private tutoring compared to those in cities with the lowest policy enforcement. This pattern mirrors the effects observed in private tutoring participation.

5.2 Effect on parental outcomes

The DR policy not only affects children's outcomes but can also influence parental behaviour through its effects on children. For example, as schools are required to reduce homework, parents may compensate by spending more time assisting their children with schoolwork. In addition, as the demand for private tutoring rises, households, in anticipation of increased spending on private tutoring, may adjust their labour supply accordingly, which typically occurs on the mother's side, as the majority of fathers in China are already participate full-time in the labour market.

Table 7 presents the results of estimated Equations (1) (top panel) and (2) (bottom panel). As shown in the top panel, on average, parents spend more time on their children's school-related work at home after the DR policy. In addition, mothers are more likely to work full time and to participate in the labour market. The bottom panel highlights that, relative to parents in cities with the lowest policy enforcement, parents in other cities spend 0.11 to 0.34 hours more time helping their children with schoolwork. However, the magnitude of the effects on mothers' labour market involvement is quite small. For full-time job participation, the effects range from 0.3 to 1.6 percentage points, while for labour market participation, they range from 1 to 2.3 percentage points.

5.3 Inequality of the DR policy impacts

The above analyses show the DR policy affected average households in cities with varying levels of policy enforcement. However, these average impacts are not equally experienced by all households. In this subsection, we examine how the DR policy affects children from households with different income levels. To do so, we rank household income into four or ten quantiles, generating dummy variables to indicate these income groups, and then interact these dummy variables with the variable DRP_{jt} in Equation (1).

$$Y_{ijt} = \alpha_0 + \alpha_1 DRP_{jt} + \sum_{q=1}^{n} \lambda_q Q_q * DRP_{jt} + \alpha_3^{'} W_{ijt}^{p} + \alpha_4^{'} C_{jt} + \eta_i + \delta_t + \epsilon_{ijt}, \tag{4}$$

where Q_q is a group of the dummy variables for the different income levels, with the highest income group as the omitted category.

The coefficients on these interaction terms (λ_q) indicate the differential impacts of DR policy for households in the respective quantiles relative to the omitted top quantile households. The actual impact for each quantile is the sum of α_1 and λ_q. Tables 8 and 9 report the results from estimating Equation (4) for children and parental outcomes, respectively. For simplicity, we report three key variables for children's outcomes: the probability of participating in private tutoring, the log of spending on private tutoring, and the parent-reported ranking of children's achievement. The results in Table 8 show that while households in the second to the fourth quartiles all increased their private tutoring participation and tutoring spending, households in the bottom quartile neither increased private tutoring participation nor the relevant spending (see the bottom panel of Table 8). As a result, the DR policy has an adverse impact on the educational achievement of children from households in the bottom income quartile, even though the policy did not affect children's educational achievement on average. We also present Equation (4) using income deciles instead of quartiles: the results for children's outcomes are shown in Figure 8. The figure clearly shows that the DR policy negatively affected both participation in private tutoring and spending on private tutoring for households in the bottom two income deciles. These groups also experienced the main adverse impact on children's educational achievement. It is possible that as the DR policy increased the overall demand for private tutoring and reduced its supply, tutoring prices rose significantly, making it much harder for low-income households to afford these services.

Table 9 and Figure 9 further explore the impact of the DR policy on parental responses for households with varying income levels. It is important to note here that when examining the mother's labour market responses, the income rank is based on the father's income alone rather than the household's income. The most interesting finding from these analyses is that low-income households spent significantly more time helping with their children's schoolwork to compensate for their inability to afford private tutoring. In addition, mothers from low-income households increased their labour supply (both labour force participation and full-time work), presumably to prepare for future need to increase their children's education spending, such as private tutoring, even though they were currently unable to afford it. The fact that these parents sacrifice more of their leisure time to support their children's education and these mothers are prepared to work harder in the marketplace highlights their determination. They strive to give their children a better future, despite being at the lower end of the socioeconomic ladder.

Recall that one of the most important motivations for implementing the DR policy was to reduce potential intergenerational inequality. However, our results suggest that the policy may have had the opposite effect. It is the children from the lowest income households who suffered the most academically from the DR policy due to their parents' inability to afford private tutoring. If children's current educational performance can affect their future income levels, the DR policy may exacerbate income inequality for the next generation, undermining the government's goal of reducing future income inequality. This finding is concerning and serves as a critical reminder for policymakers: effective policy-making is a gaming process that requires policymakers to anticipate the behavioural reactions of the society towards proposed policies. In a society where being educated and ensuring one's children receive a good education are highly valued, blunt policies such as bans on school homework or after-school tutoring can trigger significant reactions. As it happened, the ban on school homework caused anxiety among parents, who have long upheld the cultural norm of prioritising their children's education. Such anxiety led parents to seek alternative options. The additional ban on private tutoring institutions did not, and cannot, allay this anxiety. Naturally, less efficient and more expensive forms of individualised private tutoring dominated the market. This shift increased the monetary cost of private tutoring, placing a greater burden on those who could not afford it and exacerbated the adverse effects of the DR policy on the children it was meant to help.

6 Sensitivity tests

In this section, we examine the sensitivity of our results against a series of assumptions we made in our estimation.

Our identification strategy relies heavily on the assumption that our variable that captures the intensity of DR policy implementation does not correlate with other omitted variables that also affect our outcome variables of interest. This is why we assume that in the pre-policy period there was a parallel trend. Given that our policy variable is continuous, in Section 4 we defined two imperfect alternative control groups to facilitate our pre-trend test. In this section, we conduct several other alternative tests to verify whether the pre-parallel trend assumption is indeed satisfied.

The first test is a placebo test. It involves using the policy variable in the years when the policy was in effect to replace the year before the implementation of the policy. If the policy-enforcement variable in the post-policy years does not relate to the outcomes in the pre-policy year, it will lend support to our assumption that the DR policy-enforcement intensity is indeed capturing the DR policy, not some omitted pattern that is correlated with our outcome variables even when the policy was not introduced. We adapt the test from Acemoglu and Finkelstein (2008) and Clemens and Gottlieb (2017) by interacting the post-DR policy treatment levels for each year with a dummy variable for 2020, one year at a time. If the parallel trends assumption is valid, the coefficient of the interaction term between the 2020 year dummy and any post-DR treatment policy level should be close to zero and statistically insignificant. Table 10 reports the results for several key children's outcomes. The results confirm that neither 2022 nor 2023 policy intensity is related to outcomes in 2020.

The second test examines whether our choice of defining the least intense policy as the control group is sensitive to the level of the policy intensity we chose. In our previous analysis, we used the frequency of 200 as a cutoff to define the control group. Figure 10 presents the results using alternative thresholds of 150 and 250 to define the control and treated groups. The graph demonstrates that in both cases, the parallel trends assumption holds, suggesting that the results are not sensitive to the decision on the cutoff levels used to define the control and treated groups.

Next, We assess the robustness of our results using an alternative measure of policy implementation intensity. Our preferred measure counts both the number of city government policy documents and related news articles containing any of our keywords, reflecting the view that enforcement efforts must be publicly visible to be effective. However, it may be argued that only official government documents truly represent enforcement effort.[23]

The main limitation of this approach is that city governments typically issue only one or a very small number of policy documents at the time a policy is introduced. Consequently, this alternative measure treats implementation intensity as fixed after the initial introduction and generates very coarse variation across cities and no within-city variation over time. This lack of cross-section and temporal variation makes the measure less informative and, in our view, less suitable for capturing changes in enforcement intensity. Nevertheless, Table 11 presents the results using this alternative policy measure.

Among the 306 cities for which we identified government policy documents, 192 mention at least one of the five keywords—indicating stronger monitoring—while the remaining 114 do not. We interact this dummy variable with a post-policy indicator equal to one for 2021 and later, and zero otherwise. Panel A reports the average policy effect, while Panel B examines heterogeneity across income quantiles. Overall, the pattern of results closely mirrors our main findings based on the preferred policy measure.

[23]During earlier presentations of the paper, concerns were raised that relying exclusively on official policy documents might provide a more precise measure of government effort. To address this concern, we construct a dummy variable indicating whether a city government's DR policy document mentions any of the five keywords.

However, because this alternative measure is considerably coarser and lacks variation across cities and over time, the estimated effects are smaller and less precisely estimated.

We also investigate potential omitted variable biases. Here we first include provincial-specific time trends to account for localised policies or conditions that could affect the outcome variables. Table 12 reports the results. Comparing the first panel (based on the original Equation (1) results) with those in the second panel (which includes provincial-specific time trend), it is clear that our results are not sensitive to such an inclusion. In Table 13 we include additional city-level time varying variables, including log of per capita GDP and the student/teacher ratios for the primary and high schools separately. Although these inclusions modestly reduce the measured city-level policy effects, the central findings and overall narrative remain robust. Finally, our results are not driven by the choice of Covid-19 controls. In untabulated analyses, we obtain quantitatively similar estimates when either excluding Covid-19 variables or incluing an additional variable capturing the maximum daily number of confirmed cases.

Our final test addresses potential limitations to the policy inferences of our study due to sample representativeness. To evaluate this, we take two steps. First, in the Data section, we have already compared our sample's representativeness with some benchmarks: (1) sample locality relative to the national population; (2) children's age distribution and mothers' education levels relative to the CFPS 2022 survey; and (3) household income distributions relative to the NBS urban household income data. Overall, our sample aligns closely with national population regional distribution and urban income distributions, though with slightly greater variation in the top quintile. However, we observe two discrepancies relative to the CFPS 2022 sample: our survey oversampled children aged 7 and 13 (for unclear reasons) and overrepresented children whose mothers have education levels above senior high school by approximately 10 percentage points. Notably, the CFPS sample's representativeness for this subgroup is also uncertain, as its household per capita income distribution (see Figure A3 in Appendix A) skews toward middle- to low-income households compared to the NBS data.

Second, despite these limitations, we estimate Equation (1) using CFPS data from 2018, 2020, and 2022 waves. We focus on outcome variables comparable to our study: private tutoring participation, individualised private tutoring participation, parental time spent assisting with homework, and mothers' labor force participation. The CFPS data also provide granular metrics, including hours spent on tutoring and individualised tutoring, as well as mothers' hours worked. Results are presented in Table B2 in Appendix B. The table reveals that coefficients for the main policy variable ("DRP") in almost all regressions share the same direction of signs as those in our primary analysis. For individualised tutoring participation, the magnitude is nearly double that of our main estimates. Parental time spent assisting with schoolwork also shows a large effect. However, none of the coefficients are statistically significant. We attribute this imprecision to two possible factors: (1) The CFPS sample of households with school-aged children (6-15 years) is notably small for instance, in 2022 (the treated period), CFPS includes only around 1,400 observations from 181 cities, compared to 8,388 observations from 313 cities in our main sample. (2) The CFPS income distribution is more compressed relative to the NBS urban household data, likely further reducing estimation precision.

7 Conclusions

China's Double Reduction policy has been in place since 2021. The policy aims to reduce students' excessive homework and decrease demand for private tutoring, with the goals of fostering balanced student development, controlling household education expenses, and relieving parents from additional time spending on their children's education. The DR policy was intended to ultimately reduce intergenerational educational and income inequality.

Our results, however, show that the policy has induced higher private tutoring participation, increased the cost of private tutoring, increased parental time invested in their children's school-related work. More importantly, as private tutoring costs rose, low-income households were unable to afford private tutoring, leading to adverse impacts on their children's educational achievement. All our results seem to suggest that the introduction of the DR policy has brought about the opposite of what the policy intended to achieve.

An important lesson from our study is that policy-making needs to account for potential societal reactions. In a society where education is highly valued and market competition is fierce, any attempt to reduce the level of educational burdens and competition will inevitably lead to strong reactions from parents. Thus, effective policy-making requires a much more nuanced understanding of how to induce behavioural changes in the society. Blunt policy instruments, such as administratively reducing students' homework or forbidding private tutoring institutions, may not result in desired outcome.

References

Acemoglu, D. and A. Finkelstein (2008). Input and technology choices in regulated industries: Evidence from the health care sector. *Journal of Political Economy 116*(5), 837–880.

Agnew, H., T. Kinder, and H. Lockett (2021). Investors rethink China strategy after regulatory shocks. *Financial Times*. Available at: `https://www.ft.com/content/0de80b60-4809-41f6-a287-a3b0f88a15d2` (Accessed: June 21, 2024).

Appleton, S., L. Song, and Q. Xia (2005). Has China crossed the river? The evolution of wage structure in urban China during reform and retrenchment. *Journal of Comparative Economics 33*(4), 644–663.

Becker, G. S. and N. Tomes (1979). An equilibrium theory of the distribution of income and intergenerational mobility. *Journal of Political Economy 87*(6), 1153–1189.

Becker, G. S. and N. Tomes (1986). Human capital and the rise and fall of families. *Journal of Labor Economics 4*(3, Part 2), S1–S39.

Black, S. E. and P. J. Devereux (2011). *Recent Developments in Intergenerational Mobility*, pp. 1487–1541. Elsevier.

Chen, A. and X. Zhang (2020). The difficulties and solutions in implementing policies in reducing elementary and secondary students' burden in China. In D. Yang, M. Yang, and S. Huang (Eds.), *China Education Development Report — 2020 (In Chinese)*, Chapter B17, pp. 228–240. Beijing, China: Social Sciences Academic Press.

Chen, M. H., L. Kang, W. Lu, Y. Wei, and J. Xing (2025). Government bans, household spending, and academic performance: Evidence from private tutoring in china. *Working paper*.

Choi, H. and A. Choi (2016). Regulating private tutoring consumption in korea: Lessons from another failure. *International Journal of Educational Development 49*, 144–156.

Clemens, J. and J. D. Gottlieb (2017). In the shadow of a giant: Medicare's influence on private physician payments. *Journal of Political Economy 125*(1), 1–39.

Dai, K. (2023). "double reduction" policy in education industry and firm values: Evidence from China. *Finance Research Letters 54*, 103696.

Dang, H.-A. (2007). The determinants and impact of private tutoring classes in Vietnam. *Economics of Education Review 26*(6), 683–698.

David, B. (2024, December). How the ivy league broke america: The meritocracy isn't working. we need something new. *The Atlantic December.*

Deloitte (2019). Revitalizing education opportunities in dynamics. Technical report.

Deng, Y., X. Huang, T. Li, and S.-J. Wei (2022). Online learning and the education gap: A digital footprint approach. *Working paper*.

Doepke, M. and F. Zilibotti (2017). Parenting with style: Altruism and paternalism in intergenerational preference transmission. *Econometrica 85*(5), 1331–1371.

Dong, Y., X. He, Y. Lizhen, L. Sun, J. Li, J. Xu, Y. Cui, Z. Li, L. Hu, and B. Guannan (2023). Determinants of depression, problem behavior, and cognitive level of adolescents in China: Findings from a national, population-based cross-sectional study. *Frontiers in Psychiatry*.

Genicot, G. and D. Ray (2017). Aspirations and inequality. *Econometrica 85*, 489?519.

Gong, D., A. Yan, and J. Yu (2024, July). The costs of zero-covid: Effects of anti-contagious policy on labor market outcomes in China. *Journal of Labor Research*.

Goodman, R. (2003). The why, what and how of education reform in Japan. In R. Goodman and D. Phillips (Eds.), *Can the Japanese Change their Education System*, pp. 7–30. Providence: Symposium Books Ltd.

Guo, J. and X. Qu (2022). Competition in household human capital investments: Strength, motivations and consequences. *Journal of Development Economics 158*, 2–17.

Guo, Y., Q. Chen, S. Zhai, and C. Pei (2020). Does private tutoring improve student learning in China? Evidence from the China Education Panel Survey. *Asia & the Pacific Policy Studies 7*(3), 322–343.

Guryan, J., E. Hurst, and M. Kearney (2008). Parental education and parental time with children. *Journal of Economic Perspectives 22*(3), 23–46.

Hale, T. (2023). China's anxious parents turn to tutoring black market after Xi Jinping's crackdown. *Financial Times*. Available at: `https://www.ft.com/content/a23cdb7b-8bda-402a-af4e-04f06f93e264` (Accessed: June 21st, 2024).

Hou, J. and Z. Chen (2021). Interannual evolution of adolescents' mental health status in 2009 and 2020 (in Chinese). In X. Zhan, K. Zhang, and X. Chen (Eds.), *Report on National Mental Health Development in China (2019-2020)*, pp. 188–202. Beijing: Social Sciences Academic Press (China).

Huang, B., M. Tani, Y. Wei, and Y. Zhu (2022). Returns to education in China: Evidence from the great higher education expansion. *China Economic Review 74*, 101804.

Huang, Z., Y. Liu, M. Ma, and L. Yang (2024). Biting the hand that teaches: Unraveling the economic impact of banning private tutoring in China. *Available at SSRN 4758676*.

Jang, Y. and M. Yum (2024). Aggregate and intergenerational implications of school closures: A quantitative assessment. *American Economic Journal: Macroeconomics 16*, 90–130.

Jheng, Y.-J. (2015). The influence of private tutoring on middle-class students' use of in-class time in formal schools in Taiwan. *International Journal of Educational Development 40*, 1–8.

Jiang, B. (2024). Factors of educational anxiety for Chinese students entering higher education based on educational expectations. *International Journal of Education and Humanities 12*(2), 102–106.

Johnston, A. (2021). Unemployment insurance taxes and labor demand: Quasi-experimental evidence from administrative data. *American Economic Journal: Policy 13*(1), 266–293.

Jung, J. H. and K. H. Lee (2010). The determinants of private tutoring participation and attendant expenditures in Korea. *Asia Pacific Education Review 11*(2), 159–168.

Kang, H. (2023). *Parental investment, child's efforts, and intergenerational mobility.* PhD Thesis, State University of New York at Stony Brook.

Kim, H. (2004). Analyzing the impact of high school equalization policy on private tutor ing expense in Korea. *Journal of Korean Education 31*(1), 365–383.

Kim, S., M. Tertilt, and M. Yum (2024). Status externalities in education and low birth rates in Korea. *American Economic Review 114*(6), 1576–1611.

Liu, Y., R. Wang, and C. Zhanming (2022). Regulating private tutoring: Family responses to the double-reduction policy in China.

Markovits, D. (2019). *The Meritocracy Trap: How America's Foundational Myth Feeds Inequality, Dismantles the Middle Class, and Devours the Elite.* New York: Penguin Press.

McMorrow, R., S. Yu, T. Kinder, and T. Hale (2021). China's education sector crackdown hits foreign investors. *Financial Times*. Available at: https://www.ft.com/content/dfae3282-e14e-4fea-aa5f-c2e914444fb8 (Accessed: June 21st, 2024).

Meng, X. (2012). Labor market outcomes and reforms in China. *Journal of Economic Perspective 26*(4), 75–102.

Ministry of Education of the People's Republic of China (2021a). Guidelines to Classify Academic and Non-academic Off-campus Tutoring Activities for Students Undergoing Compulsory Education (in chinese). Technical report. http://www.moe.gov.cn/srcsite/A29/202107/t20210730_547807.html.

Ministry of Education of the People's Republic of China (2021b). Guidelines to ease the burden of excessive homework and off-campus tutoring for students undergoing compulsory education, jointly issued by the General Office of the Communist Party of China Central Committee and the General Office of the State Council (In Chinese).

Ministry of Education of the People's Republic of China (2022). Response to Recommendation No. 2173 of the Fifth Session of the Thirteenth National People's Congress (in chinese).

Ministry of Education of the People's Republic of China (2024, January). Moe holds national meeting on implementation of "double reduction" policy. http://en.moe.gov.cn/news/press_releases/202401/t20240111_1099736.html. Official press release describing the January 4, 2024 national meeting on strengthening implementation and enforcement of the Double Reduction policy.

Ministry of Education of the People's Republic of China (2025). National after-school tutoring supervision and service platform (in chinese).

Ministry of Education of the People's Republic of China and National Bureau of Statistics of China (2020). *China Educational Finance Statistical Yearbook - 2020 (In Chinese).* China Statistics Press.

Mulder, M. B., S. Bowles, T. Hertz, A. Bell, J. Beise, G. Clark, I. Fazzio, M. Gurven, K. Hill, P. L. Hooper, W. Irons, H. Kaplan, D. Leonetti, B. Low, F. Marlowe, R. McElreath, S. Naidu, D. Nolin, P. Piraino, R. Quinlan, E. Schniter, R. Sear, M. Shenk, E. A. Smith, C. Von Rueden, and P. Wiessner (2009). Intergenerational wealth transmission and the dynamics of inequality in small-scale societies. *Science 326*(5953), 682–688.

National Bureau of Statistics (2023). *China Statistical Yearbook 2023 (in Chinese)*. Beijing, China: China's Statistics Press.

OECD (2014). Does homework perpetuate inequities in education? Report. `https://www.oecd-ilibrary.org/docserver/5jxrhqhtx2xt-en.pdf?expires=1721614093&id=id&accname=guest&checksum=30EAF84B5B38BFCD13F30F119DE74BE`.

Qian, H. and S. Chen (2024). The 'Double-Reduction' education policy in China: Three prevailing narratives. *Journal of Education Policy 39*(4), 602–621.

Ryu, D. and C. Kang (2013). Do private tutoring expenditures raise academic performance? Evidence from middle school students in South Korea. *Asian Economic Journal 27*(1), 59–83.

Sandel, M. J. (2020). *The Tyranny of Merit: What's Become of the Common Good?* New York: Farrar, Straus and Giroux.

Schuman, M. (2015). *Confucius: And the World He Created*. Basic Books.

TAL Education Group (2024, May). Tal education group, 2024 annual report.

Timpe, B. (2024). The labor market impacts of America's first paid maternity leave policy. *Journal of Public Economics 231*.

Tomes, N. (1981). The family, inheritance, and the intergenerational transmission of inequality. *Journal of Political Economy 89*(5), 928–958.

Wai, J., S. M. Anderson, K. Perina, F. C. Worrell, and C. F. Chabris (2024). The most successful and influential americans come from a surprisingly narrow range of 'elite' educational backgrounds. *Nature: Humanities and Social Science Communications 11*(1), 1129–1140.

Wang, A. and D. Guo (2019). Technical and vocational education in China: Enrolment and socioeconomic status. *Journal of Vocational Education & Training 71*(4), 538–555.

Watkins, D. (2000). Learning and teaching: A cross-cultural perspective. *School Leadership and Management 20*(2), 161–173.

Wiseman, A. W. (2021). Does inequality stay in the shadow? The cross-national effects of educational equity on private tutoring and student achievement. *International Journal of Educational Research 109*, 101808.

Xiang, X. (2019). A historical perspective on the two education initiatives of alleviating academic burden in China since 1949 (in chinese). *Journal of East China Normal University (Educational Sciences) 37*(5), 67.

Yang, D. T. (2005). Determinants of schooling returns during transition: Evidence from Chinese cities. *Journal of Comparative Economics 33*(2), 244–264.

Yang, X. (2019). Analysis of the mixtures of positives and negatives in the effort to reduce school burden in primary schools (in Chinese). *Journal of Chinese Education 2019*(8), 6–12.

Yen, H.-C. and Y.-Y. Wu (2015). *The Conflict Between Social Mobility and Individual Development*, pp. 201–221. Singapore: Springer Singapore.

Yu, Q. (2019). Review of the positioning and scale evolution of vocational education since the founding of new China (in Chinese). *Journal of Zhejiang Normal University (Social Sciences) 44*(5), 10.

Yum, M. (2022). Parental time investment and intergenerational mobility. *International Economic Review 64*, 187?223.

Zang, W. (2022). A deep understanding of the importance of the 'double reduction' policy (in Chinese).

Zeng, X., S. Chu, and X. Chen (2022). China's labor market demand in the shadow of Covid-19: Evidence from an online job board. *Working paper*.

Zhang, J., Y. Zhao, A. Park, and X. Song (2005). Economic returns to schooling in urban China, 1988 to 2001. *Journal of Comparative Economics 33*(4), 730–752.

Zhang, W. and M. Bray (2018). Equalising schooling, unequalising private supplementary tutoring: Access and tracking through shadow education in China. *Oxford Review of Education 44*(2), 221–238.

Zhang, Y. and Y. Xie (2016). Family background, private tutoring, and children's educational performance in contemporary China. *Chinese Sociological Review 48*(1), 64–82.

Zhao, G. (2015). Can money 'buy' schooling achievement? Evidence from 19 Chinese cities. *China Economic Review 35*, 83–104.

Zhao, L., H. Yuan, and X. Wang (2024). Impact of homework time on adolescent mental health: Evidence from China. *International Journal of Educational Development 107*, 103051.

Zhao, N., C. Shi, and C. Wang (2024). Effects of the "double reduction" policy on the commercial tutoring sector in China. *International Journal of Educational Development 105*, 102989.

Zheng, X., C. Wang, Z. Shen, and X. Fang (2020). Associations of private tutoring with Chinese students' academic achievement, emotional well-being, and parent-child relationship. *Children and Youth Services Review 112*, 104934.

Zhou, Z., X. Lei, and Y. Shen (2023). Education burden reduction, family education investment, and education equality (in Chinese). *China Economic Quarterly 23*(3), 841–859.

Table 1: Policy Summary Comparison: Compulsory Education Ages v.s. Senior High Ages

Key policy	Compulsory education ages	Senior high ages
Homework burden reduction	Yes	Not applicable
On-campus activities and hours	Expand	Not applicable
Allowing for-profit institutions	No	Yes
New licenses for institutions	Not allowed	Not allowed

Note: This table summarises the policy differences between two age groups: compulsory education ages (grade 1 to grade 9) and senior high (grade 10 to grade 12).

Table 2: Summary Statistics of Parental Variables

Panel A:	Parental Characteristics in 2023			
	Grades 1–9		Grades 10–12	
	Mother	Father	Mother	Father
Age	35.76	36.90	42.25	43.53
Education distribution:				
Junior high and below	0.05	0.05	0.09	0.10
Senior high	0.58	0.40	0.53	0.42
Uni/College	0.35	0.51	0.37	0.44
Masters	0.02	0.03	0.01	0.03
PhD	0.002	0.005	0.004	0.005
Marital status:				
First marriage	0.96		0.92	
Remarried	0.02		0.05	
Divorced	0.02		0.03	
Parenting style based on the 10-attribute question:				
Authoritarian	0.26		0.25	
Authoritative	0.54		0.57	
Permissive	0.20		0.18	
Observations	8,740	8,740	919	919

Panel B:		Parental information changes over time			
Grades 1–9	2019	2020	2021	2022	2023
Mother with full-time job	0.70	0.71	0.74	0.77	0.77
Mother LFP rate	0.84	0.85	0.88	0.91	0.92
Mother income (Yuan)	62630.75	63115.49	68381.75	74235.96	82155.47
Father income (Yuan)	91532.86	92568.52	96926.69	102338.07	131245.43
Parents' time spent helping homework (hour)	9.01	9.28	9.35	9.60	10.22
Observations	5239	6382	7200	8325	8740
Grades 10–12	2019	2020	2021	2022	2023
Mother with full-time job	0.49	0.64	0.72	0.70	0.68
Mother LFP rate	0.86	0.88	0.89	0.89	0.88
Mother income (Yuan)	76478.29	57496.10	65870.05	66157.87	73323.46
Father income (Yuan)	63591.73	77237.44	83027.33	83822.21	109047.70
Parents' time spent helping homework (hour)	4.85	9.46	9.07	8.86	8.82
Observations	6	79	288	647	919

Notes: Although parents were instructed to report the eldest of their children aged 6–18, some with more than one child reported an eldest child who was already over 18 in 2023. As a result, in 2019 and 2020 we have a small number of observations who were already in grades 10–12. These observations are excluded from our main estimation. Although these entries reflect reporting errors, they inadvertently provide useful control observations for our parallel-trend analysis.

Table 3: Summary Statistics of Children's Variables

	Grades 1–9				
	2019	2020	2021	2022	2023
Tutoring participation	0.38	0.36	0.41	0.53	0.66
Where received tutoring (Conditional on participation):					
Tutoring:individual	0.26	0.27	0.25	0.24	0.24
Tutoring:institution.	0.83	0.84	0.84	0.85	0.87
Tutoring:school	0.12	0.13	0.15	0.15	0.17
Tutoring spending	3,856	4,253	4,967	6,552	8,357
Education ranking	70.08	70.63	71.05	71.80	73.38
No. of observations	5,708	6,471	7,275	8,388	8,841
	Grades 10–12				
Tutoring participation	0.45	0.46	0.47	0.47	0.55
Where received tutoring (Conditional on participation):					
Tutoring:individual	0.00	0.37	0.29	0.28	0.35
Tutoring:institution	1.00	0.69	0.80	0.80	0.79
Tutoring:school	0.67	0.25	0.22	0.15	0.21
Tutoring spending	8,994	6,045	6,263	7,041	7,950
Education ranking	75.02	60.86	66.71	65.45	67.56
No. of observations	8	79	288	648	931

	Grades 1–9		Grades 10-12	
	Mean	SD	Mean	SD
Age in 2023	10.17	2.88	16.84	0.76
Share of boys in 2023	0.61		0.60	

Table 4: DR Impact on Children's Tutoring (Fixed Effects)

		Type of Tutoring		
Panel A: Eq. (1)	Tutoring	Institution	Individual	School
DRP	0.045**	-0.004	0.052***	-0.004
	(0.020)	(0.015)	(0.018)	(0.014)
Log household inc	0.008***	0.001	0.002	0.005*
	(0.003)	(0.004)	(0.004)	(0.003)
Covid-19 controls	Yes	Yes	Yes	Yes
Education streaming control	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Child fixed effects	Yes	Yes	Yes	Yes
No. of observations	35,886	17,550	17,550	17,550
No. of clusters	313	311	311	311

		Type of Tutoring		
Panel B: Eq. (2)	Tutoring	Institution	Individual	School
DRP range 200–400	0.019	0.000	0.014	0.001
	(0.016)	(0.010)	(0.011)	(0.010)
DRP range 400–600	0.027*	-0.020*	0.036***	0.001
	(0.016)	(0.011)	(0.014)	(0.012)
DRP range 600–800	0.066***	-0.021	0.056***	0.001
	(0.019)	(0.014)	(0.014)	(0.012)
DRP range 800–1000	0.045**	-0.009	0.031*	-0.000
	(0.019)	(0.013)	(0.016)	(0.013)
DRP range 1000–1200	0.030	0.003	0.041**	-0.006
	(0.020)	(0.015)	(0.018)	(0.013)
Log household income	0.008***	0.001	0.002	0.005*
	(0.003)	(0.004)	(0.004)	(0.003)
Covid-19 controls	Yes	Yes	Yes	Yes
Education streaming control	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Child fixed effects	Yes	Yes	Yes	Yes
No. of observations	35,886	17,550	17,550	17,550
No. of clusters	313	311	311	311

Notes: Robust standard errors in parentheses, which are clustered at the prefectural level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: DR Impact on Types of Tutoring

	Equation 1		Equation 2	
	Academic	Arts&PE	Academic	Arts&PE
DRP	0.055***	0.026*		
	(0.020)	(0.015)		
DRP range 200–400			0.028**	-0.001
			(0.014)	(0.012)
DRP range 400–600			0.040**	0.000
			(0.016)	(0.012)
DRP range 600–800			0.079***	0.033**
			(0.018)	(0.013)
DRP range 800–1000			0.059***	0.028**
			(0.018)	(0.013)
DRP range 1000–1200			0.030	0.009
			(0.021)	(0.017)
Log household income	0.009***	0.001	0.009***	0.001
	(0.003)	(0.002)	(0.003)	(0.002)
Covid-19 controls	Yes	Yes	Yes	Yes
Education streaming control	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Child fixed effects	Yes	Yes	Yes	Yes
No. of observations	35,886	35,886	35,886	35,886
No. of clusters	313	313	313	313

Notes: Robust standard errors in parentheses, which are clustered at the prefectural level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 6: DR Impact on Tutoring Spending and Educational Ranking

	Equation 1		Equation 2	
	Edu ranking	log(spending)	Edu ranking	log(spending)
DRP	-0.230	0.435**		
	(0.307)	(0.176)		
DRP range 200–400			0.113	0.183
			(0.263)	(0.145)
DRP range 400–600			-0.029	0.246*
			(0.283)	(0.140)
DRP range 600–800			-0.271	0.621***
			(0.299)	(0.173)
DRP range 800–1000			-0.002	0.396**
			(0.272)	(0.164)
DRP range 1000–1200			-0.063	0.313*
			(0.319)	(0.184)
Log household income	0.222**	0.073***	0.223**	0.072***
	(0.087)	(0.026)	(0.087)	(0.026)
Covid-19 controls	Yes	Yes	Yes	Yes
Education streaming control	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Child fixed effects	Yes	Yes	Yes	Yes
No. of observations	35,885	35,886	35,885	35,886
No. of clusters	313	313	313	313

Notes: Robust standard errors in parentheses, which are clustered at the prefectural level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: DR Impact on Parents'/Mother's Outcomes (Fixed Effects)

	Time Spent Helping schoolwork	Mother's Labour Market Outcomes Full-time Work	LFP
DRP	0.320^{*}	0.018^{*}	0.018^{**}
	(0.193)	(0.009)	(0.009)
Log household income	-0.054		
	(0.033)		
Log fathers' income		0.018^{***}	0.023^{***}
		(0.002)	(0.003)
Covid-19 controls	Yes	Yes	Yes
Education streaming control	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Child fixed effects	Yes	Yes	Yess
No. of observations	35,886	35,886	35,886
No. of clusters	313	313	313
	Time Spend Helping school work	Mother's Labour Market Outcomes Full-time Work	LFP
DRP range 200–400	0.251^{*}	0.003	0.013^{**}
	(0.141)	(0.007)	(0.006)
DRP range 400–600	0.114	0.004	0.015^{**}
	(0.171)	(0.008)	(0.007)
DRP range 600–800	0.330^{*}	0.014^{*}	0.023^{***}
	(0.180)	(0.008)	(0.007)
DRP range 800–1000	0.336^{*}	0.016^{*}	0.020^{**}
	(0.186)	(0.009)	(0.008)
DRP range 1000–1200	0.296	0.013	0.010
	(0.186)	(0.010)	(0.010)
Log household income	-0.054		
	(0.033)		
Log fathers' income		0.018^{***}	0.023^{***}
		(0.002)	(0.003)
Covid-19 controls	Yes	Yes	Yes
Education streaming control	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Child fixed effects	Yes	Yes	Yess
No. of observations	35,886	35,886	35,886
No. of clusters	313	313	313

Notes: Robust standard errors in parentheses, which are clustered at the prefectural level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 8: DR Distributional Impact on Children's Outcomes

	Private Tutoring	Log Spending	Education Ranking
DRP	0.064***	0.654***	0.549
	(0.023)	(0.206)	(0.344)
Quartile 1 × *DRP*	-0.077***	-0.770***	-1.760***
	(0.024)	(0.219)	(0.486)
Quartile 2 × *DRP*	-0.011	-0.189	-1.141***
	(0.019)	(0.185)	(0.361)
Quartile 3 × *DRP*	0.000	-0.031	-0.538
	(0.017)	(0.166)	(0.376)
Log household income	0.007**	0.061**	0.198**
	(0.003)	(0.026)	(0.088)
Covid-19 controls	Yes	Yes	Yes
Education streaming control	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Child fixed effects	Yes	Yes	Yes
DRP+Quartile 1× *DRP*	-0133	-0.116	-1.211***
F-test *p*-value	[0.617]	[0.615]	[0.008]
DRP+Quartile 2× *DRP*	0.053**	0.465**	-0.592
F-test *p*-value	[0.025]	[0.025]	[0.110]
DRP+Quartile 3× *DRP*	0.064***	0.624***	0.011
F-test *p*-value	[0.005]	[0.002]	[0.980]
No. of observations	35,886	35,886	35,285
No. of clusters	313	313	313

Notes: Robust standard errors in parentheses, which are clustered at the prefectural level. The numbers in square brackets are the *p*-vlaues for the F-test statistics. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 9: DR Distributional Impact on Parental Outcomes

	Parents'	Mother's Labour Market	
	Time-spent	LFP	Full-Time
DRP	0.102	0.004	0.007
	(0.219)	(0.010)	(0.010)
Quartile 1 × *DRP*	0.446*	0.037***	0.016
	(0.254)	(0.010)	(0.011)
Quartile 2 × *DRP*	0.167	0.024**	0.015
	(0.188)	(0.010)	(0.011)
Quartile 3 × *DRP*	0.309	0.003	0.013
	(0.223)	(0.006)	(0.008)
Log household income	-0.048		
	(0.034)		
Log father's income		0.023***	0.019***
		(0.003)	(0.002)
Covid-19 controls	Yes	Yes	Yes
Education streaming control	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Child fixed effects	Yes	Yes	Yes
DRP+Quartile 1×DRP	0.548**	0.041***	0.023**
F-test *p*-value	[0.035]	[0.001]	[0.048]
DRP+Quartile 2×DRP	0.269	0.028**	0.022*
F-test *p*-value	[0.220]	[0.012]	[0.052]
DRP+Quartile 3×DRP	0.411	0.007	0.020**
F-test *p*-value	[0.105]	[0.484]	[0.045]
No. of observations	35,886	35,886	35,886
No. of clusters	313	313	313

Notes: Robust standard errors in parentheses, which are clustered at the prefectural level. The numbers in square brackets are the *p*-vlaues for the F-test statistics. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Parallel Trends Test: Assigning Pre-period the Post-period Policy, Children's Outcomes

	Tutoring	Individualised T	Log(spending)	Edu Ranking
	Replacing 2020 with 2022 policy-intensity level			
$DRP \times 2020$	-0.014	-0.017	-0.187	-0.076
	(0.030)	(0.036)	(0.262)	(0.524)
$DRP \times 2021$	0.016	0.027	0.156	-0.295
	(0.022)	(0.020)	(0.194)	(0.336)
$DRP \times 2022$	0.087^{***}	0.077^{***}	0.775^{***}	0.328
	(0.032)	(0.029)	(0.285)	(0.536)
$DRP \times 2023$	0.092^{**}	0.108^{***}	0.889^{***}	-0.765
	(0.038)	(0.033)	(0.335)	(0.699)
	Replacing 2020 with 2023 policy-intensity level			
$DRP \times 2020$	-0.033	-0.008	-0.356	0.335
	(0.029)	(0.031)	(0.254)	(0.558)
$DRP \times 2021$	0.010	0.029	0.101	-0.179
	(0.022)	(0.020)	(0.198)	(0.360)
$DRP \times 2022$	0.080^{**}	0.080^{***}	0.710^{**}	0.490
	(0.033)	(0.029)	(0.288)	(0.544)
$DRP \times 2023$	0.083^{**}	0.110^{***}	0.808^{**}	-0.593
	(0.038)	(0.033)	(0.334)	(0.723)
Covid-19 controls	Yes	Yes	Yes	Yes
Education streaming control	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Child fixed effects	Yes	Yes	Yes	Yes
No. of observations	35,886	17,550	35,886	35,285
No. of clusters	313	311	313	313

Notes: Robust standard errors in parentheses, which are clustered at the prefectural level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Alternative Policy Measure

	Tutoring	Individual Tut	log(spending)	Edu ranking	Time spend help
	Panel A: Average effect				
Policy * Post	0.007	0.031^{**}	0.103	0.148	-0.026
	(0.019)	(0.014)	(0.175)	(0.282)	(0.174)
Covid-19 controls	Yes	Yes	Yes	Yes	Yes
Education streaming control	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Child fixed effects	Yes	Yes	Yes	Yes	Yes
No. of observations	35144	17212	35144	34550	35144
No. of clusters	292	290	292	292	292
	Panel B: Effect by income Quantile				
Policy*Post	0.027	0.034^{**}	0.326	0.846^{**}	-0.101
	(0.022)	(0.017)	(0.203)	(0.328)	(0.210)
Policy*Post*Qtile 1	-0.075^{***}	-0.008	-0.734^{***}	-1.346^{***}	0.152
	(0.019)	(0.017)	(0.174)	(0.356)	(0.196)
Policy*Post*Qtile 2	0.005	-0.004	-0.037	-0.762^{***}	0.073
	(0.017)	(0.019)	(0.159)	(0.291)	(0.175)
Policy*Post*Qtile 3	0.003	-0.003	-0.010	-0.444	0.129
	(0.014)	(0.012)	(0.135)	(0.276)	(0.178)
Covid-19 controls	Yes	Yes	Yes	Yes	Yes
Education streaming control	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Child fixed effects	Yes	Yes	Yes	Yes	Yes
No. of observations	35144	17212	35144	34550	35144
No. of clusters	292	290	292	292	292

Notes: Robust standard errors in parentheses, which are clustered at the prefectural level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.The alternative policy measure is constructed as a dummy variable indicating whether a city government's DR policy document mentions any of the five keywords, which is then interacted with a post-policy indicator equal to one for 2021 and later, and zero otherwise.

Table 12: Sensitivity Test Adding Provincial Time Trend

	Tutoring	Individualised T	Log(spending)	Edu Ranking
	Original Results of Eq. 1			
DRP	0.045**	0.052***	0.435**	-0.230
	(0.020)	(0.018)	(0.176)	(0.307)
	Eq. 1 Plus Provincial Time Trend			
DRP	0.046**	0.046**	0.431**	-0.509*
	(0.020)	(0.019)	(0.178)	(0.302)
	Eq. 2 Plus Provincial Time Trend			
DRP range 200–400	0.019	0.013	0.169	0.074
	(0.015)	(0.011)	(0.135)	(0.256)
DRP range 400–600	0.035**	0.034***	0.302**	-0.240
	(0.014)	(0.013)	(0.128)	(0.266)
DRP range 600–800	0.067***	0.053***	0.612***	-0.491
	(0.017)	(0.014)	(0.149)	(0.299)
DRP range 800–1000	0.050***	0.031*	0.431**	-0.283
	(0.019)	(0.018)	(0.168)	(0.289)
DRP range 1000–1200	0.032	0.038**	0.324*	-0.297
	(0.020)	(0.018)	(0.186)	(0.324)
Covid-19 controls	Yes	Yes	Yes	Yes
Education streaming control	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Child fixed effects	Yes	Yes	Yes	Yes
No. of observations	35,886	17,550	35,886	35,285
No. of clusters	313	311	313	313

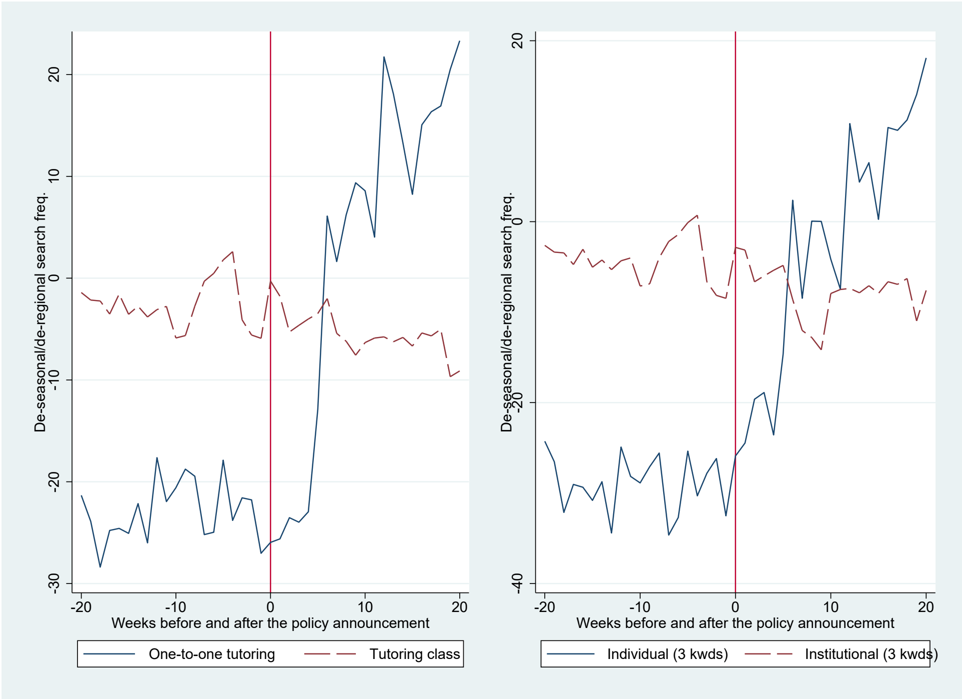
Notes: Robust standard errors in parentheses, which are clustered at the prefectural level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 13: Sensitivity Test Adding City Level Additional Controls

	Tutoring	Individualised T	Log(spending)	Edu Ranking
	Original Results of Eq. 1 for this Sample			
DRP	0.051**	0.053***	0.482***	-0.298
	(0.020)	(0.018)	(0.177)	(0.307)
	Eq. 1 Plus Additional City Controls			
DRP	0.039*	0.048***	0.380**	-0.214
	(0.020)	(0.018)	(0.176)	(0.309)
	Eq. 2 Plus Additional City Control			
Policy range 200-400	0.021	0.012	0.198	0.034
	(0.016)	(0.011)	(0.142)	(0.263)
Policy range 400-600	0.022	0.032**	0.199	-0.059
	(0.015)	(0.014)	(0.138)	(0.285)
Policy range 600-800	0.060***	0.052***	0.555***	-0.283
	(0.019)	(0.015)	(0.168)	(0.304)
Policy range 800-1000	0.043**	0.028*	0.381**	-0.029
	(0.019)	(0.017)	(0.164)	(0.279)
Policy range 1000-1200	0.026	0.038**	0.271	-0.042
	(0.020)	(0.018)	(0.180)	(0.322)
Covid-19 controls	Yes	Yes	Yes	Yes
Education streaming control	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Child fixed effects	Yes	Yes	Yes	Yes
No. of observations	35460	17348	35460	34863
No. of clusters	298	295	298	298

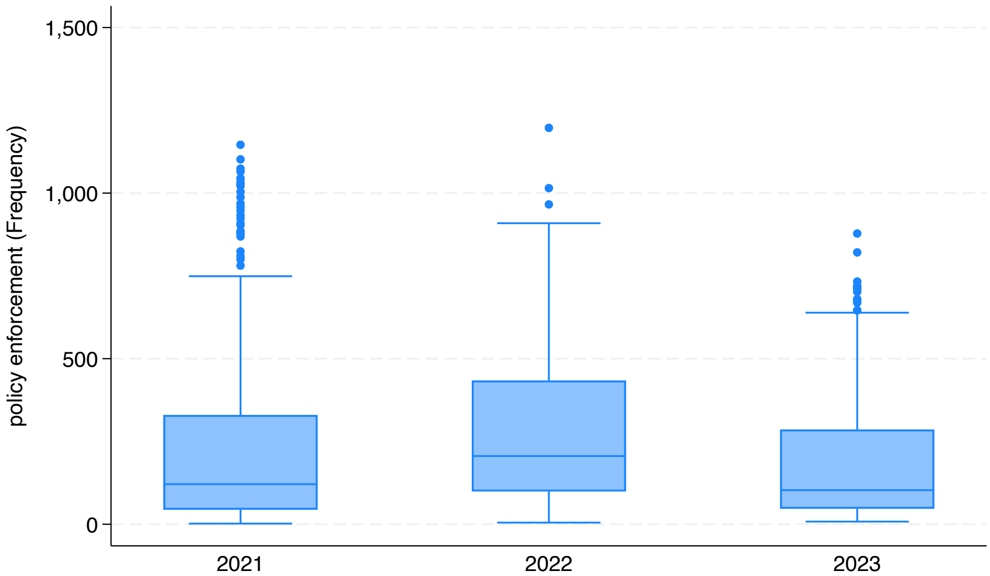
Notes: Robust standard errors in parentheses, which are clustered at the prefectural level. Additional city level controls include log per capita GDP, the student/teacher ratios for primary and high schools. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Baidu Search Frequency on Individual and Institutional Tutoring Before and After DR Announcement



Note: The three keywords for individualised tutoring are: one-on-one tutoring, one-on-few, and family tutoring. The three keywords used for institutional tutoring are: training class, after-school training, and after-class training. The variable used is the de-seasoned and de-regionalized residual search frequency.

Figure 2: Distribution of the Policy Keywords Appearance by Year



Note: The five keywords are: 1. DR undercover visit; 2. DR black list; 3. DR Inspection; 4. DR violations; 5. DR publicly disclosure.

Figure 3: Distribution of the COVID-19 daily cases by year

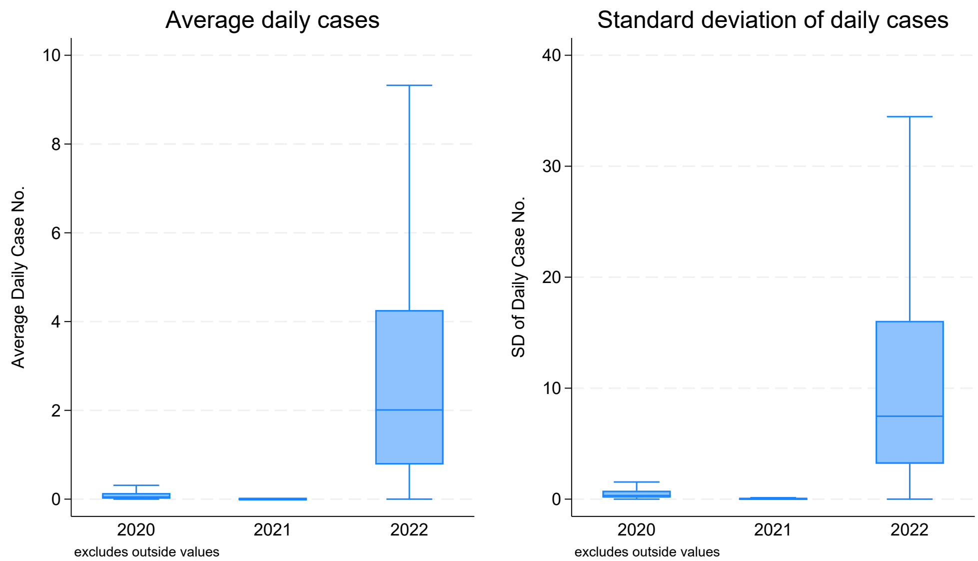


Figure 4: Distribution of the Shares of the Senior High Enrolments Among the Junior High Graduates

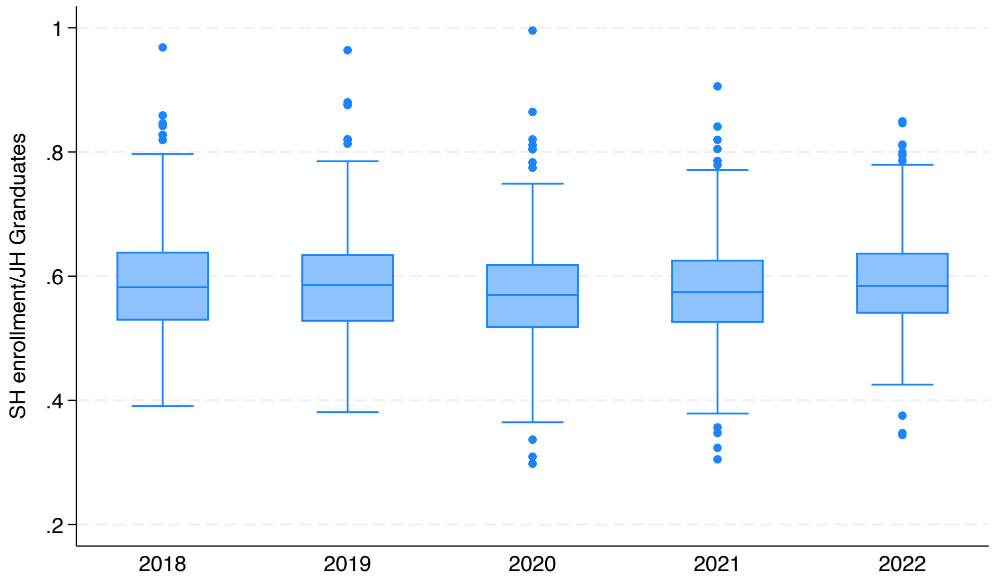
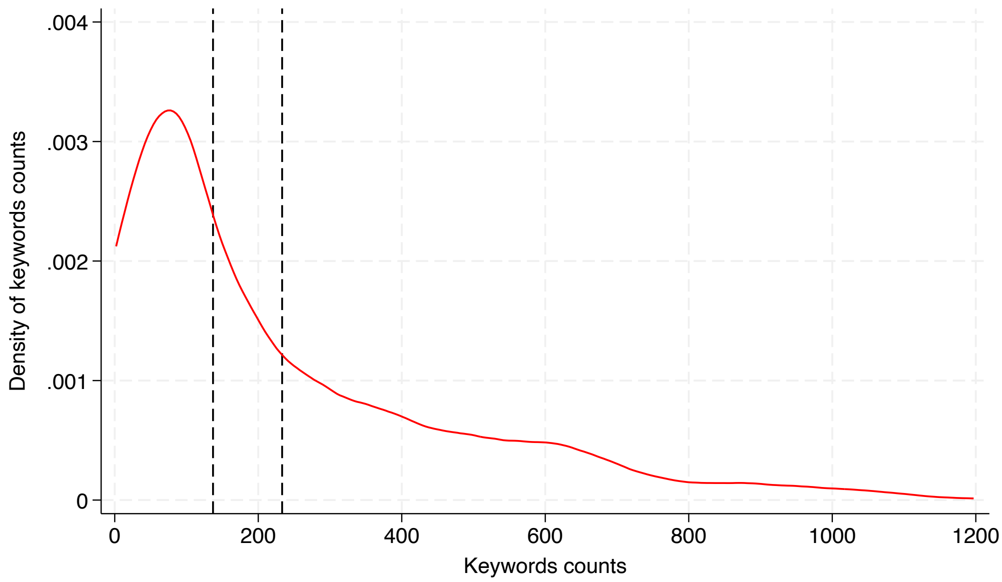


Figure 5: Distribution of the DR Policy Variable



Note: The two vertical lines represent the median and mean levels of the keyword density. The median and mean are 137 and 233, respectively.

Figure 6: Parallel Trends Test – Low Policy Density as the Control

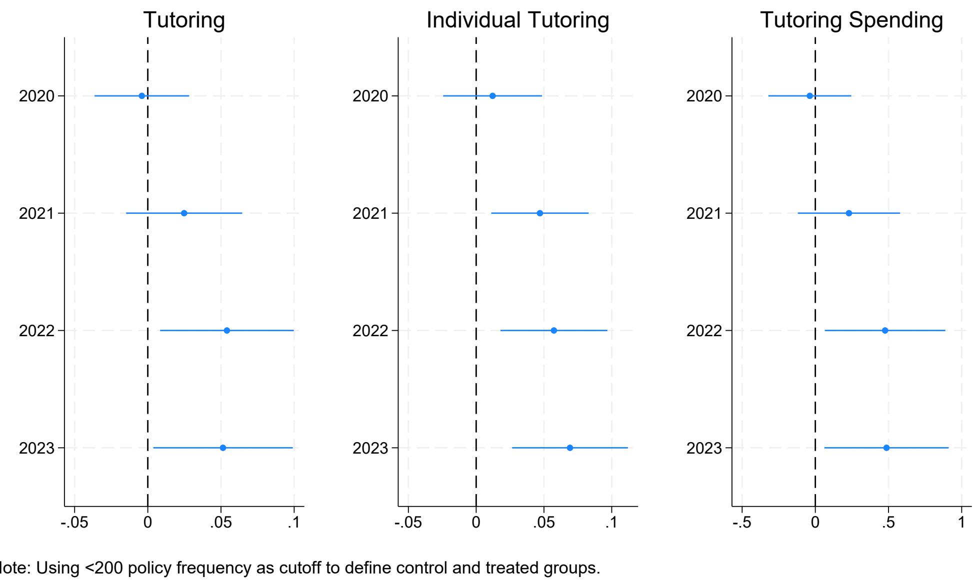
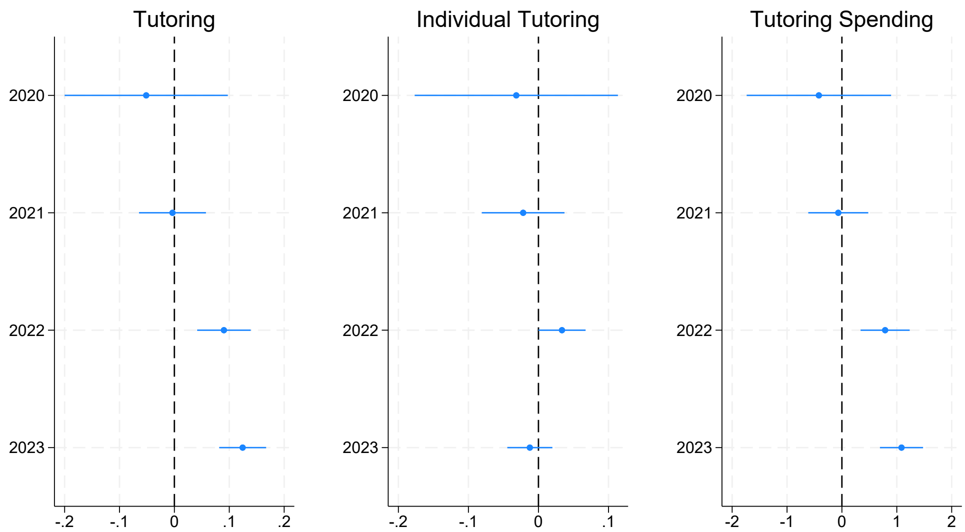


Figure 7: Parallel Trends Test – Senior High School Students as the Control



Note: Using Senior high group as the control.

Figure 8: Distributional Impact of the DR Policy on Children's Outcomes

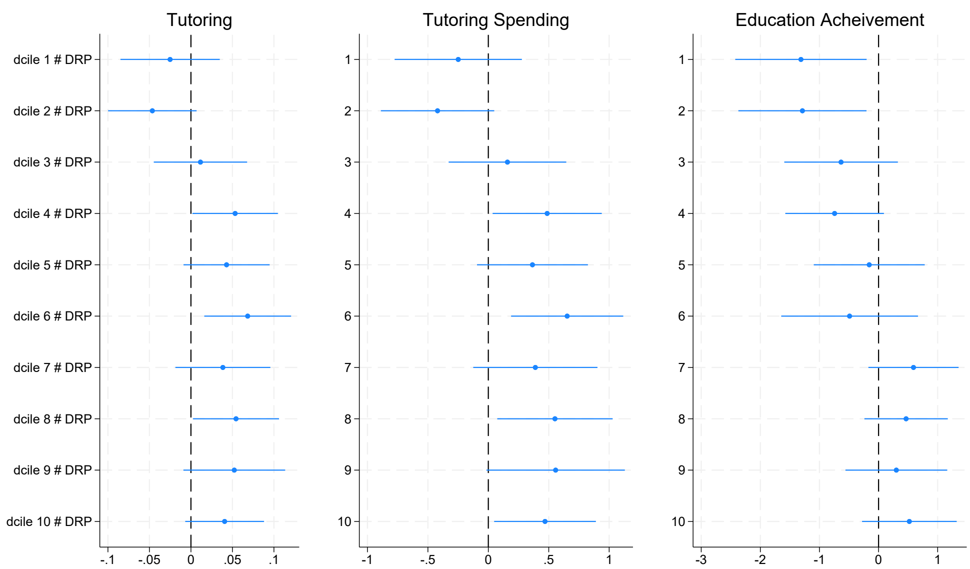


Figure 9: Distributional Impact of the DR Policy on Parents' Outcomes

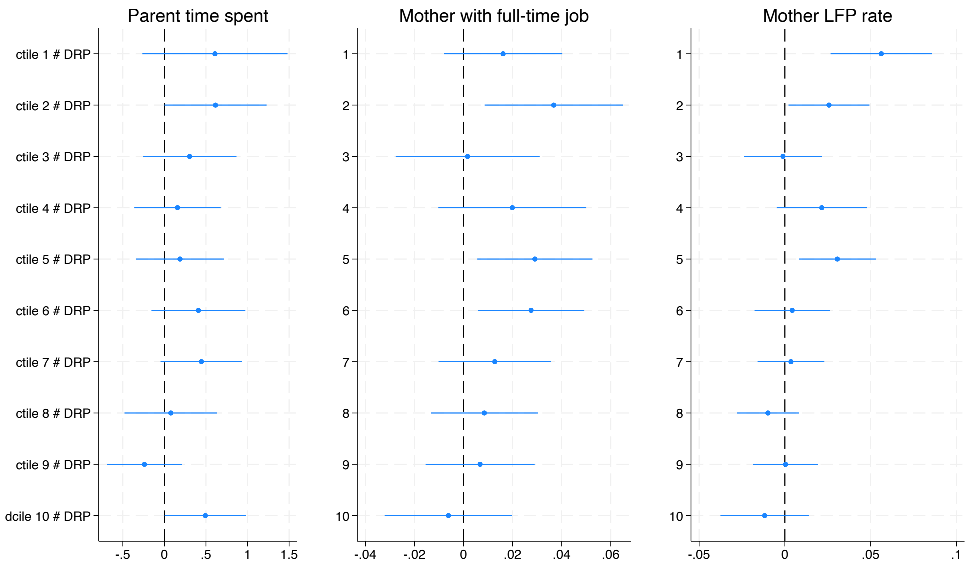
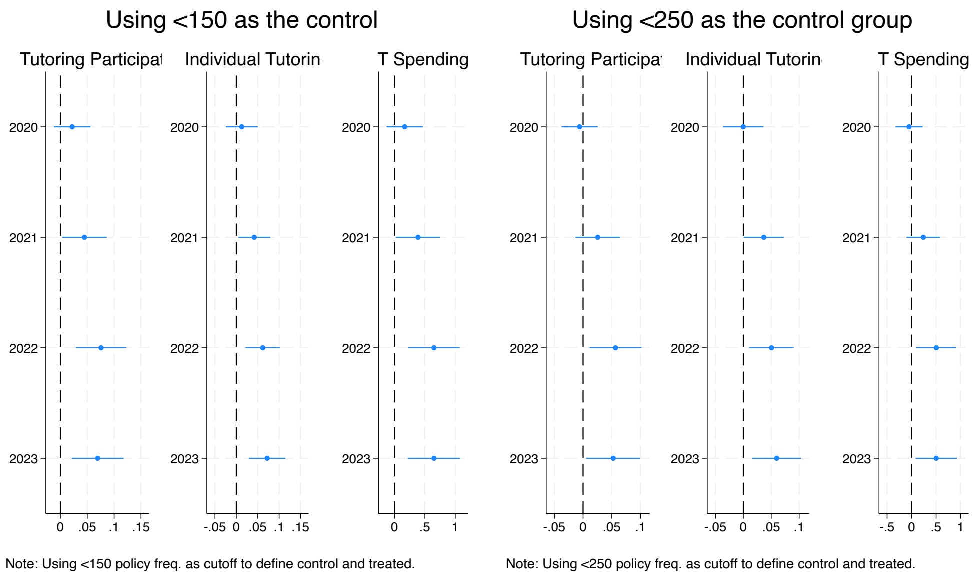
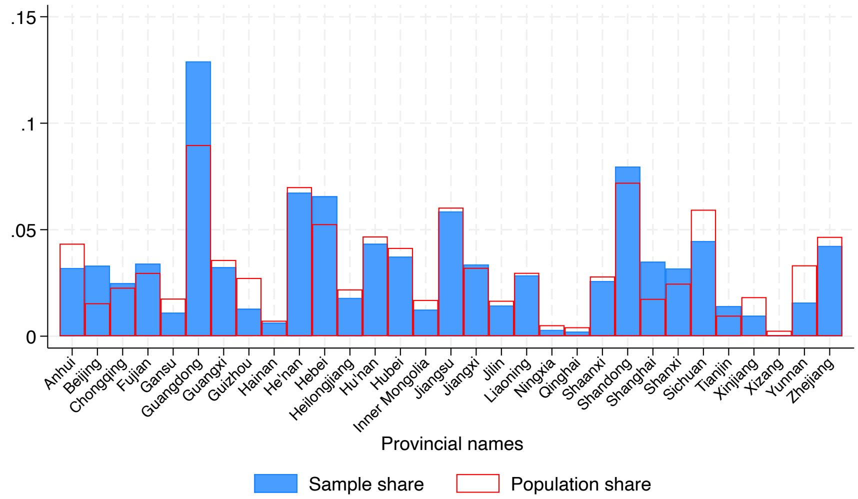


Figure 10: Parallel Trends Test: Using Alternative Definition of Control Group



APPENDIX A Appendix Figures

Figure A1: Regional Distribution of the Sample and the Population



Note: The data for the provincial population distribution are from National Bureau of Statistics (2023).

Figure A2: Children's Age Distribution: DR Sample vs. CFPS Sample

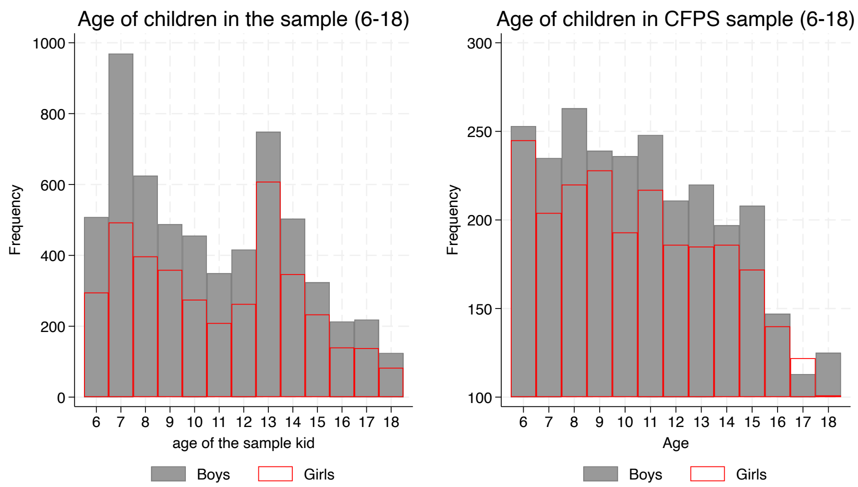
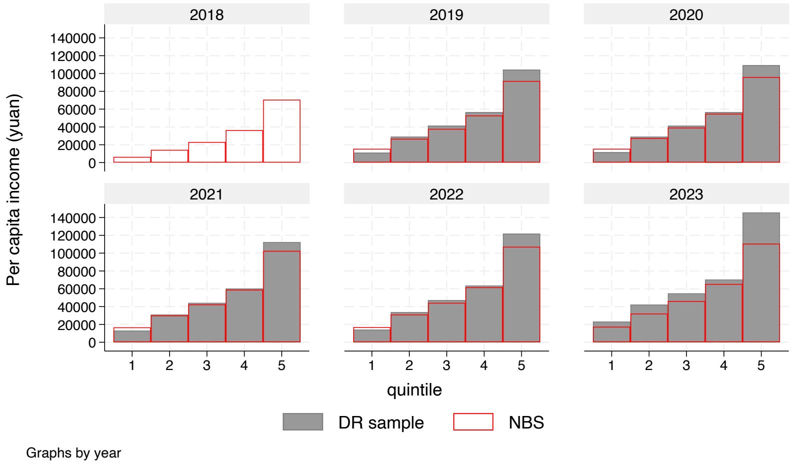


Figure A3: Income Distribution by Quintile: DR, CFPS, vs. NBS

Panel A: DR Sample vs. NBS



Panel B: CFPS Sample vs. NBS

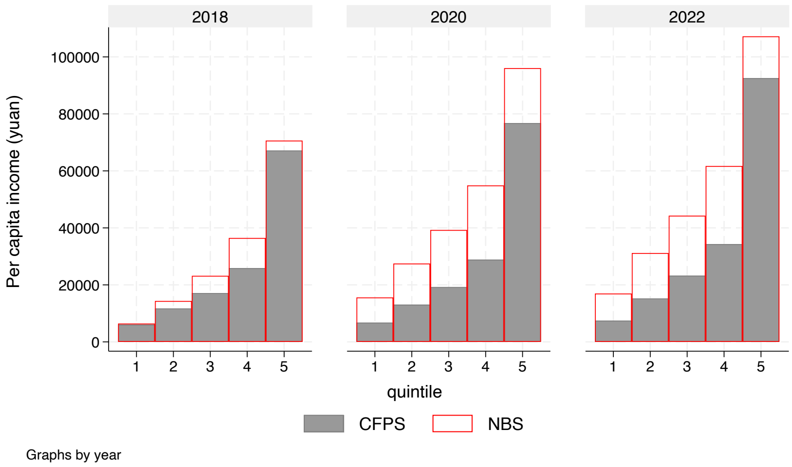
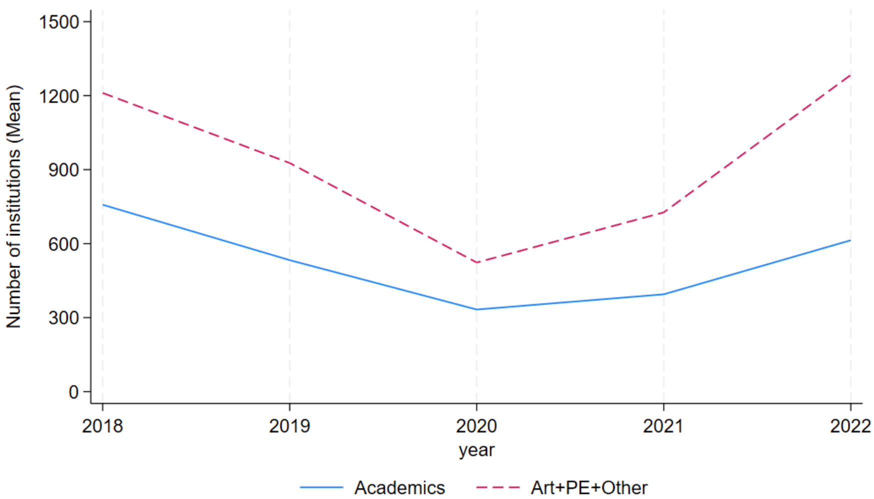


Figure A4: Average Number of Tutoring Institutions at City Level: 2018–2022



APPENDIX B Appendix Tables

Table B1: DR Impact on Children's Tutoring

		Type of Tutoring		
	Tutoring	Institution	Individual	School
Policy	0.042**	-0.018	0.028	-0.006
	(0.021)	(0.017)	(0.023)	(0.016)
Dummy for Boy	0.006	0.014*	-0.004	0.014*
	(0.008)	(0.009)	(0.011)	(0.008)
Age 7	0.035***	0.009	0.008	0.005
	(0.010)	(0.009)	(0.009)	(0.009)
Age 8	0.047***	0.011	-0.001	0.002
	(0.011)	(0.010)	(0.013)	(0.011)
Age 9	0.028**	0.000	0.017	-0.016
	(0.012)	(0.012)	(0.013)	(0.012)
Age 10	0.002	-0.006	0.027**	-0.019
	(0.013)	(0.012)	(0.012)	(0.012)
Age 11	0.009	-0.004	0.043***	-0.026*
	(0.012)	(0.013)	(0.014)	(0.014)
Age 12	0.019*	-0.025*	0.059***	-0.021
	(0.012)	(0.014)	(0.015)	(0.015)
Age 13	0.011	-0.012	0.062***	-0.023
	(0.012)	(0.014)	(0.014)	(0.015)
Age 14	0.025*	-0.027*	0.074***	-0.022
	(0.013)	(0.016)	(0.015)	(0.018)
Age 15	0.003	-0.051***	0.104***	-0.010
	(0.017)	(0.019)	(0.020)	(0.017)
Authoritative	-0.004	0.011	-0.042***	-0.008
	(0.008)	(0.010)	(0.012)	(0.010)
Permissive	-0.007	0.014	-0.051***	-0.011
	(0.010)	(0.011)	(0.015)	(0.013)
Remarried	0.030	-0.033	0.047	0.026
	(0.020)	(0.030)	(0.037)	(0.027)
Divorced/widow	-0.031	-0.084*	0.047	0.011
	(0.027)	(0.045)	(0.049)	(0.047)
Mother Senior High	0.063***	0.072**	0.002	-0.054**
	(0.017)	(0.030)	(0.025)	(0.023)
Mother Uni/College	0.101***	0.094***	0.013	-0.045**
	(0.018)	(0.029)	(0.024)	(0.023)
Mother Master's	0.132***	0.095**	0.055	0.006
	(0.029)	(0.039)	(0.043)	(0.037)
Mother PhD	0.130**	0.099**	0.163**	0.052
	(0.054)	(0.043)	(0.078)	(0.074)
Log household income	0.017***	0.018***	-0.006**	-0.001
	(0.002)	(0.003)	(0.003)	(0.003)
2020	-0.006	0.003	0.007	0.015*
	(0.007)	(0.009)	(0.011)	(0.008)
2021	0.018	0.008	-0.020	0.030**
	(0.016)	(0.013)	(0.015)	(0.014)
2022	0.129***	0.010	-0.035**	0.032**
	(0.016)	(0.013)	(0.015)	(0.013)
2023	0.254***	0.020*	-0.032**	0.049***
	(0.014)	(0.012)	(0.013)	(0.013)
Prefectural fixed effects	Yes	Yes	Yes	Yes
Covid-19 controls	Yes	Yes	Yes	Yes
Edu streaming controls	Yes	Yes	Yes	Yes
No. of observations	35381	17319	17319	17319
Adj. R^2	0.073	0.052	0.046	0.047
No. of clusters	313	311	311	311

Notes: Robust standard errors in parentheses, which are clustered at the prefectural level. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

Table B2: DR impacts on children and parents' outcomes (CFPS)

	(1)	(2)	(3)	(4)
Panel A: Children's results				
	Tutoring Participation	Academic Tutoring	Academic Tutor hours	Total tutoring hours
Mean	0.31	0.22	2.07	3.97
Policy	0.005	0.118	2.098	1.941
	(0.142)	(0.118)	(1.620)	(1.710)
Log hinc PC	0.009	-0.015	0.029	0.092
	(0.035)	(0.037)	(0.326)	(0.466)
Covid Mean	0.001	0.004	0.022	-0.111
	(0.004)	(0.004)	(0.028)	(0.033)
Covid SD	0.000	-0.001	-0.007	0.036
	(0.001)	(0.001)	(0.009)	(0.010)
SH Enr/JH Grd	-0.454	-0.173	-3.333	-6.406
	(0.553)	(0.395)	(5.191)	(6.122)
Constant	0.484	0.265	-3.598	0.236
	(0.538)	(0.582)	(9.663)	(10.149)
No. of observations	4674	4652	4700	4700
No. of clusters	181	181	181	181
Panel B: Parents' results				
	Parent help hours	Mother LFP	Mother workhours	
Mean	4.92	0.65	38.54	
Policy	1.197	0.011	4.244	
	(1.501)	(0.104)	(7.765)	
Log hinc PC	0.280	0.008	0.727	
	(0.355)	(0.038)	(2.043)	
Covid Mean	0.014	0.003	0.076	
	(0.035)	(0.005)	(0.119)	
Covid SD	-0.005	-0.001	-0.021	
	(0.011)	(0.002)	(0.038)	
SH Enr/JH Grd	3.337	0.240	-14.506	
	(8.425)	(0.515)	(33.138)	
Constant	1.312	0.415	39.235	
	(6.471)	(0.463)	(27.465)	
No. of observations	4629	4629	3697	
No. of clusters	181	181	170	

Notes: All regressions control for the log of household income per capita, the annual mean and standard deviation of covid cases at the city, the education streaming policy, and the fixed effects of individuals, survey years. For the children's outcome, the survey months fixed effects are also controlled for. The first row of each panel reports the means of the dependent variables. Robust standard errors in parentheses, which are clustered at the prefectural level city. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.