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Biting the hand that teaches: Unraveling the economic impact of banning private tutoring in China[☆]

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ABSTRACT

Shadow education in China is a significant social issue and a leading factor in exacerbating education inequality that fosters over-competition. In July 2021, the Chinese government implemented the Double Reduction Policy, which banned for-profit academic private tutoring. We estimate the economic consequences of this policy on the education industry in China by employing two novel datasets containing online job postings and firm registration information. We find that within four months after the policy implementation, online job postings for tutoring-related firms decreased by 89%, tutoring-related firm entries decreased by 50%, and their exits tripled. Cities with 10,000 (2%) more children lost 50 (2.2%) more education-related job opportunities, experienced 0.4 (2.8%) fewer firm entries, and 0.03 (0.8%) more firm exits per month. Surprisingly, not only academic tutoring firms were impacted, but also untargeted businesses involving in arts and sports tutoring were heavily struck, although they were encouraged by the policy to promote children's non-academic ability. This negative spillover can be partly explained by the interconnected ownership structure among academic and non-academic tutoring firms. Back-of-the-envelope calculations show that this policy led to 3 million job losses in four months and at least 11 billion RMB Value Added Tax losses in 18 months nationally.

1. Introduction

Industrial regulation remains a contentious issue within economic scholarship, centering on its effectiveness in ameliorating market failures versus its propensity to introduce further distortions and adversely affect the labor market, particularly in developing nations (He et al., 2020). Although there is a rich body of literature detailing governmental interventions in various industries for environmental, safety, or other considerations (Sickles et al., 1986; Ciliberto and Tamer, 2009; Cairns and Liston-Heyes, 1996; Currie and Walker, 2019; Buchholz, 2022), two significant gaps are apparent. First, studies on how government actions, through

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administrative directives or policies, can dismantle entire industries are markedly rare. Second, there is a dearth of analysis on the spillover effects of industrial regulation policies, especially regarding their unintended consequences on non-targeted firms. This shortage of research can be attributed to two main factors. First, governments typically focus on regulating rather than undermining the industry, making it difficult to identify policies with such stringent objectives. Second, on the rare occasions that such policies are implemented, as seen in the prohibition of alcohol in the U.S. and other nations (Blocker Jr., 2006; Biderman et al., 2010), gathering real-time, comprehensive data to scrutinize their economic responses is formidable. The task of assessing spillover effects compounds this complexity, as acquiring data on firms that were not the direct targets of these policies is notably more arduous.

How can a destructive industrial regulation policy affect an industry? What are industrial regulation policy's spillover effects on untargeted firms? In this study, we consider a national-level destructive industrial regulation policy in China to answer these questions.

In July 2021, the Chinese government implemented the Double Reduction Policy (hereafter, DR Policy), which aimed to ban all for-profit private academic tutoring firms. It is considered as one of the most controversial and influential education policies in contemporary China. In this study, we examine the economic impact of this policy on job creation and firm registrations using two novel datasets. Our findings reveal that this policy resulted in massive job opportunity losses and firm closures. Job postings from education and training (hereafter, education-related) firms have substantially decreased, and a considerable number of firms have chosen to cease operations. Although the policy targeted only academic private tutoring and encouraged the development of sports, arts, and other extracurricular education, non-academic tutoring firms were also heavily affected, showing strong evidence of negative spillovers. Interestingly, many former tutoring firm owners stayed in the education-related business, but they explicitly steer clear of academic private tutoring services.

China has a long tradition of selecting government officers based on high-stakes standardized exams, known as *keju* (Chen et al., 2020; Yu and Suen, 2005; Kung, 2021). Confucian culture regards success in these exams as an honor for both the family and the local community. This tradition persists today with students taking the College Entrance Exam (*Gaokao*) to gain admission to colleges, with scores serving as the primary admission criterion. Consequently, competition in the *Gaokao* is intense, leading to an educational arms race. Parents often enroll their children in private tutoring classes during weekends and weekdays after regular school hours. According to data from the China Education Panel Survey, Chinese families spent an average of 3296 RMB (480 USD) per year on shadow education in 2013, accounting for 18% of the average per capita annual income (Guo and Qu, 2022). This spending has led to severe educational over-competition, resulting in mental pressure and physical stress for students (Wang et al., 2015; Li et al., 2017). Additionally, it has been identified as a key factor contributing to the growing education inequality, as wealthy families can afford high-quality private tutoring courses, giving them a significant advantage over less affluent families.

In an effort to reduce the burden on children and alleviate educational inequality, the Chinese government implemented the DR Policy in July 2021. This policy aims to decrease both school homework and after-school tutoring pressures. Specifically, it prohibits for-profit academic private tutoring firms, requiring existing firms to either re-register as non-profit institutions or completely cease their tutoring services. This created a considerable shock in China's labor market since the private tutoring industry plays a significant role in employing new college graduates.[1] While the media extensively covered the ensuing massive layoffs and employment losses, no accurate estimations of the economic consequences resulting from this sudden shock have been estimated. Our study provides the first empirical evidence of the impact of the DR Policy on the economy.

We use two novel datasets to evaluate the economic consequences of the DR Policy. First, we employ online job posting data to estimate the impact of the DR Policy on job openings. This dataset contains job posting information from six major online job posting platforms in China, which cover almost the entire online job market. To our knowledge, this is the most comprehensive real-time labor demand data in China. Second, we use firm registration data to examine the impact of the DR Policy on firm entries and exits. This dataset encompasses all Chinese firms' registration information, including their industry, business scope, location, and entry/exit dates. In the descriptive analysis, we observe that for academic private tutoring firms, the number of job postings declined by 89%, new firm entries decreased by 50%, and firm exits tripled from July through to the end of 2021.

Our empirical strategy employs a difference-in-differences (DID) exposure design. We compare the outcomes of cities with larger numbers of children, which are more heavily impacted by the policy, to those with smaller numbers of children, before and after the implementation of the DR Policy. We find that after the policy's implementation, cities with 10,000 more children experience 50 (2.2%) more job opportunity losses for all education-related firms per month, 20 (1.9%) for academic private tutoring firms, and 1.3 (2.0%) for large private tutoring corporations. These results show that the DR Policy adversely affects not only its primary target, but also all types of education-related firms, showing an initial evidence of negative spillover effects.

Regarding firm registration, we demonstrate that after the policy's implementation, cities with 10,000 more children experience 0.394 (2.8%) fewer firm entries for all education-related firms per month, and 0.351 (2.8%) fewer for academic private tutoring firms. Additionally, cities with 10,000 more children experience 0.031 (0.8%) more firm exits per month for all education-related firms, and 0.028 (0.8%) more for academic private tutoring firms. Utilizing the firms' shareholder structure information, we track the activities of former tutoring firm owners who have deregistered their firms after the DR Policy. We find that most of them stay in the service sectors if they start new businesses. Specifically, 33% of them continue to operate within the education industry, though most of these new firms are not providing any academic tutoring services.

To further examine the unintended spillover of the DR Policy on untargeted firms, we categorize non-academic tutoring firms in more detail. Our findings reveal that firms specializing in talent-based tutoring, such as arts and sports, have experienced significant

[1] A report in 2020 indicated that total employment in the private tutoring industry exceeded 10 million, 88% of which have college degrees. For more details, please refer to https://chinaiid.bnu.edu.cn/docs/2021-01/20210105171435185731.pdf.

job opportunity losses. The introduction of new firms in these sectors was impeded, and their exit rates increased significantly. In contrast, businesses like adult education and occupational certificate tutoring have been relatively less impacted. Despite official encouragement for talent-based tutoring firms to expand in order to promote children's holistic development beyond mere academic performance, these firms were also caught in the widespread spillover impact of the DR Policy. This suggests that the DR Policy's primary objective of reducing academic burdens and promoting diverse extracurricular activities may not have been fully realized, at least from the perspective of education service providers. This negative spillover can be partly attributed to the complementarity and connection between academic and non-academic education. We find that many owners and shareholders who deregistered their academic tutoring firms following the DR Policy also owned other firms focused on arts and sports education. This interconnected ownership structure partly explains the significant spillover effects observed on untargeted firms.

Using the regression results, we further estimate the total job posting losses and firm VAT losses. Our back-of-the-envelope analysis shows that within the first four months, the loss of online job postings exceeded 3 million nationally, with major cities and developed provinces experiencing the most significant impact due to their high demand for private tutoring. Furthermore, we find a total VAT loss of over 11 billion RMB (1.6 billion USD) in the 18 months following the implementation of the DR Policy.

We conducted a series of robustness checks and provided additional evidence to validate our identification strategy and to assess the persistence of the DR Policy's labor market effects over time and across different types of firms. Our findings consistently reveal substantial impacts, robust to various measures of policy exposure and evident in both large and small firms. Even with data extending three years beyond the policy's implementation, we observe only limited signs of recovery.

Our study contributes to four strands of literature. First, our research builds upon the economic analysis of industrial regulation's influence on sectoral growth. A considerable body of literature highlights the industrial regulation policies in various sectors (Newell et al., 2013; Currie and Walker, 2019; Shapiro and Walker, 2018), including manufacturing (He et al., 2020), airlines (Sickles et al., 1986; Ciliberto and Tamer, 2009), and taxi industries (Cairns and Liston-Heyes, 1996; Buchholz, 2022). We extend this literature from two perspectives. First, few studies have investigated the impact of a devastating industrial regulation policy. Second, virtually no previous literature has empirically evaluated the spillover effect of an industrial regulation policy on untargeted firms. As we discuss below, the DR Policy represents the most sudden and stringent policy targeting China's education industry. Examining this policy can help us understand the effects of destructive policies on the entire industry and its spillovers on untargeted firms.

Second, our paper aligns with research on entrepreneurial activities over business cycles (Rampini, 2004) and firm behavior during economic crises (Fang, 2020; Winberry, 2021; Bernanke and Gertler, 1989). By utilizing firm registration and recruitment datasets, we can discern the effects of an industry-wide negative shock, specifically, a strict halt in private tutoring, on the entry and exit of firms and the subsequent creation of employment within the education sector over a short period. In particular, our paper investigates how entrepreneurs adapt or show resilience in the face of adversity. We find that entrepreneurs affected by the DR Policy were only partially able to adapt in the short run, often by shifting their businesses to related industries. However, the absolute number of new firms established by former private tutoring firm owners declined substantially—not only in private academic and non-academic education industries, but also in non-education industries.

Third, this paper contributes to the extensive and contentious discourse on shadow education and related regulation by examining the firms' responses to the regulation and the ensuing labor market repercussions. The unchecked expansion of the private tutoring industry is not an issue confined to China, but manifests across many East Asian countries (Guo, 2022; Dawson, 2010; Choi and Choi, 2016; Kim and Lee, 2010). The debate has primarily centered on the demand-side impacts of private tutoring, such as its ability to compensate for the deficiencies of subpar public education (Glewwe and Kremer, 2006; Galiani et al., 2008; Andrabi et al., 2013; Das et al., 2013), to enhance students' academic performance (Psacharopoulos and Papakonstantinou, 2005; Kim and Lee, 2010), or to address the inequality (Zhang and Xie, 2016; Zhang and Bray, 2018) and psychological issues arising from excessive competition (Akerlof and Kranton, 2002; Niederle and Vesterlund, 2007; Heckman and Kautz, 2012; Wang et al., 2015; Li et al., 2017). However, it is equally crucial to comprehend the private tutoring industry's supply-side responses to market dynamics, given the growth of the tutoring industry as a large employer for new college graduates. Our study represents the first empirical analysis to investigate this supply-side concern.

Fourth, our study contributes to the research investigating the impact of the DR Policy. Despite being one of the largest and most controversial education policies in China, studies on the DR Policy remain scarce due to data limitations. Prior research in sociology and education has explored various aspects of this policy (Meng et al., 2024; Zhou, 2023; Jin and Sun, 2022; Zhang, 2022; Feng, 2022). However, none of these studies employ rigorous causal inference or analyze the economic consequences of this policy. Our work complements this literature on the DR Policy by conducting the first quantitative analysis.

The remainder of the paper is organized as follows. Section 2 describes the background of the DR Policy. Section 3 introduces the data employed in this study. Sections 4 and 5 conduct descriptive and regression analyses respectively. Section 6 presents the back-of-the-envelope analysis. We provide concluding remarks in Section 7.

2. Background

2.1. Overcompetition in China's education system

In China, as well as in many other Asian countries, centralized admissions systems serve as the primary method for entering nearly all higher education institutions, establishing a series of educational ladders. To gain admission to high schools, students must take the High School Entrance Exam (*Zhongkao*). These exams are administered at the city level, with scores serving as the predominant criterion for high school admission. Similarly, college-bound students are required to take the College Entrance Exam (*Gaokao*). Like the *Zhongkao*, *Gaokao* scores determine college admissions.

Although this examination method promotes fairness by basing student admissions solely on their performance in the examination, the zero-sum game nature of this mechanism and the imbalance between the supply and demand of education lead to excessive competition among students. Annually, over 10 million students participate in the *Gaokao*, rendering the Chinese education system one of the most competitive in the world.[2] Despite the massive college expansion program initiated in 1999 (Che and Zhang, 2018), the enrollment rate for elite universities (the 985 project) remains at a mere 2%.[3] Extensive literature demonstrates that attending prestigious universities correlates with higher wages in the labor market, thereby intensifying competition within China's educational landscape (Li et al., 2012; Wang et al., 2014).

To succeed in this highly competitive examination environment, wealthier families usually afford superior educational resources, such as private tutoring, extracurricular activities, and access to high-quality schools, further expanding the achievement gap (Wang et al., 2014; Chi and Qian, 2016; Golley and Kong, 2018). Conversely, lower-income families often lack the necessary resources to provide their children with equivalent educational opportunities, perpetuating the cycle of poverty. Thus, shadow education and private tutoring have been an important reason for education inequality (Guo and Qu, 2022).

Apart from exacerbating existing inequalities, the highly competitive environment in education also yields other detrimental consequences. Influenced by Confucian tradition, Chinese society frequently regards academic success as a reflection of an individual's abilities and potential, which would honor not only the individual, but the whole family (Chen et al., 2020; Yu and Suen, 2005; Kung, 2021). This perception has fostered an environment wherein students, parents, and educators prioritize top scores and rankings, often overshadowing other facets of personal and social growth. Consequently, the considerable pressure to succeed in the *Zhongkao* and the *Gaokao* has been linked to a range of mental health issues among Chinese students, including anxiety, depression, and in some instances, suicide (Wang et al., 2015; Li et al., 2017). Moreover, an overemphasis on competition may lead to a singular focus on academic success, disregarding the significance of holistic development, such as social skills, emotional intelligence, and personal interests (Akerlof and Kranton, 2002; Niederle and Vesterlund, 2007; Cunha and Heckman, 2007; Heckman and Kautz, 2012). These adverse consequences undoubtedly have the potential to decrease human capital in the long run (Weinberger, 2014; Deming, 2017; Deming and Kahn, 2018).

2.2. *Private tutoring industry and education inequality*

To attain high scores in the *Zhongkao* and *Gaokao*, parents invest substantial amounts of money in hiring tutors and private instructors to assist their children with academic work during after-school hours and on weekends (Chi and Qian, 2016). This "education fever" and the unmet demand for public education contribute to the widespread growth of private tutoring institutions in China (Yu and Suen, 2005). In 2015, the average household education expenditure exceeded 10% in total household expenditures (Guo and Qu, 2022). According to a report published by the Chinese Education Association, in 2016, the tutoring industry in mainland China had already exceeded 800 billion RMB, with more than 137 million student enrollments and a teaching workforce of 7 to 8.5 million in tutoring institutions.[4] A more recent report estimates that the total employment in private tutoring is over 10 million in 2020.[5] The booming market fostered the growth of several prominent private tutoring enterprises, including *New Oriental (Xindongfang)* and *TAL Education Group (Haoweilai)*, both of which have been listed on the New York Stock Exchange.[6]

2.3. *Double reduction policy*

In response to China's mounting apprehension regarding the escalating academic demands placed on students, as well as the rampant commercialization of the private tutoring sector, the Chinese central government issued the *Opinions on Further Reducing the Homework Burden and Off-Campus Training Burden of Students in Compulsory Education* on July 24th, 2021, officially initiating the DR Policy. The policy endeavors to address these concerns through a two-pronged approach.

First, the policy seeks to stop over-competition and alleviate the academic burden on students by reducing the volume of homework. It establishes explicit guidelines for educational institutions and educators regarding the quantity, difficulty, and expected time commitment for students to complete homework. This component of the policy ensures that students' academic responsibilities are more appropriately balanced with their personal development.

Second, the DR Policy addresses the expanding private tutoring industry and aims to reduce the education inequality it has fostered. It requests all private tutoring firms to register as non-profit organizations. Revenue of these non-profit organizations can only be used to pay for the education cost and cannot be distributed to their shareholders. The policy also describes other specific regulations that govern the operations of tutoring institutions, which include prohibitions against public listings, restrictions on

[2] The number of *Gaokao* participants has surpassed 10 million for the past four consecutive years. For more details, please refer to https://news.eol.cn/yaowen/202206/t20220606_2230030.shtml.

[3] The 985 project is an educational initiative launched by the Chinese government in 1998, with the goal of establishing world-class universities for the 21st century. The project includes 39 of the top universities in China.

[4] For more details, please refer to https://www.sohu.com/a/123071427_460424.

[5] Please refer to https://chinaiid.bnu.edu.cn/docs/2021-01/20210105171435185731.pdf.

[6] As shown in Appendix Figure A1, the stock prices of New Oriental and TAL Education Group exhibited steady growth prior to the first half of 2021, reflecting the booming market.

operational hours (no operation in national holidays and summer/winter breaks), and prohibitions on commercial advertisement. The policy mainly targets academic tutoring, and it has no direct restrictions on art or sports classes.

To ensure effective policy enforcement and oversight, the central government assumes responsibility for the supervision and approval of new tutoring institutions—a role previously fulfilled by local governments. Meanwhile, local governments maintain their jurisdiction over the monitoring and regulation of tuition fees in accordance with official guidelines. This delineation of responsibilities between central and local authorities facilitates comprehensive and efficient policy implementation.

The DR Policy was officially enacted on July 24th, 2021,[7] and has been gradually implemented in cities across China. In the same year, the State Council Education Supervision Committee issued a special notice, mandating that from August 30, 2021, each province is required to submit the progress of their "Double Reduction" implementation on the 15th and 30th of each month. Consequently, the DR Policy is regarded as a sudden and highly stringent policy. Due to the rigorous enforcement of the policy, it is anticipated that the private tutoring industry will experience a significant hit. Consistent with these expectations, the stock prices of publicly listed education firms on the New York Stock Exchange exhibited immediate declines following the policy's implementation, as illustrated in Appendix Figure A1. This market reaction underscores investor concerns regarding the stringent regulatory environment and its potential impact on the performance of private tutoring enterprises. Furthermore, as illustrated in the figure, these companies' stock prices had already begun to drop relative to the Nasdaq Golden Dragon China Index around May 2021. This suggests that rumors regarding potential government restrictions on the tutoring industry had already begun circulating in the financial markets before the formal policy announcement. To account for this earlier market reaction, we conducted a robustness check by using May as the policy shock period, instead of July, which is used in our main regression setting. The corresponding results are reported in Appendix Table A1 through Table A4.

3. Data

In this study, we aim to estimate the impact of the DR Policy on the tutoring industry in China, utilizing two datasets: online job postings and Chinese firm registration data. Our analysis focuses on changes in labor demand and firm dynamics within the tutoring industry following the policy's implementation in July 2021.

3.1. Online job posting data

To accurately evaluate the impact of the DR Policy on labor demand, we assembled a dataset comprising approximately 500 million recruitment entries posted on major Chinese online recruitment platforms between January 2016 and November 2021.[8] These platforms include Zhaopin, 51job, 58.com, Ganji, Lagou, and Liepin.[9] As the most popular online job search platforms, they encompass the majority of online job postings in China, making our data on online job postings the most comprehensive real-time labor demand dataset available in China.

We obtained raw data through a web scraping process and carefully cleaned the dataset to remove any duplicate or irrelevant entries. The resulting dataset consisted of information on job postings, including the number of recruitments, job titles, job descriptions, company names, company profiles, job locations, and posting dates. Additionally, we extracted the salary information, which is presented as a range, and calculated the average salary for each job posting.

Using a dictionary-based algorithm, we analyzed job titles, responsibilities, company names, and company profiles to filter out 13,368,933 recruitment positions in the educational industry affected by the DR Policy. These positions spanned job locations across 31 provinces and 337 cities in China. The algorithm was validated using a random sample of job postings to ensure the precision and recall rates were sufficiently high (90%), minimizing false positives and negatives.

To control for variations in labor market conditions across different geographical areas and time periods, we also collected information on overall job postings in the same cities and time periods. This allowed us to compare the changes in tutoring-related job postings with the broader labor market trends and to control for macroeconomic factors affecting the labor market such as the COVID-19 pandemic.

To the best of our knowledge, this dataset represents the most comprehensive online recruitment dataset used for academic research in China to date, providing valuable insight into the effects of the DR Policy on labor demand. The unique features of the dataset, including its large sample size, extensive geographical coverage, and rich set of variables, enable us to conduct a rigorous and detailed analysis of the policy's effects on the tutoring industry's labor market dynamics. Specifically, we will assess the policy's impact on job postings in the tutoring-related industry and its different segments, such as academic specific tutoring and art tutoring.

[7] For the original official document, please refer to http://www.moe.gov.cn/jyb_xxgk/moe_1777/moe_1778/202107/t20210724_546576.html.

[8] We also obtained a new dataset containing job posting data from January 2022 to January 2025 to investigate a longer run impact of the DR Policy as supplemental evidence. However, due to differences in data sources, this new dataset is not directly comparable to the dataset we used for the main analysis. We show the results with this new dataset in Appendix E.

[9] Their web links are as follows: https://www.zhaopin.com/ https://www.51job.com/ https://www.58.com/ https://www.ganji.com/ https://www.lagou.com/ https://www.liepin.com/.

3.2. Firm registration data

We also employed a comprehensive dataset of Chinese firm registration to examine the impact of the DR Policy on the tutoring industry in China. We obtained the raw data through a web scraping process from Tianyancha (https://www.tianyancha.com/). This dataset, covering the entire history of firm registrations from 1949 to 2022, allowed us to explore long-term trends and patterns within the Chinese tutoring industry and identify the consequences of the policy on firm dynamics.[10]

We compiled the data from official registries and repositories, which included detailed information for each registered firm (including branches or subsidiaries), such as company names, registration dates, registered capital, industry classifications, business scope descriptions, and geographical locations. Additionally, we retrieved updated registration statuses for firms, enabling us to track both firm entry and exit before and after the implementation of the DR Policy in July 2021.

To identify the companies targeted by the policy, we developed a dictionary-based approach similar to the one employed for job posting data. By scrutinizing company names and business scope descriptions, we systematically selected firms primarily engaged in education-related activities that fall under the scope of the DR Policy. This led to the identification of 431,459 education-related firms up until December 2022.

Focusing on education-related firms, we aim to capture the policy's direct impact on their registration patterns, as well as entry and exit dynamics. We will investigate the temporal distribution of firm registrations, analyzing the changes in the number of new education-related firms entering the market before and after the policy's implementation. We will also assess the policy's impact on different industry sub-segments, including academic-specific tutoring and art tutoring. Furthermore, we will consider the circumstances of other enterprises associated with the legal representatives of these directly impacted firms, including those where they hold positions as legal representatives or shareholders.

By leveraging the unique features of this dataset, including its historical depth, extensive geographical coverage, and rich set of variables, together with the insights from the online job posting data, we aim to provide a comprehensive understanding of the overall consequences of the DR Policy for the tutoring sector in China.

4. Descriptive analysis

We first demonstrate the overall trend and the basic statistical patterns of online job postings and firm registrations before and after the implementation of the DR Policy. For simplicity, we denote academic private tutoring firms as "private tutoring" in all tables and figures.

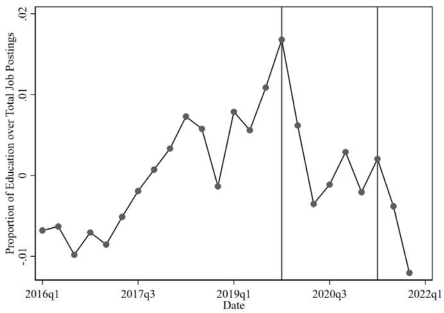
Fig. 1 displays the changes in online job postings from the first quarter of 2016 to the fourth quarter of 2021. To rule out the effects of the general trend of the economy and the changes in the web scraping efficiency across time, we illustrate the changes in the proportions of job postings from different types of education firms over the total job postings from all firms. We examine three types of firms: (1) all education and training firms (hereafter, education-related firms), which encompass academic private tutoring institutions and also those involved in arts, sports, or other non-academic training; (2) academic private tutoring firms, which are the primary target of the DR Policy and are directly affected; (3) large private tutoring corporations, such as *New Oriental (Xindongfang)* and *TAL Education Group (Haoweilai)*, with the complete list provided in Appendix Table A5. The first vertical line is located in Q4 of 2019, when the COVID-19 pandemic started. The second vertical line is located in Q2 of 2021, just before the DR Policy was implemented.

We observe that online job postings for education-related firms have been increasing since 2016. This steady increment reveals two key insights. On the one hand, the education industry sector experienced rapid expansion. On the other hand, online platforms became increasingly important as a tool for education-related firms to recruit workers. The COVID-19 pandemic had a significant negative impact on job postings during early 2020, as evidenced by a dramatic dip. However, labor demand rebounded quickly and remained consistent until Q3 of 2021 when the DR Policy was introduced.

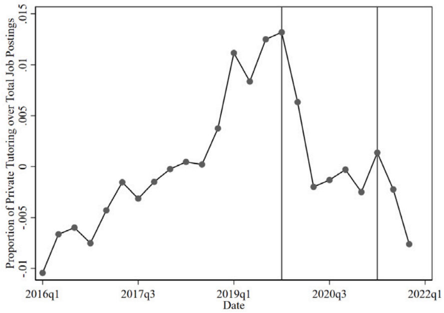
The decline in job postings for various types of firms was sudden and drastic following the implementation of the DR Policy. Additionally, the effect on all education firms was as large as the effect on the academic private tutoring firms. This shows a potential negative impact on untargeted firms such as those involved in arts and sports tutoring. We will discuss it in the following sections. Table 1 displays the number of online recruitments from May to November in 2021. Compared to July, the number of job postings decreased by 81, 89, and 94 percent for all education-related firms, private tutoring firms, and large tutoring corporations, respectively. In general, the negative shock affects not only academic private tutoring firms but also all education and training firms.

Figs. 2 and 3 display the firm entry and exit trends from the first quarter of 2016 to the fourth quarter of 2022. Similar to job postings, we observe a steady increase in education-related firm entries. Firm exits remain at a low level compared to their entries. We detect a sharp decline and a swift recovery at the beginning of the COVID-19 pandemic for both firm entry and exit. This is due to the temporary government shutdown during the initial wave of city lockdowns. The entry of firms nearly vanished following the DR Policy. Panel A in Table 2 shows that the monthly number of newly-registered education-related (academic private tutoring) firms declined from 1696 to 117 (from 1384 to 93) within one and a half years, corresponding to a 93% decrease. Large private tutoring corporations were also severely affected. In contrast, the exit of firms skyrocketed after the DR Policy as many firms could not survive under the heavy restrictions on their businesses. Panel B in Table 2 reveals that the number of cancellation

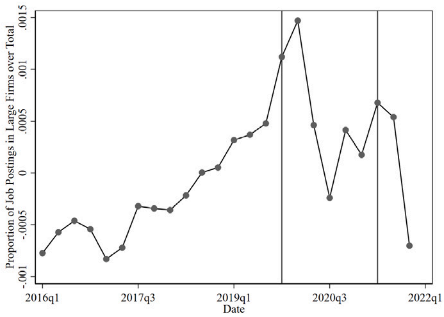
[10] We also re-collected data on firm registrations via web scraping to analyze the longer-term effects of the DR Policy, covering the period from January 2016 to December 2024. We show the results with this new dataset in Appendix E.



(a) Education



(b) Private Tutoring



(c) Large Private Tutoring Corporations

Fig. 1. Changes of Job Postings in Proportions (2016 Q1 to 2021 Q4).
Notes: The *x*-axis represents the date from 2016 Q1 to 2021 Q4. We remove the seasonality by first regressing the original data on the quarter fixed effect and then take the residual to draw these figures. Subfigure (a) shows the proportion of the number of postings for all education and training firms over all job postings. Subfigure (b) shows the proportion of the number of postings for academic private tutoring firms directly impacted by the Double Reduction Policy over all job postings. Subfigure (c) shows the proportion of the number of postings for large private tutoring corporations over all job postings. The first vertical line locates in Q4 2019, when the COVID-19 pandemic started. The second vertical line locates in Q2 2021, just before the Double Reduction Policy was implemented.
Source: Online Job Posting Dataset.

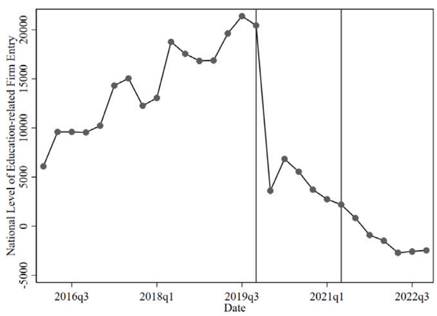
Table 1
Changes of job postings from May to November in 2021.

Month	(1) Education	(2) Private tutoring	(3) Large
May	441,348	198,431	18,456
June	454,689	211,854	15,256
July	509,015	240,556	19,114
August	300,803	115,455	13,278
September	140,552	61,034	5483
October	131,163	59,680	2681
November	98,109	25,386	1146
Changes (Jul to Nov)	−80.7%	−89.4%	−94.0%

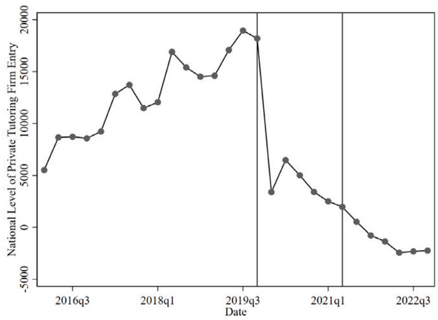
Notes: The table presents data on the online job postings of various types of firms in China from May to November 2021. Column (1) shows the number of postings for all education and training firms. Column (2) shows the number of postings for academic private tutoring firms directly impacted by the Double Reduction Policy. Column (3) shows the number of postings for large private tutoring corporations. The final row shows the percentage change in job postings from July, the month the policy was implemented, to November. Sources: Online Job Posting Dataset.

for all education-related firms and academic private tutoring firms quadrupled in five months. Fig. 4 then depicts the total number of active registered firms. The fast increase in the education and tutoring industry was interrupted by the COVID-19 pandemic and subsequently saw a contraction following the DR Policy in 2021. In particular, branches of large private tutoring corporations persisted in expanding even after the COVID-19 pandemic, an expansion that was ultimately terminated by the DR Policy.

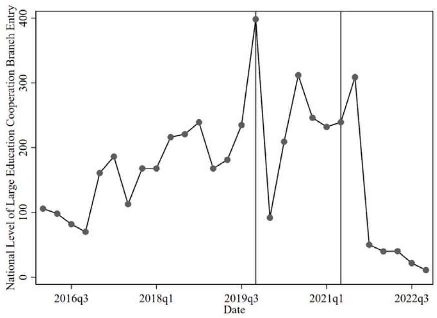
In summary, we draw the following conclusions from our descriptive analysis. First, the education and tutoring industry had been expanding prior to the COVID-19 pandemic. Second, the pandemic struck the industry hard, but it recovered after that. Third,



(a) Education



(b) Private Tutoring



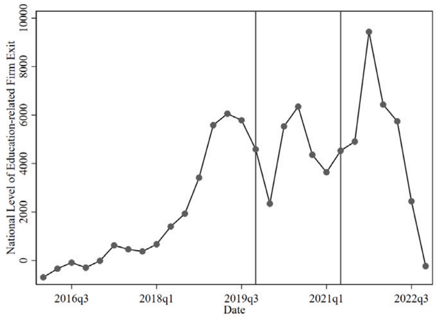
(c) Large Private Tutoring Corporations

Fig. 2. Changes of Firm Entries (2016 Q1 to 2022 Q4).
Notes: The *x*-axis represents the date from 2016 Q1 to 2022 Q4. We remove the seasonality by first regressing the original data on the quarter fixed effect and then take the residual to draw these figures. Subfigure (a) shows the number of newly-registered education and training firms. Subfigure (b) shows the number of newly-registered academic private tutoring firms directly impacted by the Double Reduction Policy. Subfigure (c) shows the number of newly-registered large private tutoring corporation branches. The first vertical line locates in 2019 Q4, when the COVID-19 pandemic started. The second vertical line locates in 2021 Q2, when the Double Reduction Policy was implemented.
Source: Firm Registration Dataset.

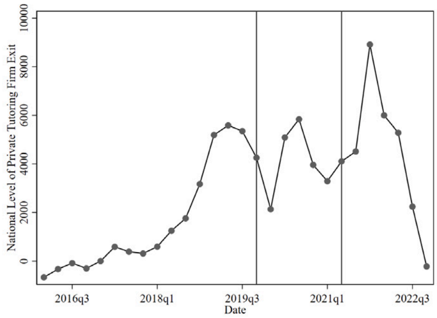
Table 2
Changes of firm registrations.

Month	(1) Education	(2) Private tutoring	(3) Large
Panel A. Entry			
July 2021	1696	1384	130
December 2021	764	719	36
December 2022	117	93	16
Panel B. Exit			
July 2021	1711	1558	18
December 2021	5150	4851	130
December 2022	214	202	12
Panel C. Total Registration			
July 2021	325,138	288,331	6755
December 2021	314,277	277,913	6746
December 2022	297,078	261,824	6571

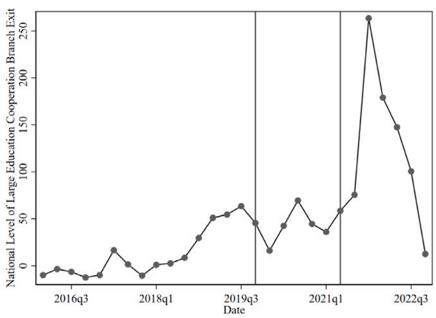
Notes: The table presents data on the registration of various types of firms in China from July 2021 to December 2022. Column (1) shows the number of education and training firms. Column (2) shows the number of academic private tutoring firms directly impacted by the Double Reduction Policy. Column (3) shows the number of large private tutoring corporation branches. Panel A shows the number of firm entries. Panel B shows the number of firm exits. Panel C shows the number of total registered firms. Sources: Firm Registration Dataset.



(a) Education



(b) Private Tutoring



(c) Large Private Tutoring Corporations

Fig. 3. Changes of Firm Exits (2016 Q1 to 2022 Q4).
Notes: The x-axis represents the date from 2016 Q1 to 2022 Q4. We remove the seasonality by first regressing the original data on the quarter fixed effect and then take the residual to draw these figures. Subfigure (a) shows the number of deregistrations for all education and training firms. Subfigure (b) shows the number of deregistrations for academic private tutoring firms directly impacted by the Double Reduction Policy. Subfigure (c) shows the number of deregistrations for large private tutoring corporation branches. The first vertical line locates in 2019 Q4, when the COVID-19 pandemic started. The second vertical line locates in 2021 Q2, when the Double Reduction Policy was implemented.
Source: Firm Registration Dataset.

the implementation of the DR Policy halted this recovery and led to a total contraction of the education industry. New firms ceased to enter, many existing firms exited, and job postings from the surviving firms plummeted to their lowest levels.

5. Regression analysis

5.1. Regression specification

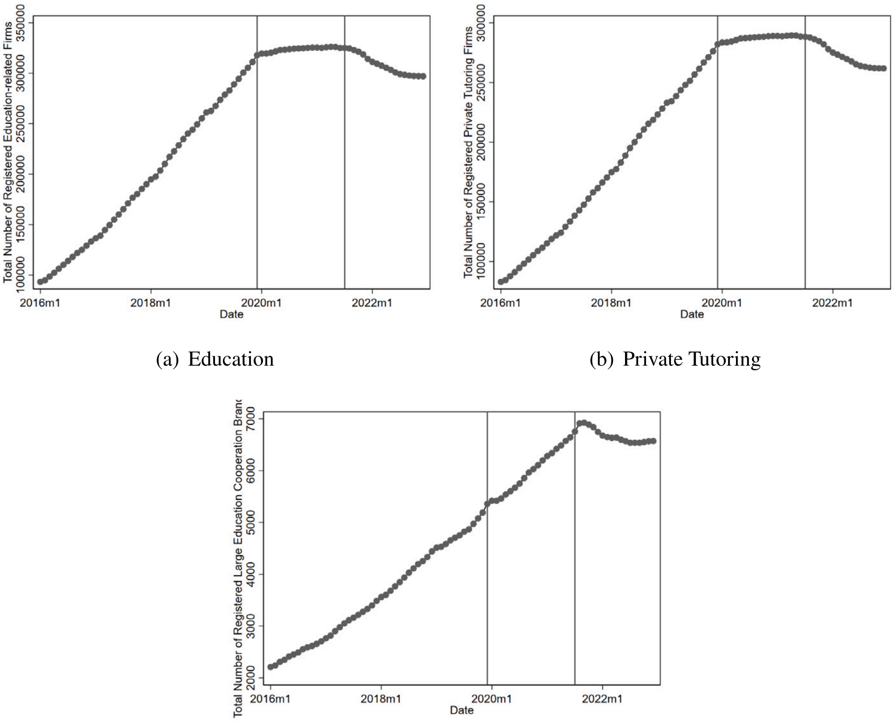
To causally identify the impact of the DR Policy on the private tutoring industry and the overall education industry, we employ a DID exposure design with two-way fixed effects. For city i in year t month m, we estimate the following regression equation:

$$y_{itm} = \beta_0 + \beta_1 \text{policy}_{tm} \times \text{children}_i + \text{COVID}_{itm} + \eta_i + \gamma_{tm} + \delta_{im} + \epsilon_{itm} \tag{1}$$

y_{itm} represents the primary outcome variables, which include the number of recruitments in the online job postings, as well as the number of firm entries, exits and survival.[11] policy_{tm} is an indicator equal to one if the time period is after July 2021. Since the policy was officially announced and implemented on July 24th, we exclude the month of July from the treatment group in the baseline regression.[12] children_i denotes the number of children aged 5 to 14 according to the Population Census in 2020 for city i, measured in thousands. This variable proxies the intensity of policy exposure of different cities. Cities with a higher number of children within the compulsory education age range are more affected by the DR Policy.[13] Appendix Figure A2 shows the probability density distribution of the population of children of ages 5 to 14 across Chinese cities. The average number of children is 516,000,

[11] We do not use log-like transformations for our outcome variables because there are many instances of *zeros* for job postings and firm entry/exits at the city-time level in our dataset. Chen and Roth (2024) argues that applying logarithmic transformations to outcomes with zeros can create ambiguity in interpreting the results. They recommend expressing Average Treatment Effects in levels as percentages, calculated as: $\theta_{ATE\%} = \frac{E[Y(1)-Y(0)]}{E[Y(0)]}$. In this paper, we adopt their suggested approach.

[12] We assess robustness by including July 2021 in the treatment group in the Appendix. The results exhibit minimal change.



(a) Education

(b) Private Tutoring

(c) Large Private Tutoring Corporations

Fig. 4. Changes of Total Registered Firms (Jan 2016 to Dec 2022).
Notes: The x-axis represents the date from Jan 2016 to Dec 2022. Subfigure (a) shows the number of registered firms for all education and training firms. Subfigure (b) shows the number of registered firms for academic private tutoring firms directly impacted by the Double Reduction Policy. Subfigure (c) shows the number of registered firms for large private tutoring corporation branches. The first vertical line locates in December 2019, when the COVID-19 pandemic started. The second vertical line locates in July 2021, when the Double Reduction Policy was implemented.
Source: Firm Registration Dataset.

and the standard deviation is 437,000 at the end of 2020. COVID_{itm} measures the number of confirmed COVID-19 cases in city i during period tm (year t, month m).[14] η_i and γ_{tm} are city and year-month fixed effects, respectively. δ_{im} are the city-month fixed effects, which account for city-level seasonality. The key identification assumption in our analysis maintains that there are common trends among cities with a larger population of children and those with a smaller population of children in terms of the outcome variables in the absence of the DR Policy. We check this assumption using event study regressions in Section 5.4. We also argue that there are no other concurrent policies or differences between cities that are correlated with the DR Policy exposure.

5.2. Main results

5.2.1. Job posting results

Table 3 presents the estimated causal effects of the DR Policy on online job postings for education-related firms and its various categories and sub-categories.

In this section, we consider an increase of 10,000 children in a city, which corresponds to a 2% change of the average size of child population across cities. We find that the DR Policy negatively affects all types of firms. Following the policy's implementation, cities with 10,000 more children experience a monthly loss of 50 more job opportunities for all education-related firms, 20 for academic private tutoring firms, and 1.3 for large private tutoring corporations. These losses correspond to decreases of 2.2%, 1.9%, and 2.0%, of the average number of job postings before the DR Policy, respectively.[15] We further run the regression separately for large and

[13] In China, compulsory education spans from age 6 to 15, encompassing six years of elementary school and three years of middle school. The 2020 Census provides population numbers for various age groups, and we select the group closest to the compulsory education stage for our analysis. For more information, please refer to http://www.gov.cn/flfg/2006-06/30/content_323302.htm.

[14] Data source is Hu et al. (2020), who compile daily COVID-19 data for each city in China and make the dataset available through the Harvard Dataverse.

[15] Carefully note that the reported percentage effects correspond to a policy exposure intensity of 10,000 children per city. This interpretation scales our regression coefficients by a factor of 10, as our difference-in-differences specification estimates effects per 1,000-child exposure unit.

Table 3
The Double Reduction Policy effect on job postings.

	Education		Private tutoring		Large	
	(1)	(2)	(3)	(4)	(5)	(6)
Policy × children	−5.239***	−4.825***	−2.234***	−2.045***	−0.177**	−0.132**
	(1.308)	(1.212)	(0.483)	(0.453)	(0.0795)	(0.0548)
COVID-19 Control	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	No	Yes	No	Yes	No	Yes
Observations	23,720	23,720	23,720	23,720	23,720	23,720
R-squared	0.700	0.723	0.568	0.588	0.493	0.537

Notes: This table shows the Double Reduction Policy effect on online job postings. The dependent variables represent the number of job postings for each type of firms. Columns (1) and (2) illustrate the results for all education and training firms. Columns (3) and (4) illustrate the results for academic private tutoring firms directly impacted by the Double Reduction Policy. Columns (5) and (6) illustrate the results for large private tutoring corporations. The unit of the number of children is one thousand. Sources: Online Job Posting Dataset. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 4
Policy effect on job postings proportion (Over total postings).

	Education		Private tutoring		Large	
	(1)	(2)	(3)	(4)	(5)	(6)
Policy × children	−0.00128	−0.00116	−0.00203***	−0.00201***	−0.000582**	−0.000599**
	(0.000785)	(0.000785)	(0.000711)	(0.000723)	(0.000241)	(0.000243)
COVID-19 Control	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	No	Yes	No	Yes	No	Yes
Observations	23,698	23,698	23,698	23,698	23,698	23,698
R-squared	0.288	0.381	0.280	0.367	0.104	0.221

Notes: This table shows the Double Reduction Policy effect on online job postings in terms of their proportions. The dependent variables represent the proportion of job postings for each type of firm to the total job postings for all firms within the same city and time period. To enhance the clarity of the table, we multiply the original proportion by 100. Thus, the coefficients can be interpreted as changes in percentage points. Columns (1) and (2) illustrate the results for all education and training firms. Columns (3) and (4) illustrate the results for academic private tutoring firms directly impacted by the Double Reduction Policy. Columns (5) and (6) illustrate the results for large private tutoring corporations. The unit of the number of children is one thousand. Sources: Online Job Posting Dataset. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

small firms in Appendix Table B1. We find that the job postings of both large and small firms are reduced. We explain the details of the results in Appendix B. The size of these effects is substantial. Although the primary target of the DR Policy is for-profit academic private tutoring firms, the overall effect on education-related firms is twice as large as the effect on academic private tutoring firms alone. This indicates a spillover of the policy on non-academic tutoring education businesses. Therefore, we will discuss the policy effects across the spectrum of non-academic private tutoring services in Section 5.6.

To investigate the relative policy effects on different types of academic tutoring firms, we perform an additional set of regressions using job posting proportions as the dependent variable. The new dependent variable is the proportion of job postings of a specific type of firms in total postings in the same city and time period. Table 4 presents the results for these job posting proportions. In cities with 10,000 more children, the proportion of job postings for all education-related firms and private tutoring firms decreased by 1.2 and 2.0 percentage points, respectively.

Private tutoring firms employ not only teachers but also non-teaching staff, including managers, clerks, and custodial personnel. We explore how the policy impact varies across different occupational categories in private tutoring firms in Table 5. Columns (1) and (2) present the policy effect on teaching positions, while Columns (3) and (4) display the policy effect on non-teaching positions. Following the policy's implementation, cities with an additional 10,000 children experience a monthly reduction of 8 job opportunities (2.4% of pre-policy mean) in teaching positions and 12 job opportunities (4.1% of pre-policy mean) in non-teaching positions. The reduction in non-teaching positions is greater than that in teaching positions, probably because firms tend to eliminate non-core services and staff when faced with a crisis.

We also explore the effect on the wages offered in these job advertisements. We observe a negative effect for all education-related firms and no discernible effect for academic private tutoring firms. Appendix Table A8 provides a detailed presentation of the results.

Table 5
The Double Reduction Policy effect on private tutoring firms by occupation.

	Teaching position		Non-teaching position	
	(1)	(2)	(3)	(4)
Policy × children	−0.909***	−0.826***	−1.325***	−1.219***
	(0.152)	(0.133)	(0.339)	(0.328)
COVID-19 Control	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
City-Month FE	No	Yes	No	Yes
Observations	23,720	23,720	23,720	23,720
R-squared	0.685	0.705	0.488	0.510

Notes: This table shows the Double Reduction Policy effect on online job postings for private tutoring firms by occupation. We consider two types of occupations, teaching positions and non-teaching positions. The dependent variables represent the number of job postings for each type of firms. Columns (1) and (2) illustrate the results for teaching positions in private tutoring firms. Columns (3) and (4) illustrate the results for non-teaching positions in private tutoring firms. The unit of the number of children is one thousand. Sources: Online Job Posting Dataset. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 6
Policy effect on firm entry.

	Education		Private tutoring		Large	
	(1)	(2)	(3)	(4)	(5)	(6)
Policy × children	−0.0382***	−0.0394***	−0.0342***	−0.0351***	−0.000410	−0.000417
	(0.00953)	(0.00976)	(0.00935)	(0.00958)	(0.000331)	(0.000333)
COVID-19 Control	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	No	Yes	No	Yes	No	Yes
Observations	28,008	28,008	28,008	28,008	28,008	28,008
R-squared	0.726	0.748	0.732	0.754	0.598	0.626

Notes: This table shows the Double Reduction Policy effect on the number of newly-registered firms. The dependent variables represent the number of registered firms for each type of firm for all firms within the same city and time period. Columns (1) and (2) illustrate the results for all education and training firms. Columns (3) and (4) illustrate the results for academic private tutoring firms directly impacted by the Double Reduction Policy. Columns (5) and (6) illustrate the results for large private tutoring corporations. The unit of the number of children is one thousand. Sources: Firm Registration Dataset. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 7
Policy effect on firm exit.

	Education		Private tutoring		Large	
	(1)	(2)	(3)	(4)	(5)	(6)
Policy × children	0.00285**	0.00310***	0.00257**	0.00279***	0.000301*	0.000311*
	(0.00110)	(0.00103)	(0.00111)	(0.00105)	(0.000176)	(0.000180)
COVID-19 Control	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	No	Yes	No	Yes	No	Yes
Observations	28,008	28,008	28,008	28,008	28,008	28,008
R-squared	0.644	0.683	0.639	0.678	0.275	0.337

Notes: This table shows the Double Reduction Policy effect on the number of canceled firms. The dependent variables represent the number of canceled firms for each type of firm within the same city and time period. Columns (1) and (2) illustrate the results for all education and training firms. Columns (3) and (4) illustrate the results for academic private tutoring firms directly impacted by the Double Reduction Policy. Columns (5) and (6) illustrate the results for large private tutoring corporations. The unit of the number of children is one thousand. Sources: Firm Registration Dataset. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

5.2.2. Firm registration results

Tables 6 and 7 present the effects of the DR Policy on firm entry and exit, as evidenced by firm registration data. We examine the same three categories or sub-categories of firms as in the job posting analysis.[16]

[16] We do not consider the proportions as the dependent variables for firm entry and exit, as scraping the registration status for all firms at a month-level frequency is too costly.

Regarding firm entry, the results show that after the policy's implementation, cities with an additional 10,000 children experience a monthly decline of 0.394 new entries for all education-related firms, 0.351 for academic private tutoring firms, and 0.004 for large private tutoring corporation branches or subsidiaries. These declines correspond to decreases of 2.8%, 2.8%, and 1.7% of the pre-policy mean, respectively.

As for firm exit, the results indicate that following the policy's implementation, cities with an additional 10,000 children experience a monthly increase of 0.031 new exits for all education-related firms, 0.028 for academic private tutoring firms, and 0.003 for large private tutoring corporation branches. These increases correspond to 0.8%, 0.8%, and 7.0% of the pre-policy mean, respectively. Similarly to job postings, we also compare the policy effect for large and small firms in Appendix Table B2 and find that both large and small firms are harmed. We explain the details of the results in Appendix B.

5.3. Regression validations

In this section, we show more evidence to validate our main regression assumptions. Our regression specification assumes that cities with more children are more affected by the DR Policy. To further validate this research design, we investigate the correlation between the number of children and the scale of the education tutoring industry in different cities using data before the DR Policy. Tables A6 and A7 in the appendix show that cities with more children have more job postings from education related firms and more tutoring firms registered in the pre-policy periods. The coefficients of the simple univariate regressions are significant both economically and statistically.

Another important concern with using the number of children as the policy exposure measure is that it may reflect overall population scale effects, since cities with larger populations naturally tend to have more children. To address this issue, we conduct a series of robustness checks using five alternative exposure measures, detailed in Appendix C. First, we use the initial proportion of job postings from education-related firms in January 2016 (relative to total postings) in each city as the exposure. Second, we use the initial number of registered education-related firms in January 2016. These two measures assess the scale and importance of the education and tutoring industry within each city. Third, we use the density of *jinshi* during the Ming and Qing dynasties as the exposure. As shown in previous studies, *jinshi* represents the highest degree in the ancient Chinese education and civil examination system, which has long-lasting impacts on education today (Bai and Jia, 2016; Chen et al., 2020). This measure captures the local educational traditions and culture derived from historical factors, serving as a proxy for education competition intensity. Fourth, we use the logarithm of the number of children as the exposure. Lastly, we replace the number of children with search intensity as the treatment variable to proxy for local education demand. Search intensity is measured by the search volume for the keywords "primary school tutoring" and "secondary school tutoring" on both PC and mobile platforms, covering the period from June 2020 to June 2021. To further ensure the robustness of our results using this exposure measure, we also apply a logarithmic transformation to the search volume. Overall, across all five alternative exposure definitions, our results remain robust, as reported in Appendix C.

5.4. Dynamic effects

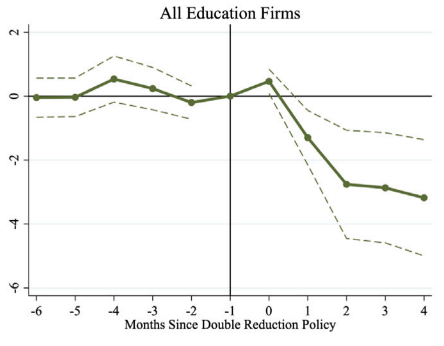
To further capture the dynamic effects of the DR Policy, we conduct an event-study regression as follows:

$$y_{itm} = \beta_0 + \sum_{tm} \beta_{tm} \mathbf{1}(\mathbf{tm}) \times \text{children}_i + \text{COVID}_{itm} + \eta_i + \gamma_{tm} + \delta_{im} + \epsilon_{itm} \tag{2}$$

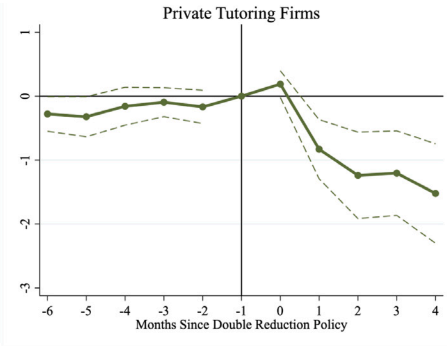
In this approach, we estimate coefficients for each year-month period, normalizing the coefficient for June 2021 (one month before the policy implementation) to zero. Figs. 5, 6, and 7 display the results for job postings, firm entries, and firm exits, respectively. We did not observe significantly differential trends before the implementation of the DR Policy, which bolsters our main assumption of identification. In Appendix Figure A3, we further show the event-study results when job posting proportion is used as the dependent variable. We find that the parallel trend assumption remains valid.

Regarding job postings, the policy effect was not prominent in July, which could be attributed to the policy announcement occurring at the end of the month and the lagged responses of firms. The policy effect progressively intensified from August to November, with education-related firms in cities with larger child populations posting fewer job vacancies online. Due to data limitations, we do not show the estimated effects after November 2021 in the main context. We illustrate the long-term impact after November 2021 in Appendix E using data from other sources and find that the decreasing trend appears to persist.

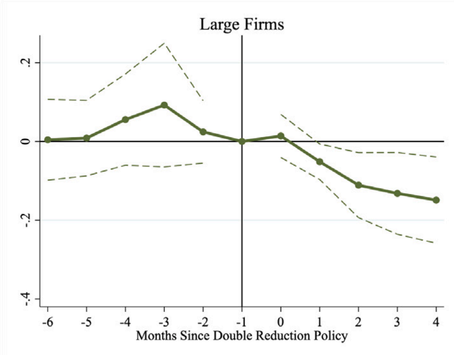
In terms of firm entry, the policy effect manifested immediately after implementation, with the decreasing trend becoming more significant from July 2021 to December 2022. It is evident that the DR Policy not only hindered the growth of the private tutoring industry but also impeded the expansion of the broader education-related industry by deterring new firms from entering the market. Conversely, firm exits measured by cancellation of registrations surged following the DR Policy and continued up to 12 months after the policy implementation. It is important to note that our results represent conservative estimates of the adverse effects on education-related firms. It is highly possible that rather than canceling their registrations, many severely affected firms opted to change their primary business. Some firms may have chosen to cease operations without undergoing the bureaucratic procedure to cancel their registrations, potentially in the hope of resuming their business in the future. To provide readers with a clearer understanding, we calculate the net firm entry and perform the main regressions. The results are presented in Table 8, which demonstrate the negative net effect of the policy on firm registration.



(a) Education



(b) Private Tutoring



(c) Large Private Tutoring Corporations

Fig. 5. Dynamic Effects on Job Postings.
Notes: The vertical line marks June 2021, one month prior to the implementation of the Double Reduction Policy. The x-axis represents the number of months relative to July 2021, with negative numbers indicating months prior to implementation and positive numbers indicating months following implementation. The dashed line represents 95% confidence interval. Subfigure (a) shows the event study regression results for all education and training firms. Subfigure (b) shows the event study regression results for academic private tutoring firms directly impacted by the Double Reduction Policy. Subfigure (c) shows the event study regression results for large private tutoring corporations.
Source: Online Job Posting Dataset.

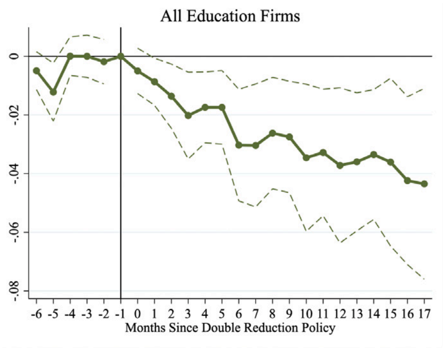
Table 8
Policy effect on net firm entry.

	Education		Private tutoring		Large	
	(1)	(2)	(3)	(4)	(5)	(6)
Policy × children	−0.0411***	−0.0425***	−0.0367***	−0.0379***	−0.000711	−0.000729
	(0.00989)	(0.0101)	(0.00977)	(0.0100)	(0.000503)	(0.000509)
COVID-19 Control	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	No	Yes	No	Yes	No	Yes
Observations	28,008	28,008	28,008	28,008	28,008	28,008
R-squared	0.465	0.490	0.466	0.491	0.427	0.460

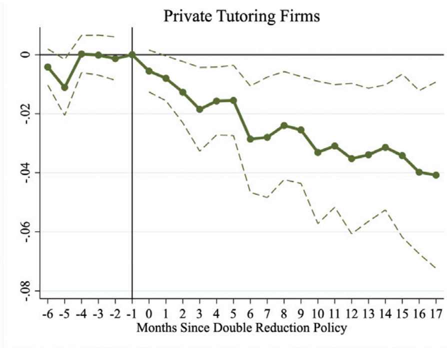
Notes: This table shows the Double Reduction Policy effect on the net number of registered firms. The dependent variables represent the difference between the number of newly-registered firms and the number of canceled firms for each type of firm within the same city and time period. Columns (1) and (2) illustrate the results for all education and training firms. Columns (3) and (4) illustrate the results for academic private tutoring firms directly impacted by the Double Reduction Policy. Columns (5) and (6) illustrate the results for large private tutoring corporations. The unit of the number of children is one thousand. Sources: Firm Registration Dataset. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

5.5. Heterogeneity over local education fever

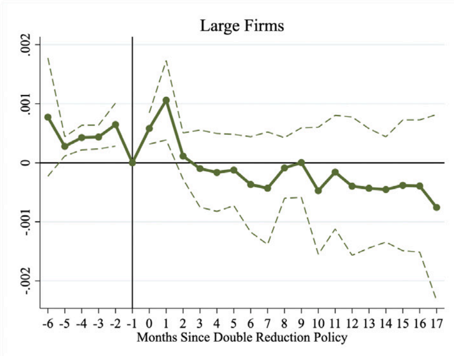
In our primary regression analysis, we use the number of children in a city to measure the treatment intensity of the DR Policy, reasoning that a larger potential customer base results in greater exposure to the policy. However, another critical aspect of policy exposure is the intensity of education fever, which transforms these potential customers into actual ones. To understand the DR



(a) Education



(b) Private Tutoring



(c) Large Private Tutoring Corporations

Fig. 6. Dynamic Effects on Firm Entry.
Notes: The vertical line marks June 2021, one month prior to the implementation of the Double Reduction Policy. The x-axis represents the number of months relative to July 2021, with negative numbers indicating months prior to implementation and positive numbers indicating months following implementation, spanning from January 2021 to December 2022. The dashed line represents 95% confidence interval. Subfigure (a) shows the event study regression results for all education and training firms. Subfigure (b) shows the event study regression results for academic private tutoring firms directly impacted by the Double Reduction Policy. Subfigure (c) shows the event study regression results for large private turtoring corporations.
Source: Firm Registration Dataset.

Policy's impact more comprehensively on employment and firm development, we consider the heterogeneous treatment effect across cities with different education fever intensity. We use the following specification:

$$\begin{aligned} y_{itm} = {} & \beta_0 + \beta_1 \text{policy}_{tm} \times \text{children}_i + \beta_2 \text{policy}_{tm} \times \text{children}_i \times \text{search}_i \\ & + \text{COVID}_{itm} + \eta_i + \gamma_{tm} + \delta_{im} + \epsilon_{itm} \end{aligned} \tag{3}$$

where search_i represents the search volume on PC and mobile for keywords "primary school tutoring" and "secondary school tutoring" from June 2020 to June 2021 in city i. This variable serves as a proxy for the intensity of tutoring engagement in different cities, with a higher search volume suggesting greater local reliance on tutoring services. The units for the number of children and the search volume are both scaled to 1000 to facilitate comparison.[17]

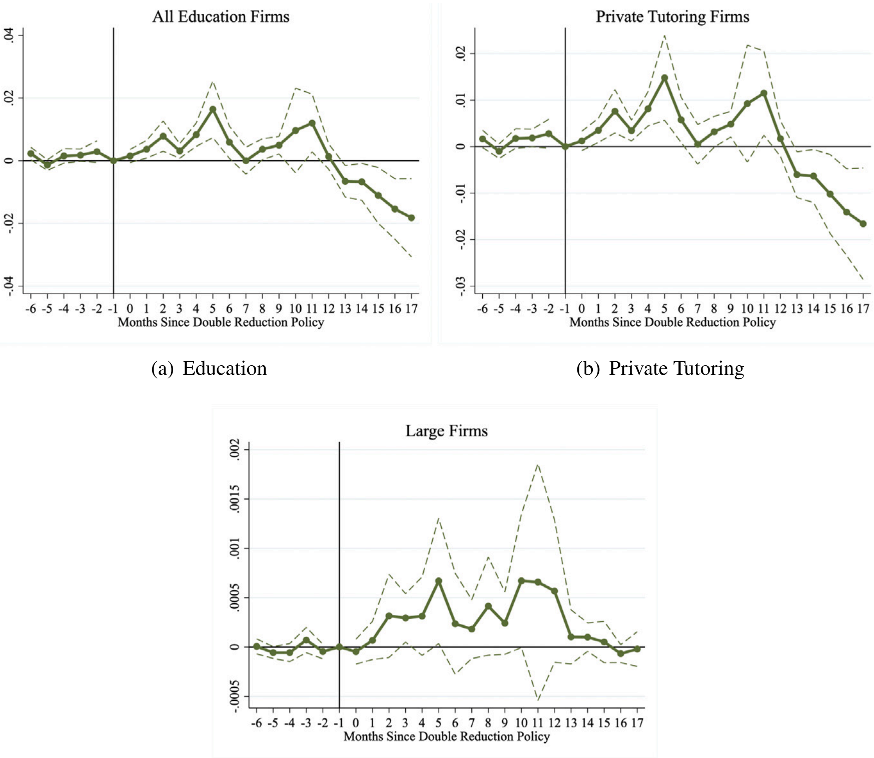
Appendix Table A9 presents the results. It demonstrates that the effect of the DR Policy is larger in cities with more intensive education fever. Specifically, for cities with same number of children, an increase of 10,000 more online searches can lead job opportunities to decrease by approximately 21 for all education-related firms, 8 for academic private tutoring firms, and 1 for large private tutoring corporations. These results illustrate the differential impact of the DR Policy, suggesting that business responses are closely linked to local educational demand.

Tables A10 and A11 detail the effects of the DR Policy on firm dynamics. Post-policy implementation, for cities with same number of children, an increase of 10,000 more online searches can lead to a decline in new firm entries: 0.2 fewer entries for both general

[17] A robustness practice we implement is to directly replace the number of children by the search intensity as the treatment exposure. We perform the following regression:

$$y_{itm} = \beta_0 + \beta_1 \text{policy}_{tm} \times \text{search}_i + \text{COVID}_{itm} + \eta_i + \gamma_{tm} + \delta_{im} + \epsilon_{itm} \tag{4}$$

The corresponding results are presented in Tables C17, C19 and C20. The results are not qualitatively changed.



(a) Education

(b) Private Tutoring

(c) Large Private Tutoring Corporations

Fig. 7. Dynamic Effects on Firm Exit.
Notes: The vertical line marks June 2021, one month prior to the implementation of the Double Reduction Policy. The *x*-axis represents the number of months relative to July 2021, with negative numbers indicating months prior to implementation and positive numbers indicating months following implementation, spanning from January 2021 to December 2022. The dashed line represents 95% confidence interval. Subfigure (a) shows the event study regression results for all education and training firms. Subfigure (b) shows the event study regression results for academic private tutoring firms directly impacted by the Double Reduction Policy. Subfigure (c) shows the event study regression results for large private turtoring corporations.
Source: Firm Registration Dataset.

and academic private tutoring firms. Regarding firm exits, these same cities experienced a slight increase of 0.008 in firm closures for general and academic tutoring firms following the policy's implementation.

5.6. Spillover on untargeted tutoring

Our main regression analysis has demonstrated that the impact of the DR Policy on all education-related firms are notably pronounced, being twice as substantial as its effect on purely academic private tutoring firms. This suggests a significant, albeit unintended, adverse effect on non-academic tutoring firms, which were not the primary targets of the DR Policy. This raises critical questions: What categories of untargeted education-related firms are adversely affected? What categories remain resilient? In this section, we investigate the spillover effects of the DR Policy, focusing particularly on its implications for job postings in education and training sectors beyond academic tutoring.

The regression results of Eq. (1) for non-academic private tutoring are presented in Table 9, illustrating the estimated policy effects on tutoring in Arts (including music, painting, and dance), Occupation Certificate (such as CFA and CPA), Civil Servant Examination, Adult and Continuing Education, Graduate Admission, Sports, and General Talent (encompassing Arts, sports, and other aspects of non-academic quality education). Our findings reveal a more pronounced and adverse impact of the policy on job postings within Arts, Sports, and General Talent tutoring. Following the policy implementation, cities with an additional 10,000 children witness monthly declines of 2.7 job opportunities in Arts tutoring, 1.67 in Sports tutoring, and 4.7 in General Talent tutoring. These contractions correspond to percentage decreases of 0.79%, 1.5%, and 0.96%, respectively, relative to the average number of job postings before the enforcement of the DR Policy. Appendix Figure A4 presents the dynamic effects of the policy on these non-academic private tutoring job postings, estimated from Eq. (2). Notably, a salient drop in online recruitment is observed in Arts tutoring, Sports tutoring, and General Talent tutoring in cities with larger child populations from August 2021, persisting significantly until November, the conclusion of our sample period. This pattern aligns with the observed trends in postings related to private tutoring and all education-related services.

Table 9
Spillover on untargeted firms.

	(1) Arts	(2) Certificate	(3) Civil	(4) Adult	(5) Graduate	(6) Sports	(7) Talent
Policy × children	−0.270*	0.0580	0.00352	−0.00779	0.0203	−0.167*	−0.470**
	(0.143)	(0.0720)	(0.00729)	(0.0289)	(0.0182)	(0.0906)	(0.234)
COVID-19 Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,720	23,720	23,720	23,720	23,720	23,720	23,720
R-squared	0.234	0.208	0.187	0.286	0.191	0.351	0.284

Notes: This table shows the spillover of the Double Reduction Policy on the job postings of the untargeted education firms. Columns (1) illustrate the results for firms with arts tutoring businesses. Columns (2) illustrate the results for firms with certificate (e.g. CPA, CFA) tutoring businesses. Columns (3) illustrate the results for firms providing civil servant exam preparing businesses. Columns (4) illustrate the results for firms with adult education businesses. Columns (5) illustrate the results for firms with graduate school entrance exam preparing businesses. Columns (6) illustrate the results for firms with sports club or tutoring businesses. Columns (7) illustrate the results for firms with both arts and sports tutoring businesses. The unit of the number of children is one thousand. Sources: Online Job Posting Dataset. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

The negative impact of the DR Policy on job postings related to non-academic tutoring is notably modest compared to its effects on academic private tutoring positions. Nevertheless, the coherence in the observed patterns across both academic and non-academic private tutoring for school-age children, encompassing areas such as arts, sports and general quality education, underscores the potential for spillover and amplification of the DR Policy. These firms, not directly targeted by the DR Policy, have been encouraged by the Chinese government. The underlying objective of the DR Policy is to alleviate academic pressures on children, thereby freeing up time for them to engage in a variety of extracurricular activities, including arts and sports. Despite these intentions, our findings indicate that firms operating in these sectors have not reaped the anticipated benefits.

Several reasons may explain this unintended consequence. First, a notable complementarity exists between academic and non-academic private tutoring, characterized by a high degree of sectoral agglomeration. On the one hand, non-academic tutoring services often operate in close proximity to academic tutoring centers, capitalizing on the convenience for parents to enroll their children in these programs following academic sessions. On the other hand, many education firms and their owners, are involved in both academic and non-academic tutoring services. Consequently, a downturn in one area inevitably impacts the other. We examine the complementarity between various types of private tutoring on both the demand and supply sides through the following methods.

In Appendix Table A12, we examine the complementarity between academic and non-academic tutoring among students using data from the China Education Panel Survey (CEPS). This nationally representative dataset tracks the class of 2013 during their first and second years of middle school. Our findings indicate that students participating in academic tutoring are also more likely to engage in non-academic tutoring. This positive correlation remains robust even after controlling for student fixed effects. In Section 5.7, we further provide evidence that a significant proportion of owners of the exited academic private tutoring firms also owned non-academic education firms both before and after the DR Policy. This shows the close connection between academic and non-academic education firms and the negative spillover channel through owners and shareholders' networks.

There can be some other reasons for the untargeted firms to be affected. The intensified regulatory framework applied to the broader private tutoring industry, characterized by frequent investigations and more rigorous approval procedures, might also contribute to diminished labor demand in both academic and non-academic private tutoring sectors. Or, the chilling effect leads untargeted firms to worry about their fate in the future, as any company can be severely impacted by some government legislation without prior notice. The negative spillover effects may also simply stem from insufficient demand to support a large number of firms in this market.

Moreover, we expand our investigation to assess the spillover effects of the DR Policy on educational firms not directly targeted by the policy, by closely examining the entry and exit dynamics of firms, as well as the net changes in firm numbers across a range of non-academic sectors. This extensive analysis illuminates the broader implications of the policy on the educational landscape. Table 10 presents the differential impacts of the DR Policy on the establishment of new firms within diverse non-academic domains. Our analysis demonstrates that the DR Policy significantly reduces the number of new firm registrations, impacting not only targeted academic private tutorings, but also those aimed at adult learners or non-academic education, though to a lesser degree. Additionally, firm exits generally rise across sectors following the DR Policy implementation, as detailed in Table 11. It underscores the policy's dual effect of discouraging new entries and elevating exit rates, leading to market contraction. Table 12 further supports these findings, showing a net negative impact on firm entry across most sectors, except for the Occupation Certificate sector.

Combining the results from job postings and firm registrations, we reveal that firms focusing on non-academic talent tutoring, including arts and sports tutoring are the most affected untargeted ones. These findings reveal a complex interplay between policy implementation and the non-academic education sector, indicating that while the policy aims to alleviate academic pressures, it does not boost the growth of non-academic tutoring services. It particularly underscores a potential disconnect between the policy's goals and its real-world outcomes. Despite the intention to promote extracurricular activities engagement, the decline in firm dynamics indicates that regulatory actions and market reactions might not align with these ambitions.

Table 10
Spillover on untargeted firms: Firm entry.

	(1) Arts	(2) Certificate	(3) Civil	(4) Adult	(5) Graduate	(6) Sports	(7) Talent
Policy × children	−0.0323***	0.00256	-7.30×10^{-6}***	−0.00540***	-4.35×10^{-5}*	−0.0142***	−0.0388***
	(0.0121)	(0.00198)	(2.62×10^{-6})	(0.00170)	(2.34×10^{-5})	(0.00508)	(0.0136)
COVID-19 Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,008	28,008	28,008	28,008	28,008	28,008	28,008
R-squared	0.661	0.687	0.165	0.448	0.181	0.575	0.679

Notes: This table shows the spillover of the Double Reduction Policy on the number of newly-registered firms of the untargeted education firms. The dependent variables represent the number of registered firms for each type of firm for all firms within the same city and time period. Columns (1) illustrate the results for firms with arts tutoring businesses. Columns (2) illustrate the results for firms with certificate (e.g. CPA, CFA) tutoring businesses. Columns (3) illustrate the results for firms providing civil servant exam preparing businesses. Columns (4) illustrate the results for firms with adult education businesses. Columns (5) illustrate the results for firms with graduate school entrance exam preparing businesses. Columns (6) illustrate the results for firms with sports club or tutoring businesses. Columns (7) illustrate the results for firms with both arts and sports tutoring businesses. The unit of the number of children is one thousand. Sources: Firm Registration Dataset. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 11
Spillover on untargeted firm: Firm exit.

	(1) Arts	(2) Certificate	(3) Civil	(4) Adult	(5) Graduate	(6) Sports	(7) Talent
Policy × children	0.00711***	0.00229***	-1.26×10^{-6}	0.000737***	1.23×10^{-6}	0.00430***	0.00882***
	(0.00183)	(0.000424)	(1.01×10^{-6})	(0.000247)	(2.14×10^{-6})	(0.000999)	(0.00208)
COVID-19 Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,008	28,008	28,008	28,008	28,008	28,008	28,008
R-squared	0.645	0.382	0.145	0.652	0.145	0.582	0.653

Notes: This table shows the spillover of the Double Reduction Policy on the number of canceled firms of the untargeted education firms. The dependent variables represent the number of canceled firms for each type of firm within the same city and time period. Columns (1) illustrate the results for firms with arts tutoring businesses. Columns (2) illustrate the results for firms with certificate (e.g. CPA, CFA) tutoring businesses. Columns (3) illustrate the results for firms providing civil servant exam preparing businesses. Columns (4) illustrate the results for firms with adult education businesses. Columns (5) illustrate the results for firms with graduate school entrance exam preparing businesses. Columns (6) illustrate the results for firms with sports club or tutoring businesses. Columns (7) illustrate the results for firms with both arts and sports tutoring businesses. The unit of the number of children is one thousand. Sources: Firm Registration Dataset. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 12
Spillover on untargeted firms: Net firm entry.

	(1) Arts	(2) Certificate	(3) Civil	(4) Adult	(5) Graduate	(6) Sports	(7) Talent
Policy × children	−0.0395***	0.000266	-6.04×10^{-6}*	−0.00614***	-4.47×10^{-5}*	−0.0185***	−0.0477***
	(0.0139)	(0.00177)	(3.18×10^{-6})	(0.00191)	(2.33×10^{-5})	(0.00598)	(0.0156)
COVID-19 Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,008	28,008	28,008	28,008	28,008	28,008	28,008
R-squared	0.434	0.641	0.148	0.226	0.167	0.414	0.469

Notes: This table shows the spillover of the Double Reduction Policy on the net number of registered firms of the untargeted education firms. The dependent variables represent the difference between the number of newly-registered firms and the number of canceled firms for each type of firm within the same city and time period. Columns (1) illustrate the results for firms with arts tutoring businesses. Columns (2) illustrate the results for firms with certificate (e.g. CPA, CFA) tutoring businesses. Columns (3) illustrate the results for firms providing civil servant exam preparing businesses. Columns (4) illustrate the results for firms with adult education businesses. Columns (5) illustrate the results for firms with graduate school entrance exam preparing businesses. Columns (6) illustrate the results for firms with sports club or tutoring businesses. Columns (7) illustrate the results for firms with both arts and sports tutoring businesses. The unit of the number of children is one thousand. Sources: Firm Registration Dataset. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

5.7. Where have all the bosses gone

Entrepreneurs in the private tutoring industry might also invest in other industries. A compelling question arises regarding the subsequent ventures of these entrepreneurs following the closure of their tutoring businesses. By leveraging the equity structure information available in the firm registration data, we further examine the nature of the new enterprises these former owners

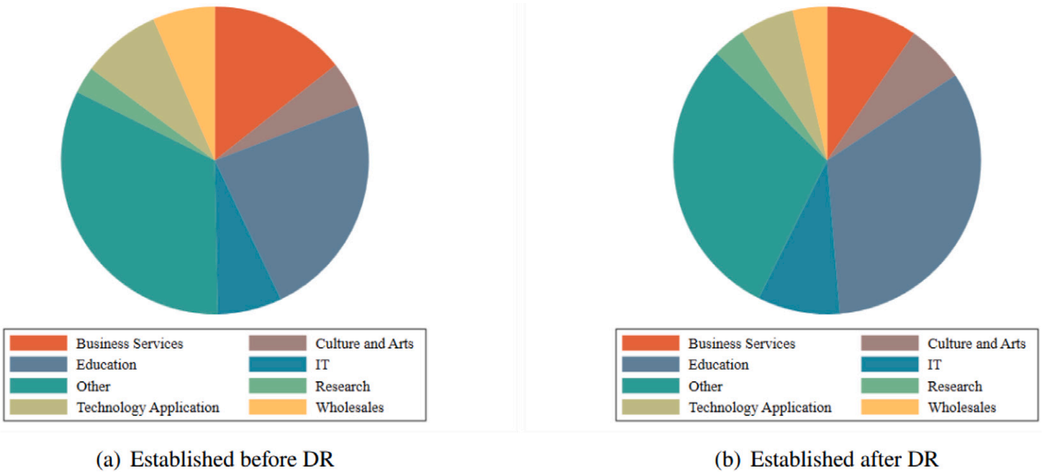


Fig. 8. Other Firms Owned by Tutoring Firm Shareholders.
Notes: This figure shows the industry composition of new firms established by tutoring firm shareholders before and after the Double Reduction Policy.
Source: Firm Registration Dataset.

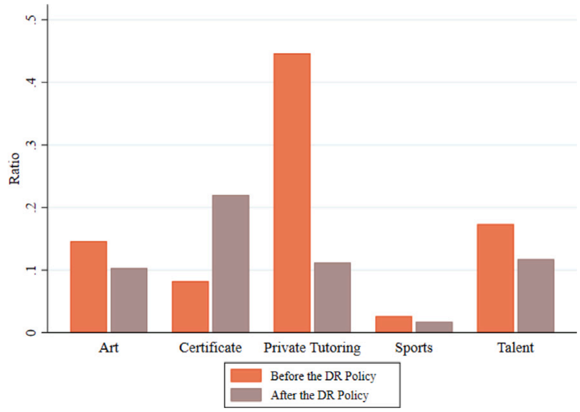


Fig. 9. Types of Education-related Firms Owned by Former Tutoring Firm Shareholders.
Notes: This figure shows the types of new education-related firms established by former tutoring firm shareholders before and after the Double Reduction Policy.
Source: Firm Registration Dataset.

of private tutoring firms choose to establish. Specifically, do they remain in the education sector or opt to shift their field of entrepreneurship?

Fig. 8 illustrates the industry composition of other firms established by private tutoring firm owners before and after the implementation of the DR Policy. Interestingly, a significant proportion, approximately 23% before the policy and 33% after the policy, of these firms are still in the education industry. This has two important implications. First, many owners who were heavily hit by the DR Policy have multiple firms related to the education industry offering various services, which explains the large spillover effects we observed on untargeted firms. Second, a significant number of owners chose to stay within the education industry even after the DR Policy. The rest of the owners ventured into different service sectors, including business services, IT, culture and arts, technology application, and wholesale.

Although nearly one third of the owners opted to remain in the education sector, the specific types of education-related firms have undergone considerable changes. As depicted in Fig. 9, the proportion of academic private tutoring firms among newly-established education firms by these owners plummeted from 45% prior to the policy to 11% after its introduction. Additionally, 70% of the new education firms established following the DR Policy explicitly state their non-involvement in private tutoring services in their business scope, a stark contrast to the mere 20% before the policy's implementation. Firms involved in certificate training increased from 8% to 22%. Similar to the results from the last section, we do not find an increase for firms offering art and sports tutoring. Overall, we find that many targeted firm owners operated firms in non-academic education both before and after the DR Policy, and the share of newly established firms in non-academic education among these owners increased following the policy's implementation.

However, Appendix Figures A5 and A6 further show that the absolute number of new firms established by targeted firm owners experienced a substantial decline for both private academic and non-academic industries, as well as non-education industries. In addition to this decline in new firm formation, there is a notable increase in firm exits among former private tutoring firm owners following the implementation of the DR Policy—particularly evident toward the end of 2021, as illustrated in Appendix Figure A7. These results further support our findings on the negative spillover effects.

5.8. Remarks on regression results

In summary, our regression analysis leads to the following conclusions: (1) In the education-related industry, cities with higher exposure to the DR Policy experienced significant declines in online job postings and firm entries, as well as an increase in firm exits. (2) Not only private academic tutoring firms, which are the main target of the DR Policy, but also other education-related firms, have been severely impacted. (3) Large-chain private tutoring corporations do not demonstrate better resilience than smaller, independent firms. (4) Firms involved in art and other non-academic private tutoring is also negatively affected, indicating a significant negative spillover on untargeted businesses. (5) The majority of former tutoring firm owners continue to operate within the education sector following the implementation of the DR Policy, but they specifically avoid engagement in academic private tutoring activities and hesitate to establish new education-related firms.

Our empirical analysis provides a conservative estimation of the negative effect of the DR Policy on China's education-related industry in the private market for several reasons. First, online job postings only represent one aspect of firms' recruitment efforts, as firms can employ other methods to hire workers. Second, online job postings only measure the loss of new job opportunities and do not account for unemployment among incumbent workers. Many large chain private tutoring corporations experienced massive layoffs following the policy implementation.[18] Third, the loss of firms in the industry is underestimated. Numerous firms have opted to change their primary business focus, while others have ceased operations without canceling their registrations.

5.9. Other robustness checks

We now conduct a series of robustness checks to further validate our regression analysis. First, in the main setting, we use the number of recruitments as the dependent variable. Each job posting advertisement includes information about the number of recruitments; however, some advertisements do not explicitly display this information. In the main setting, we assign a value of one to all these missing data points. We also investigate the results of the main regression by changing the dependent variable to the number of advertisements, which will not be affected by this imputation. We find a similarly large effect in Tables A13 and A14. Second, we include July 2021 in the treatment period and re-estimate our main regression in Tables A15, A16, A17, and A18. The main results do not change qualitatively, although the magnitudes are slightly reduced. It can be attributed to the fact that the policy was implemented in late July. Third, although the policy was implemented in July, rumors of restricting the private tutoring industry had begun circulating in early May, which was reflected in the financial market. We do not detect a significant pre-trend in the dynamic effect analysis, indicating that this rumor effect should be minimal. To account for this expectation effect, we change the starting time of the policy to May 2021 and run the main regressions in Tables A1, A2, A3, and A4. We do not find any qualitative changes.

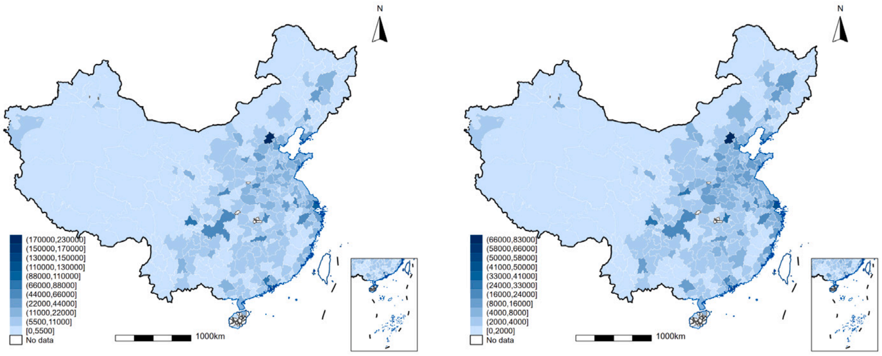
One crucial issue during the policy period is the COVID-19 pandemic. It is essential to distinguish the DR effect from the COVID effect. We address this concern with the following responses. First, COVID-19 was tightly controlled by the Chinese government in 2021 and early 2022, as illustrated in Appendix Figure A8. There were no major outbreaks or lockdowns in large cities during this period, so our results from this time are not affected by the pandemic. We further exclude all samples after December 2021 for firm registration data and re-run the regressions. No significant changes are observed, and the results are available upon request. Second, we control for the confirmed cases of COVID-19 in each city for each month in all of our regressions. We also conduct the main regressions on the proportion of education-related firms' job postings relative to the total job postings in the city. By doing so, we can mitigate the confounding effect of COVID-19 on the overall local economy. Third, we run the same main regression with the dependent variable changed to the city-year-month level number of confirmed COVID-19 cases. This regression demonstrates no correlation between the DR Policy exposure and COVID-19 shocks in Appendix Table A19.

Another robustness check involves examining how non-education firms changed their relative labor demand following the implementation of the DR Policy. If it is also decreased, then the estimated effect may be an overall trend of the labor market. This analysis is presented in Appendix D. Appendix Figure D1 and Table D1 indicate that the proportion of job postings from non-education firms increased after the DR Policy, although the effects are less precisely estimated.

6. Back-of-the-envelope calculation

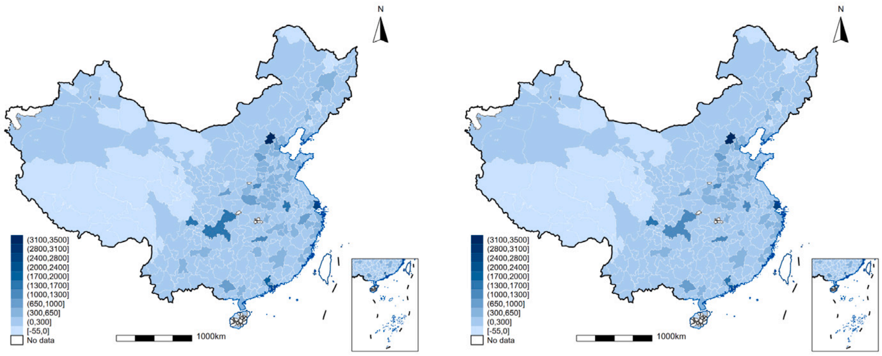
So far, we have shown the consistently significant impact of the DR Policy on the education-related and private tutoring industry through the lens of job postings and firm dynamics. Figs. 10 and 11 further illustrate the potential losses of jobs and firms across Chinese cities after the policy was officially implemented in July 2021. The loss of job postings (surviving firms) is computed as the sum of the monthly differences between the predicted number of job postings (surviving firms) when setting Policy × children to zero and the actual number of job postings (surviving firms) for each city between July 2021 and November 2021 (December 2022). These calculations use the predicted number of job postings and surviving firms as the counterfactual outcomes without the

[18] Please refer to https://www.cnbc.com/2021/08/26/chinas-after-school-crackdown-wipes-out-many-jobs-overnight.html.



(a) Education (b) Private Tutoring

Fig. 10. Predicted City-level Loss of Job Postings.
Notes: Predicted city-level loss of job postings is computed as the sum of the monthly differences between predicted number of job postings when setting policy*children to zero and the actual number of job postings for each city after the Double Reduction Policy (July 2021 to Nov 2021).



(a) Education (b) Private Tutoring

Fig. 11. Predicted City-level Loss of Firms.
Notes: Predicted city-level loss of Firms is computed as the sum of the monthly differences between predicted number of surviving firms (active registered firms) when setting policy*children to zero and the actual number of surviving firms for each city after the Double Reduction Policy (July 2021 to Dec 2022).

DR Policy (or the DR Policy did not vary across cities). As we find in the regression analyses, the losses of job postings and firms are uneven across cities. Richer and larger cities were struck harder in both education-related industry in general and the DR-targeted private tutoring industry. In particular, Beijing and Shanghai are two of the most affected cities. They are the top two cities with the most developed private tutoring industry. The geographical distributions of job losses and firm losses are essentially the same, even though the time horizons we study for job postings and firm registration are slightly different.

At the national level, we find the loss of education-related jobs posted online was about 3,339,669, out of which 1,415,445 was in academic private tutoring, within the first four months after the DR Policy. Considering the mass layoffs in the education and private tutoring industry, our estimate of job loss is, at best, a lower bound for the net effect of the DR Policy on labor demand. In addition to the cost of the DR Policy in the labor market, we also calculate the potential loss in tax revenue due to the policy. At the national level, we calculate the total reduction in surviving firms in the education industry within the first 18 months after the DR Policy, which is about 69,760 (62,400 of which are private tutoring firms). We then translate the reduction in number of surviving education-related firms into loss of tax revenue using the annual net amount of VAT of a representative education-related firm estimated from the China Taxation Survey (2016) data. We provide these estimates in two scenarios. First, we use the median value of VAT paid by an education firm, which is about 106,000 RMB per year, as the lower bound of the firm-level loss of VAT, assuming that firms with lower revenue were more likely to exit after the DR Policy. Second, we use the 75th percentile, which is about 866,000 RMB per year, as the upper bound of the firm-level loss of VAT, assuming that firms with higher revenue were more severely impacted by the DR Policy. By doing this, we get an interval for the estimated loss of VAT within the first 18 months after the DR Policy:[11,091,840,000 RMB, 90,618,240,000 RMB]. However, these are again conservative estimates of the tax revenue loss since the market size and sales of the education industry have greatly increased between 2016 and 2021. Nonetheless, our back-of-the-envelope analysis points out a sizable cost in the labor market and in terms of tax revenue for the Chinese government.

7. Conclusion and discussion

In this study, we investigated the economic consequences of a restrictive industrial regulation policy, the DR Policy in China, which aimed at a total ban on for-profit academic private tutoring. We are the first to provide detailed causal evidence on the effects on the labor market and firm dynamics of this nationwide, contentious policy using big data. In general, the DR Policy caused a sharp plummet in the number of firms operating in the academic private tutoring and education sector, leading to significant losses in job opportunities and tax revenue in the short run. Our findings indicate that the policy resulted in plummeting labor demand, as measured by online job postings, provoked more firms to exit the sector and deterred new firms from entering the education-related industry. The detrimental impact was salient not only for academic private tutoring firms but also for all education-related firms, including untargeted ones. This negative spillover can be partly attributed to the interconnected ownership structure among academic and non-academic tutoring firms. In addition to our main analysis, which focuses on the short run, we also provide a longer-term examination of the DR Policy's effects on job postings and firm dynamics, as detailed in Appendix E. The findings suggest that the policy's impact has been persistent, with only limited signs of recovery over a three-year period. Moreover, the DR Policy affected firms of all sizes—both small and large—indicating a broad and industry-wide impact.

However, our study has several limitations due to data availability. First, aside from job posting losses, massive layoffs constitute a significant part of the policy's adverse effect. Future research should consider investigating the unemployment of incumbent education workers and their responses to this abrupt shock. Second, although we have demonstrated the effectiveness of the DR Policy on the supply side of private education, it is largely unknown how it has affected the demand for tutoring from Chinese families. Does it effectively alleviate the education fever, thereby restoring a relaxed and joyful childhood for Chinese children? Does this policy shrink the educational gap between affluent and disadvantaged families, or expand it? What are the long-term consequences of education inequality? These questions remain important to the overall evaluation of the DR Policy, with mitigating education inequality and over-competition being its ambitious goals.

CRediT authorship contribution statement

Zibin Huang: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yinan Liu:** Data curation, Conceptualization, Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis. **Mingming Ma:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Leo Yang Yang:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jce.2025.07.002.

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