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# The Effect of Computer-Assisted Learning on Students' Long-Term Development

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**ABSTRACT**

In this paper, the researchers examine the effect of computer-assisted learning on students' long-term development. They explore the implementation of the "largest ed-tech intervention in the world to date," which connected China's best teachers to more than 100 million rural students through satellite internet. The authors find evidence that exposure to the program improved students' academic achievement, labor performance, and computer usage. They observe these effects up to ten years after program implementation. These findings indicate that education technology can have long-lasting positive effects on a variety of outcomes and can be effective in reducing the rural–urban education gap.

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# 1 Introduction

The increasing penetration of computers and the internet has profoundly changed how firms and markets operate, and the education industry has been no exception. The U.S. Department of Education states that "technology ushers in fundamental structural changes that can be integral to achieving significant improvements in productivity. [...] Technology also has the power to transform teaching by ushering in a new model of connected teaching. This model links teachers to their students and to professional content, resources, and systems to help them improve their own instruction and personalize learning."[1] It is not surprising, then, that the use of technology in the classroom has been the subject of growing interest among both academic researchers and policy makers.

In addition to increasing productivity inside the classroom and updating the pedagogical paradigm, technology can improve the delivery of high-quality education to underserved areas. Specifically, computer-aided learning (CAL) can narrow the education gap between urban and rural areas, reducing inequalities in education achievement. In China, the setting of our study, rural schools are facing a variety of challenges, including poorly qualified teachers, insufficient resources, and large classes (Hannum, 1999). In 2000, only 14.3% of teachers in rural secondary schools had a bachelor's degree, compared with 32% of teachers in urban secondary schools. Rural schools also had an average student–teacher ratio of 17.13, much higher than the 12.43 student–teacher ratio in urban schools.[2] Lower levels of school inputs are associated with worse outcomes. Only 7.1% of students in rural middle schools enroll in high school, while high-school enrollment is 9.4 times higher in urban schools (2000 Census). The existence of a large and persisting rural–urban educational gap is not specific to China. In fact, it is a common occurrence in most developing economies, such as India (Sonalde Desai and Veena Kulkarni, 2008; Banerjee et al., 2007), Pakistan (Beg et al., 2019), and sub-Saharan African countries (Zhang, 2006).[3] Reducing the inequality in education outcomes between rural and urban schools is not a simple task. Standard methods, such as subsidies to high-quality teachers for relocation to rural areas, are often ineffective. Experienced teachers have attractive outside options in urban areas that they prefer over subsidies to move to isolated locations with few amenities. CAL, however, could connect highly effective teachers in urban areas to students in rural schools without forcing the teachers to relocate.

In this paper, we provide the first empirical analysis of a large-scale use of technology

[1] https://web.archive.org/web/20201029162846/https://www.ed.gov/oii-news/use-technology-teaching-and-learning

[2] These statistics are obtained from the Educational Statistics Yearbook of China, 2000. Link to the data: https://web.archive.org/web/20161024074031/http://data.cnki.net/Yearbook/Single/N2006010309

[3] For more information, visit https://www.education-inequalities.org/. The data show that the rural–urban education gap is present in some developed countries as well, such as the United States (Marré, 2017).

to reduce the rural–urban education gap. Specifically, we study a 2004 reform in China that connected high-quality teachers in urban areas with more than 100 million students in rural primary and middle schools through the use of satellite internet. Over four years, the program installed satellite dishes, computer rooms, and other multimedia equipment in rural schools. At the same time, the Ministry of Education selected the most accomplished teachers in the country to record special lectures in Beijing. The lectures, as well as other study materials, were then deployed to rural schools via the internet and physical CDs. Due to its great number of targeted students, this program is often considered the largest education-technology intervention in the world to date (Yu and Wang, 2006; McQuaide, 2009).

Our data come from the China Family Panel Survey (CFPS, 2010 and 2014), which contains rich information about individual outcomes between seven and ten years after the CAL implementation. This dataset allows us to study the effect of CAL on a wide variety of outcomes, including education attainments, labor-market performance, internet usage, and noncognitive skills. Moreover, the CFPS data allow us to precisely identify the county of residence of respondents at age 12, when they were plausibly enrolled in middle school and exposed to education technology.

Our empirical strategy compares individual outcomes across two dimensions: birth cohorts and geographical locations. First, we compare outcomes of individuals who were at most 14 years old when the program was first implemented to outcomes of individuals who were at least 15 years old. Students who were at most 14 were, in fact, exposed to CAL during middle school, while older individuals were either already enrolled in a higher grade or already active in the labor market. Second, we compare outcomes across counties that received CAL in different years. The program had a staggered implementation between 2004 and 2007. This difference-in-differences strategy allows us to control for cohort-specific and county-specific fixed effects. Because we also control for county-specific linear trends, our specifications identify the causal effect of CAL through discontinuities around the implementation of the reform, which affected different cohorts in different counties.

We report four key findings. First, exposure to CAL in middle school significantly increased students' academic achievement in the long run. Completed education increased by 0.85 years (+9%), math skills measured at the time of the survey (seven to ten years after exposure to CAL) increased by 0.18 standard deviations ($\sigma$), and Chinese skills increased by $0.23\sigma$. Second, CAL significantly improved students' labor-market outcomes. Students who were exposed to CAL were more likely to be employed in occupations that focused more on cognitive skills, instead of manual skills. They also earned, on average, 59% more than individuals living in the same county but not exposed to the new education technology. This effect on earnings can be decomposed into a cross-occupation effect and a cross-migration status effect, which account for one-third of the total, and a within-occupation-and-migration effect, which accounts for the remaining two-thirds. In sum, improvements in labor market outcomes after exposure to CAL did not require a career or location change. Third, CAL increased internet and computer usage by 15% several years after middle school. Fourth, we find evidence suggesting that the program had a mild negative impact on noncognitive traits, but these effects are not precisely estimated. Overall, exposure to the policy can explain a 21% reduction in the preexisting urban–rural education gap and a 78% reduction in the preexisting earning gap.

Out of several pedagogical changes introduced by the reform, access to high-quality teachers through remote learning seems to have played the main role in increasing human capital. Other mechanisms, such as access to new technology for local teachers and the inclusion of computer science in the curriculum, are not corroborated by data and anecdotal evidence. Prior research on remote learning highlighted how online education requires a level of self-discipline that most students might not have (McPherson and Bacow, 2015). Moreover, it might induce students to postpone studying until just before the exam, leading to suboptimal learning (Figlio, Rush, and Yin, 2013). In our context, however, remote learning happened in the classroom under the direct supervision of local teachers, therefore limiting distractions and procrastination.

This study contributes to three main strands of the literature. First, this paper is related to the literature that examines the effects of computer-aided learning on student achievement (see Bulman and Fairlie (2016) and Escueta et al. (2017) for a review).[4] Papers in this strand of the literature have reported mixed results. While some studies find insignificant or even negative effects of CAL on test scores (Angrist and Lavy, 2002; Goolsbee and Guryan, 2006), other papers show positive and statistically significant effects (Banerjee et al., 2007; Barrow, Markman, and Rouse, 2009; Muralidharan, Singh, and Ganimian, 2019). In the Chinese context, there are several papers that study smaller-scale CAL experiments (Lai et al., 2013; Mo et al., 2014; Lai et al., 2015; Mo et al., 2015; Lai et al., 2016). Most of them find a positive effect of CAL on test scores and noncognitive outcomes in the short term. In light of these conflicting results, there are several unanswered questions. How do the effects of CAL change over time? While most of the available evidence is collected shortly after student exposure to education technology, little is known about the consequences of CAL several years after its implementation. In this paper, we study the impact of CAL on outcomes that are observed between seven and ten years after the use of technology in the classroom. Furthermore, what are the outcomes that might improve due to exposure to CAL? While most of the existing evidence focuses on short-term math skills, little is known about the effect of CAL in other

[4] Several papers address a related question: the effect of computer use at home on student outcomes (Malamud and Pop-Eleches, 2011; Fairlie and London, 2012; Fairlie and Robinson, 2013; Beuermann et al., 2015). Most of them document a zero or negative effect.

areas. In this paper, we analyze the effect of CAL on a wide array of outcomes, including completed education, cognitive skills in math and Chinese, performance in the labor market, skill content of occupations, internet use, and noncognitive skills.

Second, this study is related to the literature that examines the effect of educational quality on student achievement. Previous studies have documented positive effects of teacher quality on students' performance (Carrell and West, 2010; Chetty, Friedman, and Rockoff, 2014; Figlio, Schapiro, and Soter, 2015). Academics and policy makers have investigated several ways to increase teacher quality and, as a result, student performance, including teacher salary or performance pay (Lavy, 2009; Muralidharan and Sundararaman, 2011); training (Jacob and Lefgren, 2004; Harris and Sass, 2011); evaluation (Taylor and Tyler, 2012); and credentials (Clotfelter, Ladd, and Vigdor, 2009). Our paper contributes to this literature by showing how technology can be used to increase teacher quality in underserved locations. By letting the best teachers in the country connect remotely with students in rural schools, technology allowed the Chinese government to increase the quality of education in rural schools without relocating teachers. The results of our study suggest that CAL can be an effective and relatively cheap solution to decrease the education gap between urban and rural schools, which is common to both developed and developing counties.

Third, this study is related to the strand of the literature that focuses on poverty and inequality in China. Income inequality has been steadily rising in China (Zhu, 2012; Xie and Zhou, 2014). In particular, Fan, Yi, and Zhang (2019) documented an increasing pattern in intergenerational income persistence during the economic transition. To address this issue, they argued that the Chinese government should continue removing rural–urban migration barriers and implementing programs to subsidize the education of disadvantaged children. Our paper complements this branch of the literature by suggesting that technology might be a fundamental tool to reduce income inequality in China by closing the education gap between urban and rural areas.

The rest of the paper is organized as follows. Section 2 describes the institutional background. Section 3 discusses the data. Section 4 describes the empirical strategy. Section 5 presents the main results, while Section 6 tests their robustness. Section 7 includes an analysis on the mechanisms behind the main results. Section 8 concludes.

## 2 Institutional Background

### 2.1 Low–Quality Education in Rural China

In China, urban and rural schools provide significantly different educational quality. Rural schools have higher student–teacher ratios and poorer educational infrastructure. In 2000, the average per-student spending was CNY 884 in rural secondary schools and CNY 1,700 in urban secondary schools (Educational Statistics Yearbook of China). In addition, the student–teacher ratio was 17.13 in rural schools and 12.43 in urban schools. Compared with teachers in urban schools, teachers in rural schools tend to be older and less likely to hold a college degree. Stricter budget constraints further limit opportunities for professional development and continued training (Hannum, 1999; Brown and Park, 2002). In 2000, for example, only 14.3% of teachers in rural secondary schools had a bachelor's degree, compared with 31.8% of teachers in urban schools (Educational Statistics Yearbook of China, 2000). Differences in school inputs translate into significant inequality of education attainment. According to the 2000 census, in urban areas the average number of years of completed education was 9.8, compared to only 6.85 in rural locations. The percentage of individuals in urban areas with a high school diploma and a college degree was, respectively, 3.5 times and 55.5 times higher than the share of individuals in rural areas with the same level of education.

Improving teacher quality in rural areas entails significant challenges.[5] First, most teachers have been reluctant to relocate to the poorly connected and economically depressed areas of midwestern China, even if the government is willing to pay high subsidies and special allowances.[6] Second, many teachers who participated in these relocation programs and stayed in a rural area for several semesters failed to teach at a satisfactory level.[7] The high incentives offered for relocation, in fact, might have attracted teachers who just wanted to obtain extra credit for future promotion elsewhere instead of being motivated to help students in rural schools.[8] As a consequence, rural schools kept lagging behind urban schools even as the Chinese government spent substantial resources and adopted different policies to reduce the gap.

## 2.2 The Modern Distance Education Program

**Rollout plan.** Starting in September 2004, the Chinese Ministry of Education decided to exploit modern technology to improve teacher quality and education outcomes in rural schools. The resulting education policy, known as the "Modern Distance Education Program in Rural China," gave primary and middle schools in rural areas access to broadband internet and promoted the use of computers in their curricula. It is the "largest ICT project in the world" to date (Yu and Wang, 2006; McQuaide, 2009), serving more than 100 million students

[5] https://web.archive.org/web/20201029155754/https://baijiahao.baidu.com/s?id=1653430257241026007&wfr=spider&for=pc

[6] Rural schools often have poor management and high teaching loads (Ai and Liu, 2008). Moreover, the living conditions in rural areas can be harsh, especially for teachers relocating from urban locations (Zhou and Wang, 2010).

[7] Xiao (2018); https://web.archive.org/web/20201117233825/http://news.sohu.com/2004/02/01/54/news218845459.shtml.

[8] A number of empirical studies have shown that monetary incentives have negative effects on an individual's prosocial behavior (for example, Frey and Oberholzer-Gee, 1997; Mellström and Johannesson, 2008).

in 346,206 rural primary and middle schools and costing CNY 11.1 billion.[9] Providing internet access to rural schools required time to install satellite dishes and set up computer and multimedia rooms. As a consequence, the full implementation took several years (Figure 1).[10] Among 2,861 counties, 2,445 were covered by the program. Specifically, the program reached 678 counties (G1, 23.7% ) in 2004, 893 counties (G2, 31.2% ) in 2005, 493 counties (G3, 17.2% ) in 2006, and 380 counties (G4, 13.3% ) in 2007.[11] In the remaining 416 counties (G5), the government did not implement computer-assisted learning.[12] We will explore this gradual rollout in the empirical analysis.

**The treatment bundle.** The CAL program was based on three separate pedagogical "modes" (Office of Modern Distance Education Project for China's Rural Primary and Middle Schools (2009) and Figure A1). First, it delivered 440,142 DVD-player sets, comprising TVs and DVD players. These sets were used to play teaching CDs that contained lectures and learning materials prepared by some of the best teachers in the country, as further explained in Section 2.3. Second, the program installed 264,905 satellite receiving sets, comprising satellite antennas, satellite TV equipment, computers, and other related devices. These satellite sets allowed the Chinese government to deliver new lectures and learning materials through the internet, instead of relying on the transfer of physical CDs. Moreover, it allowed local teachers to use computers and the internet in preparation of their own lectures. Third, the program built 40,858 computer classrooms, which included a network of computers and a projector. In these computer rooms, students could follow from their own device the new teaching materials prepared by the central government. Moreover, the computer rooms could be used to introduce computer science in the curriculum of receiving schools.

As planned, rural primary teaching points (small-scale rural schools) received only DVD-player sets, rural primary schools received only DVD-player sets and satellite sets, while rural middle schools received all three interventions (Wang, Zeng, and Wang, 2015).

[9] Most of the information regarding the policy comes from the official implementation plan and the 2007 final report of the Ministry of Education. They are available online at `https://web.archive.org/web/20201109212237/http://old.moe.gov.cn//publicfiles/business/htmlfiles/moe/s3333/201001/xxgk_82052.html` and `https://web.archive.org/web/20201029160144/http://www.moe.gov.cn/jyb_xwfb/xw_fbh/moe_2069/moe_2095/moe_2100/moe_1851/tnull_29185.html`. Other valuable sources are Office of Modern Distance Education Project for China's Rural Primary and Middle Schools (2009) and Wang, Zeng, and Wang (2015).

[10] Appendix A.1 provides links to official sources with the full list of counties by implementation year.

[11] The implementation years refer to the school years. Therefore, 2004 refers to the school year starting in September 2004, and so forth. Moreover, the distribution of counties includes districts, which are geographical subdivisions at the same administrative level.

[12] G5 counties are mostly located in coastal regions, where teachers from urban schools are willing to teach. Therefore, G5 counties were not supposed to receive the treatment.

**Effect on pedagogy.** In rural middle schools, the focus of this paper, the implementation of DVD-player sets, satellite sets, and computer rooms may have changed pedagogy in multiple ways (Figure A3).

First, it allowed rural students to watch lectures by high-quality teachers. The central government, in fact, hired highly qualified teachers to record lectures and to prepare supporting material, such as additional readings and interactive quizzes. Once deployed to rural schools via satellite internet or physical CDs, these new lectures could be consumed by local students in computer rooms, multimedia rooms, and regular classrooms. In these instances, local teachers were in the room to solve technical issues and to ensure that students focused on class-related activities. It is also worth noting that the CAL lectures were designed to seamlessly be integrated in the standard curriculum of rural schools and not to be used as a separate teaching aid.

Second, the new technology may have helped improve the quality of lectures delivered by local teachers. While preparing their lectures, rural-school teachers with internet access could better research the topics covered by the syllabus. In addition, the introduction of multimedia equipment could have allowed local teachers to enhance their lectures with visual aids.

Third, the introduction of computer rooms allowed rural schools to add computer science to the curriculum. This change may have helped students succeed in high school and in the labor market.

In Section 7, we will perform several analyses to assess the impact of these separate channels on student achievements. The data indicate that access to lectures by high-quality teachers was the main reason for the positive results of the CAL program.

**Time allocated to CAL.** The policy did not impose strict regulations regarding the time allocated to computer-aided learning. Instead, it only required schools to make full use of the new equipment and to evaluate the program annually. According to statistics from the program administrators, most schools complied with this requirement (Office of Modern Distance Education Project for China's Rural Primary and Middle Schools, 2009). The share of schools using CAL equipment for less than five hours a week was equal to 1% for computer rooms, 3% for satellite receiving stations, and 2% for DVD-player stations. Moreover, the share of schools using CAL equipment for more than twenty hours a week was equal to 58% for computer rooms, 22% for satellite receiving stations, and 33% for DVD-player stations (Table A1).

We can use these statistics on utilization to compute a lower bound of the number of courses per week in which the average student was exposed to the equipment provided by the CAL program. In the average rural middle school, a conservative estimate of the total number of weekly hours using CAL equipment is 49.7.[13] Assuming that the mean number of classes per school is ten and that each school had only one computer room, one satellite set, and one DVD-player set, we can conclude that the average student was exposed to CAL equipment for at least 4.97 hours, or 6.6 45-minute lectures per week.

There are at least two reasons suggesting that this estimate is a lower bound of actual exposure. First, the available statistics on school-wide utilization are censored at twenty hours per week. It is plausible to assume that many schools utilized CAL equipment for longer. Second, many schools might have had more than one computer room and DVD-player set. In these cases, more than one class could have used CAL equipment contemporaneously.

**Compliance.** Anecdotal evidence from interviews in participating schools suggests that students and teachers enjoyed these technological innovations. Students appreciated the opportunity to follow lectures by highly effective teachers, who would not normally work in rural areas. Teachers and school principals liked the fact that technology contributed to eliminating outdated teaching practices and improved the delivery of lectures.[14]

Although there are not precise statistics on the number of schools reached by the program, several pieces of evidence suggest that the compliance rate was high. First, the Chinese central government greatly emphasized the importance of the CAL program (McQuaide, 2009). This fact alone should have been sufficient to induce most local governments and schools to embrace the program. Second, the central government and Ministry of Education organized annual evaluations and inspections to ensure compliance (Yu and Wang, 2006). The inspectors went to each participating school to check the installation of satellite dishes and computer rooms, to measure the use of new equipment, and to collect teachers' and students' feedback (Figure A4). Third, to ensure compliance, at least one teacher in each rural school was required to participate in a training program either in Beijing, in the provincial capital, or directly in the participating schools. In total, more than 800,000 rural teachers were trained.[15] Fourth, in 2007, the government indicated that the CAL program reached its goals.[16] Ms. Xiaoya Chen, the Vice Minister of Education, stated that the central and local governments "completed the project construction tasks on time." Moreover, "the implementation of the project has enabled more than 100 million rural primary and middle school students to access high-quality educational resources." The large number of students reached by the CAL program suggests that most schools complied with the original plan of the central

[13] Appendix A.2 provides further details on the calculation of this estimate.

[14] Appendix A.3 provides more information about these reports, including direct quotations.

[15] https://web.archive.org/web/20201029160144/http://www.moe.gov.cn/jyb_xwfb/xw_fbh/moe_2069/moe_2095/moe_2100/moe_1851/tnull_29185.html

[16] https://web.archive.org/web/20201029160144/http://www.moe.gov.cn/jyb_xwfb/xw_fbh/moe_2069/moe_2095/moe_2100/moe_1851/tnull_29185.html

government. Fifth, the total costs of the program (CNY 11.1 billion) were close to the planned expenses (CNY 10 billion), suggesting that the actual implementation closely followed the original plan.

### 2.3 Selection of High-Quality Teachers for the Program

As part of the "Modern Distance Education Program in Rural China," the Ministry of Education selected excellent teachers to deliver lectures and record them on CDs, which were then distributed to rural schools in treated cities. Successful candidates for the program had to satisfy several criteria. First, they needed an excellent educational background: all selected teachers held a bachelor's degree and most held a master's degree. Second, they had extensive teaching experience, usually more than 10 years. Third, they held either the senior or super senior title in the teaching profession.[17]

The chosen candidates were usually the most qualified teachers from the most selective primary and secondary schools in urban China. These experienced and successful teachers were asked to produce high-quality content tailored for the skill level of students in rural schools. For example, teachers delivered their lectures at a slow pace and repeated difficult content several times to ensure that rural students—who typically have weaker academic backgrounds—could fully understand and keep up with the content.[18] Moreover, the Ministry of Education routinely consulted with expert senior teachers, usually employed by high-quality urban schools or by the Ministry of Education itself, to select the best lectures and distribute them to rural schools. To further ensure the high quality of recorded lectures, the Ministry of Education regularly reviewed and updated the lectures and elicited rural students' and teachers' feedback.

As a result of this strict selection process, there are substantial differences between teachers in traditional classrooms and teachers hired to produce the lectures for the CAL program. Among traditional teachers in rural secondary schools, only 14.3% obtained a bachelor's degree, and 2.3% reached the title of senior professional (Educational Statistics Yearbook of China, 2000). In contrast, all teachers in the CAL program obtained a bachelor's degree and earned at least the senior title. The difference in teacher quality is substantial and should reflect a large divergence in value added. For example, Harris and Sass (2011) find that middle-school teachers with an advanced degree increase student grades by 0.778 additional score points, compared with other teachers. Similarly, Jacob and Lefgren (2008) find that

[17] In China, there are several professional titles for teachers: super senior title, senior title, medium-grade title, junior title, and nonprofessional title.

[18] The lectures covered all the disciplines in the middle-school curriculum and were conducted in Mandarin, the official language in most Chinese schools (with the exception of minority schools) since 1986. We found no evidence in local news and media reports that teachers or students in rural schools complained about the online lectures being recorded in Mandarin.

teachers with a master's degree have students who score roughly $0.11\sigma$ higher than students taught by other teachers.[19]

# 3 Data

## 3.1 2014 China Family Panel Studies

Our analysis relies primarily on the 2014 China Family Panel Studies (CFPS), a nationally representative sample of Chinese communities, families, and individuals. CFPS was launched in 2010 by the Institute of Social Science Survey of Peking University. This large-scale survey covers 645 communities in 25 designated provinces (out of 34 total provincial units), 14,798 households, 33,600 adults, and 8,990 children.

Due to its large sample size and advanced sampling design, the CFPS survey is representative of Chinese individuals, families, and communities. Xu and Xie (2015) show that the numerous socioeconomic and demographic variables in the CFPS dataset—for example, age, gender, educational attainment, earnings, and health—line up well with the census data. We can therefore generalize the results obtained using the CFPS survey data to all Chinese rural students. Compared with the sample of the national census that the government made available to researchers, the CFPS has fewer observations but more depth of information. In addition to employing common measures of academic and labor-market achievements, our analysis can focus on cognitive ability, noncognitive skills, and internet usage. We can use these variables to test the impact of the CAL program on student outcomes outside of the classroom. Another advantage is that CFPS allows us to precisely reconstruct when each individual in the sample was first reached by computer-aided learning. Specifically, CFPS asks the location of each individual at birth, at age 3, and at age 12. This last piece of information, location during middle school, is fundamental to assigning each individual to the correct treatment group. Any other available dataset, including the national census, would include only the birthplace or the current location and would generate significant measurement error in the presence of migration before or after the age of 12.

In the analysis, we restrict the CFPS dataset in two ways. First, we select only individuals who lived in rural areas at age 12, because the program targeted exclusively rural schools. Second, we select cohorts born between 1977 and 1994. We elected to start in 1977 because the Cultural Revolution, which negatively affected the Chinese education system and society at large, ended in October 1976. We also show that the results are robust to alternative choices

[19] Most of the literature on value added and teachers' education focuses on whether teachers hold a master's degree (compared to those with a bachelor's degree). In our setting, however, the potential difference in value added between CAL and rural teachers is likely larger. Most rural teachers completed at most high school or vocational school (12–13 years of education), while all CAL teachers obtained at least a college degree (16 years or more of education).

for the age groups included in the sample. The resulting sample includes 4,996 individuals.

## 3.2 Outcome Variables

In the analysis, we focus on four main types of outcomes: education achievement, labor-market performance, internet usage, and noncognitive skills.

For the first category of outcome variables, our main academic output is the years of completed education. While the CAL literature mostly focuses on short-term test scores, years of education allow us to objectively measure the effect of technology beyond the first months after the provision of the treatment. We also know whether respondents received a middle-school diploma, a high-school diploma, or a college degree. In addition, we know whether individuals in the sample have invested in other forms of education and training that did not lead to a formal degree.[20] Besides measuring past formal and informal education, we can evaluate the respondents' cognitive abilities at the time of the survey (2014). The CFPS, in fact, includes a math and a Chinese test, both designed by the CFPS data center and administered in person at the time of the survey (Appendix B.1). On the math test, the respondents were required to solve a set of math questions, including basic arithmetic operations, exponents, logarithms, permutations, and combination questions. The math score depends on the number of questions that were answered correctly. On the Chinese test, the respondents were required to read a set of Chinese characters. The final score depends on the number and accuracy of the characters that each individual could read. For ease of interpretation, we standardize the scores to have mean equal to 0 and standard deviation equal to 1.

The second category measures labor-market performance. From the CFPS, we know the respondents' workforce participation, their annual earnings, and their occupations. In addition, we match occupations to information on their skill content from U.S. O*NET data.[21] We can then categorize different jobs based on their reliance on cognitive and manual skills.

A third category measures how often and for what reasons respondents access the internet. Specifically, we know (1) whether respondents use the internet, and (2) how often respondents use the internet for work or socializing. We can therefore test whether computer-aided learning increased the probability of regularly using the internet several years after the policy implementation.

[20] Informal education in China includes any form of postsecondary training that does not lead to a degree or certificate, as well as secondary vocational training. It is a popular education choice. In 2017, 54.6 million Chinese were enrolled in informal education. https://web.archive.org/web/20201029162658/http://www.moe.gov.cn/s78/A03/moe_560/jytjsj_2017/qg/201808/t20180808_344697.html

[21] http://www.onetonline.org/

A fourth category includes noncognitive outcomes. There is growing evidence showing that noncognitive skills are important traits for long-term life success (Heckman and Rubinstein, 2001; Bertrand and Pan, 2013). In our analysis, we leverage several questions in the CFPS on self-reported levels of mental stress, social interactions, and satisfaction about life.[22] Specifically, three questions ask respondents about their level of life satisfaction. Individuals evaluated (1) the quantity of relationships with others, (2) the quality of their relationships, and (3) their happiness. Higher values identify higher levels of life satisfaction. Three additional questions ask individuals about their degree of mental stress. Respondents reported how often they felt (1) depressed, (2) nervous, and (3) incapable of completing tasks. Higher values in these variables identify lower levels of mental stress. Previous studies in economics have used similar measurements of noncognitive outcomes (for example, Lavy and Schlosser, 2011; Gong, Lu, and Song, 2018).[23]

Although our data rely primarily on the 2014 wave of CFPS, we use observations from the 2010 wave to fill in missing values in the education and labor-market outcomes.[24] Table 1 lists the summary statistics of all available variables for the whole sample (columns 1 and 2), for cohorts who did not experience computer-assisted learning (too old or in areas without CAL; columns 3 and 4), and for cohorts exposed to the program (columns 5 and 6).[25] These statistics provide two main insights. First, most demographic characteristics are balanced between CAL and non-CAL cohorts.[26] In the rest of the analysis, we will provide further evidence showing that cohorts included in the program were not different at baseline from cohorts who were not exposed to computer-assisted learning. Second, most outcomes show substantial improvements for CAL cohorts. Average completed education, for example, is 9.07 years among non-CAL individuals and 10.34 years among CAL individuals. In the rest of the analysis, we will show that these initial results are robust to the utilization of more-sophisticated techniques.

[22] We list all relevant questions in Appendix B.2.

[23] We standardized the variables measuring noncognitive skills and frequency of internet use to have mean equal to 0 and standard deviation equal to 1.

[24] In the case of variables on internet usage and noncognitive skills, we rely on the 2014 wave only because the questionnaire is not consistent across years (Table E1).

[25] For simplicity, we will refer to untreated cohorts as "non-CAL cohorts" and to treated cohorts as "CAL cohorts."

[26] The only clear exception is age, which is lower among treated cohorts by construction. Treated cohorts, in fact, were at most 14 years old when computer-assisted learning was implemented in their county.

# 4 Empirical Strategy

## 4.1 Main Specifications

To identify the effect of CAL on student outcomes, we exploit both time and geographical variation in the implementation of the education reform. Along the time dimension, we compare cohorts who were at most 14 years old at the time of the policy implementation to cohorts who were at least 15 years old. The first group attended middle school after the reform and was exposed to computer-assisted learning, while the second group was either already attending a higher grade or was in the labor market when the policy went into effect. Along the geographical dimension, we instead exploit the staggered implementation in different counties across four years. As described in Section 2.2, the program reached 678 counties (G1) in 2004, 893 counties (G2) in 2005, 493 counties (G3) in 2006, and 380 counties (G4) in 2007. In addition, it was not implemented in 416 counties (G5).

As a practical example of our identification strategy, we can compare education and labor outcomes between individuals born in 1990 in Jinzhai county and individuals born in the same year in Taihu county. The former group attended middle school after the policy implementation in 2004 and was exposed to CAL. In contrast, the latter group had already completed middle school when the program reached Taihu in 2006. Comparing the long-term outcomes of these two groups of individuals, however, does not isolate the effect of the program. If residents of Jinzhai, for example, tend to always complete more years of education, a single cross-county comparison could lead to biased estimates for the effect of the CAL reform. In addition to comparing outcomes along the first dimension, we can therefore compare the outcomes of individuals not exposed to the policy in either county (for example, born in 1988). The differences in outcomes between the two groups capture cross-county variation that is constant across cohorts. By subtracting this last result from the first comparison, we can isolate the effect of CAL.

We estimate the following difference-in-differences specifications:

$$Y_{ibc} = \alpha + \beta \cdot \text{Treat}_{bc} + W'_{ibc} \cdot \phi + \gamma_c + \eta_b + \text{Pol}'_c \cdot \text{Treat}_{bc} \cdot \psi + \gamma_c \cdot t_b + \varepsilon_{ibc}, \tag{1}$$

where the unit of observation is an individual $i$ who was born in year $b$ and was living in a rural part of county $c$ at the age of 12. The dependent variable $Y_{ibc}$ measures several outcomes related to education, labor-market performance, internet usage, and noncognitive skills. The regressor of interest $\text{Treat}_{bc}$ indicates the treatment status for a given county and birth cohort. It is 1 for cohorts that attended middle school after the implementation of the reform in their county. The matrix $W'_{ibc}$ is a set of individual controls: gender, an indicator variable for minority groups, an indicator for the presence of siblings, and paternal education level (three dummy variables for junior high, high school, and college or more). The controls $\gamma_c$ and $\eta_b$ are county and birth-cohort fixed effects, respectively. The matrix $\text{Pol}_c^{'}$ controls for the implementation of other education reforms in rural counties at the turn of the twenty-first century. Specifically, it takes into account a bundle of policies to increase middle-school completion rates in western counties (captured by a dummy for western counties), a reform that decreased the cost of compulsory education in some rural provinces[27] (captured by a dummy identifying targeted provinces), the construction of rural boarding schools[28] (captured by a dummy identifying 372 counties that were designated to receive the newly built boarding schools), and the consolidation of rural schools[29] (captured by the county-level percentage decrease in the number of schools between 2000 and 2007). All these variables are interacted with the main treatment $\text{Treat}_{bc}$ to check whether the effects of these concurrent policies coincided with the timing of the CAL reform. We also include a county-specific linear time trend ($\gamma_c \cdot t_b$) to control for underlying linear trends in the outcomes that differ across counties. To address the potential serial correlation and heteroscedasticity, we cluster the standard errors at the county level.

The coefficient $\beta$ measures the intent-to-treat effect of the program on outcome $Y_{ibc}$.[30] The identifying assumption underlying the difference-in-differences specification is that outcomes would have followed similar cross-cohort trends between counties in different treatment groups (counties treated at different times or never treated) had they not been affected by the CAL implementation. In this regard, a major concern is that treated counties might not have been randomly selected and, as a consequence, that the post-reform divergence in outcomes might be the result of other unobserved factors, not of education technology. In the next sections, we address this issue and other threats to identification.

## 4.2 Differences between Counties

Part of our identification strategy exploits the staggered implementation of the CAL program. In this section, we study how counties that received CAL in different years differ

[27] Xiao, Li, and Zhao, 2017.

[28] Luo et al., 2009; https://web.archive.org/web/20201029170527/http://www.moe.gov.cn/jyb_xxgk/gk_gbgg/moe_0/moe_1/moe_2/tnull_5409.html.

[29] Liu et al., 2010; Mo et al., 2012; https://web.archive.org/web/20201029170832/http://www.gov.cn/gongbao/content/2001/content_60920.htm.

[30] The analysis is an intent-to-treat for two reasons. First, the CFPS does not provide information on the actual year of completion of middle school for the respondents. We therefore use their birth cohort to determine whether they were exposed to the policy. Second, even though it stated multiple times that the implementation had been completed successfully and according to plan, the government did not release information on the program compliance rate by county. We therefore assume that all rural schools in a county received the program during the planned implementation year. Section 6 provides several tests of these assumptions.

in terms of observable characteristics at baseline. This analysis is important because it is clear that the Chinese government did not pick random areas to receive the education policy. Official documents provide several insights on the selection process.[31] In particular, the government gave priority to counties in midwestern provinces, with a larger share of rural population and poorer internet and communication infrastructure. We collected several county-level variables measured in 2002 (China County Statistical Yearbook), two years before the program implementation (Table 2), including the criteria that the government used in the selection of counties. We use this dataset to conduct an array of balancing tests between CAL and non-CAL locations.[32]

We find three main results. First, as expected, the selection criteria are strong predictors of participation in the CAL program. Compared with non-CAL areas (G5), CAL counties (G1 to G4) were 39% more likely to be located in midwestern China and had 40% more rural residents, 84% fewer cellphone users, 91% fewer internet users, 45% fewer post offices, and 67% fewer telephone users (Table 2, panel A, column 6).

Second, the selection criteria capture most of the baseline differences between CAL and non-CAL counties. Without controlling for selection criteria, 19 out of 23 variables show statistically significant differences between CAL and non-CAL areas (Table 2, panel B, column 6). Most of these unconditional means suggest that CAL counties were less economically developed than non-CAL counties at baseline. After controlling for the selection criteria, however, most estimates are economically small and only two variables still indicate a statistically significant difference between CAL and non-CAL locations (Table 2, panel B, column 7). In the case of average wages, for example, the unconditional difference is 77% (lower wages in CAL counties), while the conditional difference is only 5% (lower wages in CAL counties) and not statistically significant.

Third, CAL counties that received the education technology in different years were similar in terms of baseline characteristics (Table E2). Most of the available variables are balanced between G1 (CAL from 2004), G2 (CAL from 2005), G3 (CAL from 2006), and G4 locations (CAL from 2007). Out of 116 balancing checks, most have small magnitude and only five instances reveal statistically significant differences at the 5% level. Official government guidelines suggested that CAL implementation should start in locations with better communication infrastructure in order to ensure a smoother process. The data, however, does not reveal large differences in communication infrastructures in 2002 between counties that

[31] "Pilot work plan for modern distance education project in rural primary and secondary schools," Ministry of Education, National Development and Reform Commission, and Ministry of Finance, 2003, https://web.archive.org/web/20201029171912/http://old.moe.gov.cn//publicfiles/business/htmlfiles/moe/moe_356/200409/3886.html.

[32] These variables include both urban and rural areas. County-level statistics just for rural areas are not available.

received CAL early (G1 and G2) and counties that received CAL later (G3 and G4) (Table E3).

In addition to analyzing baseline differences, we use CFPS data to estimate linear and nonlinear trends in outcomes across cohorts that preceded the implementation of CAL technology (those born between 1977 and 1988). This analysis allows us to evaluate whether individuals in CAL and non-CAL counties were drifting apart in terms of education and labor-market outcomes even before the implementation of the program. We estimate three different types of pre-reform trends interacted with a dummy for G5 counties: linear trends in birth cohorts (Table 3, panel A), quadratic trends (Table 3, panel B), and cubic trends (Table 3, panel C).[33] The results indicate the lack of significant pre-reform trends in outcomes between CAL and non-CAL counties. A one-year age difference in birth cohorts, for example, predicts only 0.016 additional years of education in non-CAL locations, a 0.1% increase from the mean (Table 3, panel A, column 1). Similarly, a one-year age difference predicts lower math skills by only $0.002\sigma$ (Table 3, panel A, column 2). The estimation of quadratic and cubic trends confirms these findings.[34]

These findings affect the rest of our analysis in two ways. First, we acknowledge that CAL and non-CAL counties differed at baseline. We therefore include county-specific linear trends in all our specifications. Second, in addition to using all counties available in the CFPS, we show the effect of education technology using only observations from CAL locations, which were similar in terms of observable characteristics before the policy implementation.

## 4.3 Differences between Cohorts

A second source of variation in our analysis comes from differences in the exposure to CAL across birth cohorts. CAL cohorts were, at most, age 14 at the time of the policy implementation in their county, while non-CAL cohorts were either older or in non-CAL locations. In this section, we use CFPS data to show how CAL and non-CAL cohorts differ in terms of demographics.

Overall, the data indicate that cohorts with different exposure to CAL have similar demographic characteristics (Table E5, column 1). Out of 17 variables, only 3 indicate a statistically significant difference. In addition to not being statistically different from zero, most of the other coefficients are also small in magnitude. CAL individuals, for example, are only 0.6% less likely to be male and 1.5% less likely to be part of a minority group, and they have on average 0.07 more siblings. CAL and non-CAL cohorts also have similar

[33] All these specifications also include cohort fixed effects, county fixed effects, and the same set $W'_{ibc}$ of individual controls.

[34] There is no evidence of positive and significant pre-reform trends in treated counties even if we set up the dataset as an event study (Table E4).

distributions of paternal and maternal education. These results are confirmed if we limit the sample to only individuals from CAL counties (G1 to G4 locations; Table E5, column 5).

# 5 Empirical Findings

## 5.1 Event Studies

We start the analysis by showing the dynamic effect of the CAL implementation. Specifically, we estimate all the lags and leads of the effects of the program with the following event study specification:

$$Y_{ibc} = \alpha + \sum_{k=-12}^{4} \beta_k \cdot D_k + W'_{ibc} \cdot \phi + \gamma_c + \eta_b + \varepsilon_{ibc}. \tag{2}$$

The dummy variables $D_k$ are equal to 1 in areas with CAL $k$ years before or after the reform, and equal to 0 otherwise. The event periods range from -13 for cohorts who were 27 years old at the time of the policy implementation to 4 for cohorts who were 10 years old. The reference group (excluded category) is $k$ =-13. As a result, the parameters of interest identify the effects of CAL $k$ years following or preceding its implementation, relative to the earliest event period in the sample.

Most outcomes show a similar pattern (Figure 2). Among cohorts who were too old to benefit from CAL, the coefficients are not statistically different from zero and do not generate noticeable trends across cohorts. The estimates show a discontinuity starting from the first cohort exposed to CAL (14 years old). The post-reform effects indicate an improvement in the education and labor-market outcomes. Relative to individuals who were 27 at the time of the policy, for example, completed education increased by 1.20 years among 14-year-olds, by 1.21 years among 13-year-olds, by 1.11 years among 12-year-olds, by 1.62 years among 11-year-olds, and by 1.61 years among 10-year-olds. The estimates are smaller and insignificant for pre-reform cohorts: completed education increased by 0.31 years among 15-year-olds, by 0.44 years among 16-year-olds, and by 0.12 years among 17-year-olds (Figure 2, panel A).[35]

The CFPS does not provide information on the actual year of completion of middle school for each respondent. The actual exposure to the program could be different from the one imputed by birth year if a student either enrolled in school before the standard age, skipped grades, or repeated grades before completing middle school. To address this form of measurement bias, we propose a slight variation to the event study described above. The cohorts

[35] In this analysis, individuals from non-CAL counties (G5) are assigned to different periods as if CAL had been implemented in the G5 locations starting in 2004, together with the first batch of counties (G1). This assumption on the distribution of non-CAL individuals across event periods, however, does not affect the results (Figure E2 for completed education).

who are at higher risk of being mislabeled are those closer to the policy implementation. We therefore drop from the estimating sample those who were age 14 (period 0), 15 (period -1) and 16 (period -2) at the time of the reform (Figure E1). All outcomes show a clear discontinuity after the introduction of CAL.[36]

The event studies indicate that the effect of the program does not change with exposure duration to CAL. The coefficients estimated on 14 years old, treated for only 1 year, are smaller but not statistically different from the coefficients estimated on 11 or 10 years old, treated for the whole duration of middle school. The lack of a strong dose response might speak to the mechanism through which the program affected student outcomes. Specifically, CAL lectures taught rural students more-effective learning methodologies, compared to the more-rudimentary ones employed by local teachers.[37] As an example, unlike traditional lectures, CAL recorded Chinese lectures did not force memorization of traditional poems, focused on explaining their content, taught students how to search for the meaning of unknown words, and included illustrations and other audiovisual elements. These features taught students a general approach to tackle other poems and written texts. The benefits of learning a better studying method can be substantial after the first exposure (the first CAL year) and only marginal with further repetitions (additional CAL years).[38] Moreover, it should be noted that our analysis uses long-run variables and quite general cognitive skills. We might have been able to detect a stronger dose response if we had focused on short-term education achievements, such as in-class test scores, which build upon knowledge learned during previous school years. Finally, the lack of a dose response might reflect the fact that schools were using CAL recorded lectures more intensely in higher grades in order to prepare students for the high-stake high-school entry exam.[39]

## 5.2 Effect of CAL on Academic Achievement

After estimating event studies, we move to the analysis of the main difference-in-differences specification. These regressions confirm that individuals exposed to computer-assisted learn-

[36] In addition to event studies, we can estimate the main equation (1) by dropping from the sample counties in the bottom decile of average wage in 2002. In less-developed counties, in fact, the Chinese compulsory education law allows student to postpone enrollment (`https://web.archive.org/web/20200328143812/http://www.npc.gov.cn/wxzl/gongbao/2000-12/06/content_5004469.htm`). Estimating the analysis on richer counties does not affect the results, suggesting that measurement error in exposure to the policy is not a major source of bias (Table E6).

[37] This feature of the CAL lectures was also discussed in the popular press (Gong, 2005).

[38] Specifically, learning a new studying method does not necessarily build on previous knowledge, while learning math or Chinese in a given grade usually depends on notions learned during previous school years.

[39] Part of the CAL teaching materials included advice on how to prepare a study plan for an examination (Feng and Cao, 2007). This type of information would have been particularly useful for more-senior students.

ing had improved education outcomes in the long run (Table 4, panel A). Relative to non-CAL individuals, CAL cohorts completed 0.85 additional years of education. Given that the average years of education in the sample are 9.12, this estimate indicates a 9.3% increase in formal schooling. Increased years of schooling translated into a 7.2% higher probability of successfully completing middle school.[40]

In addition to enabling us to look at the impact on schooling, the CFPS allows us to measure changes in cognitive skills at the time of the survey, seven to ten years after the implementation of the program. CAL individuals' scores were on average $0.18\sigma$ higher in math and $0.23\sigma$ higher in Chinese. These increases in the CFPS test scores can explain 72% of the 0.85 additional years of education, suggesting that the test scores are able to reflect most of the observed increase in formal education.[41]

Finally, CAL individuals were 6.6% more likely to have participated in informal studies or training programs not leading to a degree. However, this coefficient is not statistically significant, suggesting that the policy primarily influenced formal academic achievements.

It can be instructive to compare these results with the findings in the literature. Most of the existing studies share two characteristics. First, they focus on test scores attained in the months immediately following the implementation of education technology. Second, they tend to focus on math tests. Our results show that the positive effects of the CAL program lasted for at least ten years after the exposure to education technology, and that they are not restricted to test scores attained in the classroom.

## 5.3 Effect of CAL on Labor-Market Outcomes

In addition to allowing us to measure the impact on academic achievement, our setting provides an opportunity to study the effect of CAL on labor-market outcomes because we observe individuals several years after the reform (Table 4, panel B).

Overall, we do observe an increase in labor-market participation, albeit imprecisely estimated. At the time of the survey, participation in the labor force of CAL individuals was 6.3% higher in the full sample with all counties (not statistically significant) and 9.6% higher in the restricted sample with only treated counties (significant at the 5% level). Conditional on being part of the labor force, CAL individuals earned more (+59%) and were employed in jobs that relied more on cognitive abilities ($+0.28\sigma$) and less on manual skills ($-0.27\sigma$). Moreover, they were 4.8% less likely (equal to a 24% decrease from the mean) to work as

[40] Moreover, Table E7 shows that the main findings are robust to computing p-values adjusted for multiple hypothesis tests.

[41] To compute this percentage, we regressed years of education on math and Chinese test scores, controlling for birth cohort and county fixed effects. This sample includes non-CAL individuals exclusively. The estimated coefficient of the math test score is 2.56, while the estimated coefficient of the Chinese test score is 0.63.

farmers, one of the most common entry-level jobs in rural counties.

Next, we investigate the relationship between education and earnings. According to the meta-analysis by Churchill and Mishra (2018) using data from 59 empirical studies on China, one additional year of education in China increases earnings by 20%. Based on this estimate, 0.85 additional years of education can explain 34% of the observed increase in earnings ($(0.85 * 0.1831)/0.463$). This result suggests that the increase in human capital associated with the CAL reform generated high returns in the labor market, at least compared to the education policies considered by Churchill and Mishra (2018).

We delve deeper into these initial findings by decomposing the total earnings effect into an across-occupation component, across-migration status, and a within-occupation-and-migration component (more details in Appendix C). In particular, the earning premium may arise because CAL education increased individuals' likelihood to work in well-paid occupations, reduced the barrier to migration from rural to urban areas, or increased productivity in the same occupation and geographical area. The results from this decomposition analysis are shown in Table E8. The dependent variable is the logged average earnings in the corresponding occupation or migration status in columns 1 and 2, and the logged earnings premium within each occupation and migration status in column 3. CAL individuals are employed in occupations with 15.5% higher average earnings. CAL individuals earn 1.3% more due to the fact that they are more likely to migrate from rural to urban areas. Moreover, CAL individuals earn on average 29.5% more within each occupation and migration status. The across-occupation, across-migration, and within-occupation-and-migration channels, then, can explain 33%, 3%, and 64% of the total effect on earnings, respectively.

In conclusion, these results suggest that the exposure to CAL in middle schools substantially improved labor-market outcomes by increasing the likelihood of being employed in a higher-paying job (close to 1/3 of the total effect) and by increasing productivity within a given occupation (2/3 of the total effect). If we focus on just the productivity-enhancing component, the earnings effect is close to a 30% increase. This effect size is large but consistent with the fact that the Chinese labor market experienced a widespread computerization over the last decade.[42] A larger share of jobs became dependent on computer skills, and CAL students might have been readier for this transition.

## 5.4 Effect of CAL on Computer and Internet Usage

In this section, we examine the effect of CAL on computer and internet use in the long run (Table 4, panel C). We exploit a set of questions from the survey that asked respondents

[42] Specifically, the inflation-adjusted price of a computer declined by 60% from 1995 to 2015, while ICT investments experienced a 9% annual growth rate (CCW Research group, https://web.archive.org/web/20201029173830/http://www.edu.cn/html/info/10plan/).

how frequently they use the internet for different purposes. CAL individuals were 8.2% more likely to use the internet. Considering that 54% of the sample had internet access in 2014, this coefficient indicates a 15% increase from the baseline. Similarly, the frequency of computer use among CAL individuals was $0.28\sigma$ higher for work-related reasons and $0.17\sigma$ higher for social networking.

These findings are in line with previous evidence of a positive effect of computer-assisted learning on student computer skills, as reported, for example, by Angrist and Lavy (2002), Fairlie and Robinson (2013), and Beuermann et al. (2015).[43] Our results contribute to these findings by showing that increased computer use persists during adulthood and is applied to a wider range of activities, such as work-related tasks.

### 5.5 Effect of CAL on Noncognitive Outcomes

Here, we examine the effect of CAL on long-run, self-reported noncognitive outcomes. Overall, CAL is associated with worse noncognitive traits, but the effects are imprecisely estimated (Table 4, panel D). Individuals exposed to CAL were less satisfied about their lives ($-0.04\sigma$, but not statistically significant) and less likely to be happy ($-0.18\sigma$, but not statistically significant). Moreover, they were more likely to be anxious ($-0.17\sigma$, significant at the 10% level) and nervous ($-0.24\sigma$, significant at the 10% level).[44]

Overall, our findings suggest that exposure to CAL in middle school is associated with a mildly negative, albeit noisy, effect on noncognitive skills. The large amount of noise in these estimates might indicate the presence of opposing forces. On the one hand, recent findings show a positive relationship between teacher quality and students' noncognitive outcomes (Jackson, 2018). On the other hand, the medical literature has emphasized that intensive computer use at work is associated with higher levels of stress (Kraut et al., 1998; Thomée, Härenstam, and Hagberg, 2012; Kim et al., 2016). Although this setting does not allow us to further explore different mechanisms, the results indicate that further research on this topic is warranted.

[43] Previous studies have highlighted how increased computer skills can have unintended consequences on academic achievement in the short term. Tech-savvy students with access to the internet might increase the time dedicated to leisure, such as playing video games, at the expense of studying. Our setting, however, is different, because rural students were unlikely to have access to the internet outside of school for noninstructional purposes.

[44] High values in the noncognitive variables identify better outcomes: higher levels of life satisfaction and less anxiety.

## 5.6 The Reduction of the Rural–Urban Gap

The CFPS data indicate that there were stark differences between urban and rural areas before the CAL implementation. On average, individuals living in rural areas had 4.1 fewer schooling years (9.09 vs. 13.22), earned 80% less, and received a score $0.84\sigma$ lower on the math test and $0.62\sigma$ lower on the Chinese test (Table E9, column 3). We then apply our estimated effects of CAL (the estimates from Table 4) to the average outcomes of individuals living in rural areas. We divide this estimated improvement in outcomes by the baseline rural–urban gap in order to quantify its reduction. Our findings suggest that the CAL program drove a significant reduction in the Chinese rural–urban economic gap. In particular, we estimate that CAL reduced the gap in schooling years by 21%, in earnings by 78%, in math skills by 22%, and in Chinese skills by 37% (Table E9, column 5).[45]

The CAL program obtained these results with relatively small costs per student. According to official data released by the government at the end of 2007, the CAL program cost CNY 11.1 billion and reached more than 100 million students in rural primary and secondary schools.[46] Therefore, the program had a direct cost per student of at most CNY 111 or USD 17.[47] This cost figure is substantially below our estimate of the individual increase in earnings discounted over the life cycle, which is equal to CNY 42,995 or USD 6,432 (Appendix D for more details).

# 6 Robustness Checks

Overall, our analysis indicates a positive effect of CAL on a wide variety of outcomes, ranging from education achievements and labor-market choices to internet usage. In this subsection, we provide a battery of robustness checks that reinforce these findings.

**Only CAL counties.** County-level data showed that CAL and non-CAL areas differed at baseline, while CAL areas shared similar characteristics. These findings indicated that, while inclusion in the program was correlated with observables, the implementation order among CAL counties was not. In this section, we further show that our results do not depend on the presence of individuals from non-CAL counties in the control group. We can, in fact, estimate the main specifications using only observations from CAL respondents (Table 4, columns 5

[45] These estimates might be an understatement of the true benefits of the policy because our data from 2014 do not allow us to compute the effect on labor-market outcomes for students who were exposed to CAL in primary school.

[46] https://web.archive.org/web/20201029160144/http://www.moe.gov.cn/jyb_xwfb/xw_fbh/moe_2069/moe_2095/moe_2100/moe_1851/tnull_29185.html. The exact number of students reached by the program is not available.

[47] The conversion uses the exchange rate available on 10/22/2020.

to 8). For most outcomes, the coefficients obtained with this restricted sample are close in magnitude to the coefficients estimated on the full sample. The standard errors, however, tend to be slightly larger due to the smaller number of observations. Completed education, for example, increased by 0.85 years among individuals exposed to CAL in the baseline sample (Table 4, column 1) and by 0.75 years in the restricted sample (Table 4, column 5). Similarly, math skills increased by $0.18\sigma$ in both the full and the restricted samples.

**Internet use outside of rural schools.** Although it is possible that the CAL program increased internet use outside of rural schools, it is unlikely that this channel confounds our findings. First, the policy installed the satellite receiving systems, necessary to receive broadband internet, as well as computers and other multimedia equipment, only in the targeted schools. Other local institutions, private firms, and households would have needed to buy a satellite dish to access the internet both before and after the program. Second, even if some spillover exists—for example, if CAL led to an increase in the internet speed in the treated regions—few Chinese families could have benefited from it. In fact, only 4.8% of households in rural China owned a computer in 2006.[48] Third, we exploit the Annual Survey of Industrial Firms (ASIF) between 2002 and 2007 to examine the effects of the CAL program on firms' outcomes, such as TFP, profits, and value added. If the use of broadband internet had spillover effects in the local economies, we should observe some changes in firm behavior (Hjort and Poulsen, 2019). In the Chinese case, however, the effects of CAL across all outcomes are economically small and statistically insignificant, indicating that the program had no effect on firm performance (Table E10).

**Changes to the ITT specification.** Our results are robust to changes in the main ITT specification. First, our treatment variable is based on the county-level implementation plan published by the government in 2004. However, our results hold if we compute exposure to the CAL reform using the prior plan at the level of prefectures, the Chinese administrative level above counties (Table E11, panel A).[49] Second, a few counties might have completed the implementation of the CAL reform earlier than planned, leading to possible measurement error in the treatment variable. Our results are robust to dropping these areas from the sample (Table E11, panel B). Third, in the original plan, some counties in the Shandong province were not supposed to receive any CAL equipment, but a report indicates that all

[48] This statistic comes from the China Health and Nutrition Survey (CHNS). Similarly, only 1.2% of individuals in urban China used a computer or the internet to search for jobs in 2003 (Chinese General Social Survey). Because our analysis is conducted in rural China, the share of internet users is expected to be much lower than 1.2%.

[49] https://web.archive.org/web/20201029171912/http://old.moe.gov.cn//publicfiles/business/htmlfiles/moe/moe_356/200409/3886.html

counties in this province implemented the program.[50] In the baseline estimations, we included counties in the Shandong province among treated locations. However, our results hold if we drop all counties in the Shandong province from the sample, suggesting that these locations are not instrumental for generating the main findings (Table E11, panel C).

**Trends correlated with selection criteria.** In the main specifications, we included county-specific linear trends to control for cross-county time-varying changes in the outcomes (Table E12, panel A). In this section, we show that our results are robust to the inclusion of different trends. First, we include more aggregated prefecture-specific linear trends, which capture time-varying variation in larger geographical areas (Table E12, panel B). Second, we already showed that the selection criteria used by the Chinese government to determine participation in the CAL program (midwestern location, share of rural residents, preexisting communication infrastructure) captured most of the baseline differences between CAL and non-CAL areas (Table 2). We also estimate alternative specifications with linear trends interacted with these six selection criteria. The inclusion of these trends does not qualitatively modify the main findings, although it leads to slightly smaller coefficients and lower $R^2$ (Table E12, panel C). Third, the estimation of specifications without any trend leads to similar treatment effects, reinforcing the idea that our main findings do not depend on the inclusion of a specific set of trends (Table E12, panel D).

**Using different birth cohorts.** Our sample includes all individuals living in rural areas at age 12 and born between 1977 (first year after the cultural revolution) and 1994 (last year available in the survey). Here, we show that adding or subtracting birth cohorts produces qualitatively similar findings. First, we drop older birth cohorts in order to have a sample of individuals who attended middle school as close as possible to the CAL implementation. We estimate a first set of specifications on individuals born between 1980 and 1994, and a second set of specifications on individuals born between 1985 and 1994. In spite of a substantial reduction in the sample sizes—up to 40% smaller than the baseline—most coefficients remain close to the baseline estimates (Table E13). Completed education, for example, increased by 0.85 years in the baseline sample (1977–1994, 4,996 observations), by 0.87 years in the sample of individuals born between 1980 and 1994 (4,189 observations), and by 0.80 years in the sample of individuals born between 1985 and 1994 (2,971 observations). Second, we include older cohorts born from 1970 to 1976. In this case, the coefficients tend to be larger than the baseline estimates (Table E13, panel D), corroborating our decision to include only cohorts born after the cultural revolution. We find similar results if we use age at the time of the

[50] https://web.archive.org/web/20201029201249/http://www.gov.cn/govweb/jrzg/2006-09/01/content_375331.htm

policy implementation, instead of birth cohorts (Table E14).

**Effects concentrated among middle-school graduates.** The Chinese government introduced CAL in primary and middle schools. In this section, we test whether the effects of CAL are stronger among individuals who completed middle school and were therefore exposed to CAL for a longer period. We estimate a set of regressions in which we further interact the effect of CAL with a dummy equal to 1 for middle-school graduates. For the majority of outcomes, the effect of CAL is larger or concentrated among the subsample of middle-school graduates (Table E15). Relative to the baseline, the effect of CAL among middle-school graduates is 77% larger for completed education, 92% larger for math skills, and 47% larger for Chinese skills. In all these cases, the difference in the effect of CAL between middle-school graduates and other individuals is statistically different from zero.

**Excluding effects from other policies.** We now test whether concurrent Chinese policies not directly targeting rural schools might be responsible for the estimated effects of CAL. There are two important Chinese reforms that were implemented in the early 2000s: the trade liberalization following WTO accession, which started in 2001; and the expansion of college enrollment, which started in 1998. We control for these concurrent policy changes by interacting birth-cohort fixed effects with two variables (pre-WTO prefecture-level import tariff, and prefecture-level number of college students) that describe the effect of these reforms on each Chinese county.[51] Our specifications, which in their baseline version already include controls for several education policies, are robust to the inclusion of these additional variables (Table E16).

**Placebo tests.** We can also perform standard placebo tests in which we randomize the implementation of CAL. First, we restrict the sample to pre-reform birth cohorts, and we randomize the first birth cohort to be exposed to CAL. We therefore simulate the policy in the pre-reform period by randomly picking a starting date in each county. For each outcome, we perform 500 estimations on 500 samples with a different randomized placebo policy. The distributions of the estimated coefficients of computer-assisted learning indicate the lack of any effect stemming from the placebo policies (Figure E3).

Second, we use all cohorts born between 1977 and 1994 (and living in a rural area at age 12), but we randomly assign counties to a different treatment group. In doing so, we fix the

[51] We follow the same strategy used by Topalova (2010) and Edmonds, Pavcnik, and Topalova (2010) to construct the prefecture-level tariff in 2001 (before treatment) and capture the effect of trade liberalization. Specifically, the prefecture-level tariff is measured as: $\text{Tariff}_{c,2001} = \sum_i \frac{\text{Emp}_{ic}}{\text{Emp}_c} \times \text{Tariff}_{i,2001}$, in which $i$ denotes the manufacturing industry; $\text{Emp}_{ic}$ is the predetermined total employment of industry $i$ in prefecture $c$ in 1990; and $\text{Tariff}_{i,2001}$ is the import tariff rate of industry $i$ in year 2001.

share of G1 (CAL in 2004), G2 (CAL in 2005), G3 (CAL in 2006), G4 (CAL in 2007), and G5 (no CAL) counties to be equal to those that we observe in the actual CAL implementation. The distributions of the coefficients of CAL suggest that the random treatment allocation does not generate significant results (Figure E4).

**Matching CAL and non-CAL individuals.** To further limit the differences between CAL and non-CAL individuals, we can match the two groups on observables using propensity scores. We compute propensity scores using the main baseline characteristics available in the CFPS: birth-cohort fixed effects, gender, minority status, number of siblings, parental education, parental occupation, and parental affiliation to the Communist Party. We employ a nearest-neighbor algorithm with a low caliper of 0.001. We then re-estimate the main specifications on the matched sample. The results are qualitatively similar to the baseline estimates, although they tend to have larger magnitudes and standard errors (Table E18). The larger magnitude of the coefficients reinforces the idea that the presence of non-CAL individuals does not drive the main findings. If anything, the better outcomes in non-CAL areas might negatively bias the effect of CAL.

## 7 Possible Mechanisms

In this section, we explore the different channels that might have generated the improvements in student achievement. The CAL reform could have improved pedagogy in three major ways. First, it allowed rural teachers to use new technology, such as computers, internet access, and multimedia rooms, to improve their own lectures and quality of teaching. Second, it allowed students to grow computer skills by installing computer rooms and including computer science in the curriculum. Third, it allowed rural students to be exposed to much-higher-quality teaching through the lectures recorded by some of the best teachers in the country.

**Rural teachers.** We start this analysis by discussing the influence of the policy on the quality of the rural teachers. Prior evidence on this topic indicates that access to computers is unlikely to improve the quality of local teachers for at least two reasons. First, access to a labor-replacing teaching technology, such as recorded lectures deployed from Beijing, can reduce the effort of local teachers, instead of stimulating it (Taylor, 2018). Second, as documented by anecdotal evidence, local teachers in Chinese rural schools did not have the experience or skills needed to incorporate the new technology in their own lectures, in spite of the training provided by the program administrators (Feng and Cao, 2007). Specifically, many articles written by teachers who had direct experience with the program report that local teachers were making ample use of the recorded lectures without modifying them or incorporating them in their own lectures.

Our data support these anecdotes. In two distinct sets of regressions, we interact the effect of CAL with a dummy equal to 1 for above-median average teacher education (Table 5, panel A) and with a dummy equal to 1 for above-median average teacher–student ratio, both measured in 2000 (Table 5, panel B).[52] This analysis indicates that the CAL program did not interact significantly with teachers' characteristics measured at baseline. In the presence of a strong influence of CAL on local teachers, instead, we should expect to see different effects for low-ability and high-ability teachers (like in Taylor (2018)). These findings are consistent with Muralidharan, Singh, and Ganimian (2019), which finds that the implementation of the education software Mindspark in India improved student outcomes without affecting the quality of local teachers.

**Computer skills.** Next, we study the role played by increased computer skills. Our findings suggest that access to computers by itself might have had a positive influence on students. In fact, students exposed to CAL in middle school were significantly more likely to use the internet and computers seven to ten years after the reform (Table 4, panel C).

However, two pieces of evidence suggest that the overall influence of access to computers on education and labor outcomes might be limited. First, it was common for Chinese middle schools to exclude computer science from the curriculum in the last year in order to better prepare students for the high-stakes high-school entry exam.[53] If computer science played a big role in increasing long-term education and labor outcomes, we should expect to observe small or zero effects on the cohort treated only during the last year of middle school (14 years old at the time of implementation; Figure 2). The lack of a dose response in the event studies indicates that this hypothesis is not supported by the data. Second, we interact the effect of CAL with a dummy equal to 1 for above-median availability of internet access in the county of residence in 2002 (China County Statistical Yearbook; Table 5, panel C). The interaction terms tend to be statistically insignificant, indicating that a more widespread internet proliferation, which could have allowed students to better exercise their computer skills outside school, did not have large effects on the outcomes.

[52] The variable "teacher–student ratio" is measured at the county level and comes from the China County Statistical Yearbook. The variable "average teacher education" is measured at the prefecture level and comes from the census data. We obtain it by restricting the sample to teachers and calculating the prefecture-level average years of education. We need to compute it at the prefecture level, instead of the more granular county level, because there are too few observations within each county.

[53] During the period under consideration, computer science was not one of the disciplines covered by the high-school enrollment exam.

**Remote learning.** Finally, we explore the role played by the lectures and the related teaching materials recorded in Beijing. Our data suggest that this change in pedagogy improved student outcomes. First, unlike the other two components of the program discussed above, the deployment of these lectures was highly standardized across different geographical areas. Therefore, the lack of cross-county heterogeneity in the treatment effects is in and of itself evidence in favor of the hypothesis that recorded lectures were important.[54] In addition to the aforementioned lack of heterogeneity with respect to school inputs and internet availability, we interact the effect of CAL with a dummy equal to 1 for counties in the midwest (Table 5, panel D) and with a dummy equal to 1 for counties with above-median average wages in 2002 (China County Statistical Yearbook; Table 5, panel E). These new interactions tend to be statistically insignificant, confirming the lack of cross-county heterogeneity. The effectiveness of remote learning in improving student outcomes in Chinese rural areas is consistent with the findings of a recent study in Ghanian primary schools (Johnston and Ksoll, 2019) and a recent study in Mexican secondary schools (Navarro-Sola, 2019).[55]

In addition, even if we do not find cross-county heterogeneities, some individual characteristics significantly interact with the effect of the CAL reform. Specifically, women (Table 5, panel F) and individuals with less-educated fathers (Table 5, panel G) experienced larger increases in completed education. Both findings are consistent with the hypothesis that the increase in education quality through remote learning played a major role. The fact that women might respond more to an increase in quality of education is in line with the findings in Chetty, Friedman, and Rockoff (2014). Moreover, students from lower-educated families might have benefited more from the recorded lectures because their parents were less likely to make up for the low-quality rural teachers before the reform (Lavy and Schlosser, 2011).

## 8 Conclusions

We analyzed a large-scale policy in China, the largest education-technology intervention in the world to date, which introduced computer-assisted learning in rural primary and middle schools. The program was designed to deploy high-quality lectures recorded by the country's best teachers to students in underdeveloped rural areas through broadband satellite internet. Our analysis indicates that the policy improved student outcomes in the long run. Individuals exposed to the program stayed in school longer and showed higher cognitive skills even ten years after the exposure to education technology. In the labor market, they received significantly higher earnings and became more likely to be employed in occupations focusing

[54] Walters (2015) uses a similar approach to study the effect of Head Start.

[55] The fact that access to higher-quality education seems to be the main channel behind the treatment effects suggests that the same reform would be less effective in urban schools, in which quality of education is already higher.

on cognitive skills. Seven to ten years after the program, the same individuals were more likely to use the internet and computers. Our analysis indicates that access to lectures by high-quality teachers was an important driver of these results. Other pedagogical changes, such as access to computers for local teachers and the introduction of computer science in the curriculum, mattered less.

It is widely believed that technology can have an important role in the education production function. Our results make three main contributions to the debate on computer-assisted learning. First, we showed that the effects of computer-assisted learning can last for several years after the initial exposure to education technology. These findings complement existing evidence that shows how computer-assisted learning might improve test scores in the months immediately after its implementation. Second, we showed that the positive effects of education technology can be tracked across different outcomes. In our setting, computer-assisted learning affected education outcomes, labor-market performance, and internet usage. Third, we showed how technology can be an effective way to close the rural–urban gap in education. Students in rural schools are often at a disadvantage because the quality of school inputs is severely lacking. The best teachers tend to work in urban schools due to more attractive geographical amenities and better career prospects. This disparity in school inputs is difficult to erase by just offering subsidies for relocation to rural areas.

As proved by the Chinese experience, monetary incentives are not sufficient to overcome the perceived disutility of living in remote rural locations. Technology, however, is able to connect students in rural schools to the best teachers in the country without teacher relocation. Considering that the rural–urban gap is a phenomenon common in both developed and developing countries, our findings have important policy implications that transcend the Chinese experience. It is important to note, however, that our results might represent an upper bound of the benefits generated by a CAL reform. In China, compliance to government policies tends to be high. Developing countries with different institutions might face bigger challenges in convincing rural schools to adopt newer technologies.

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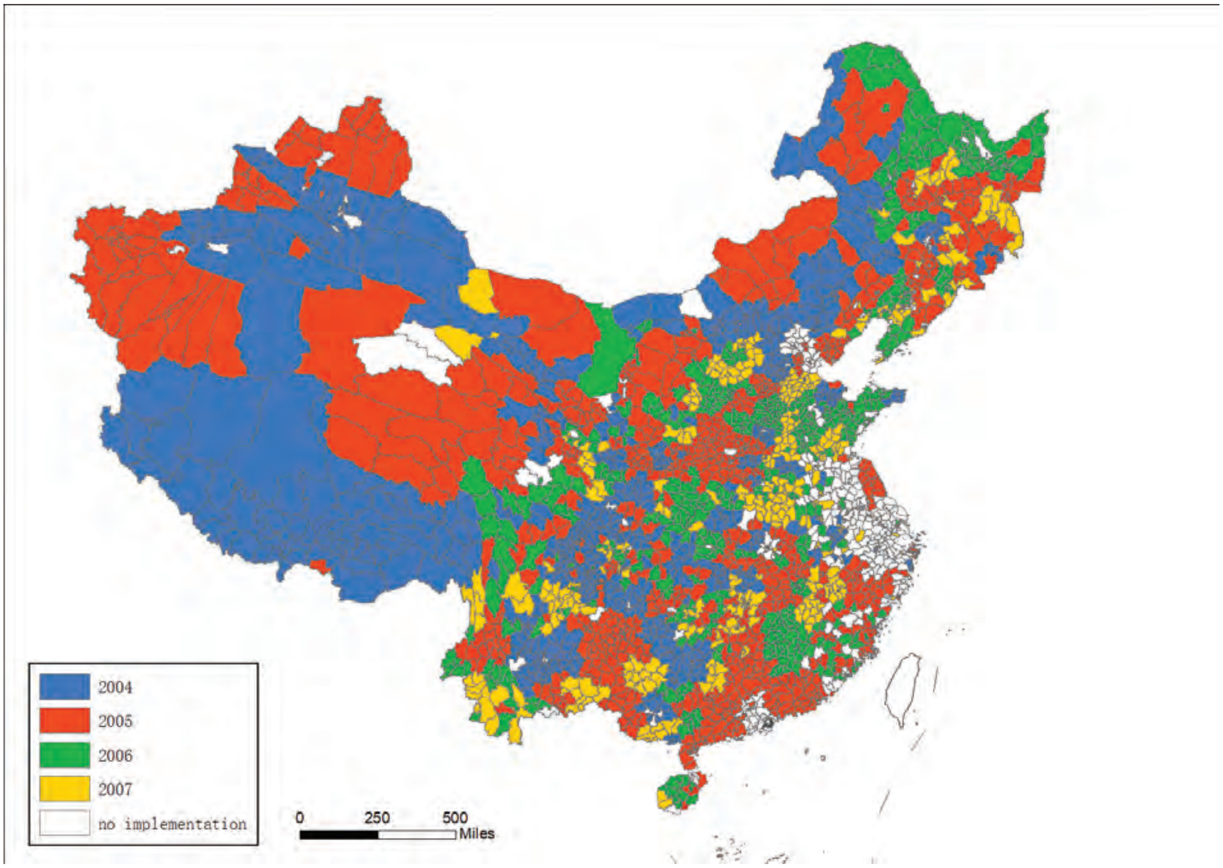
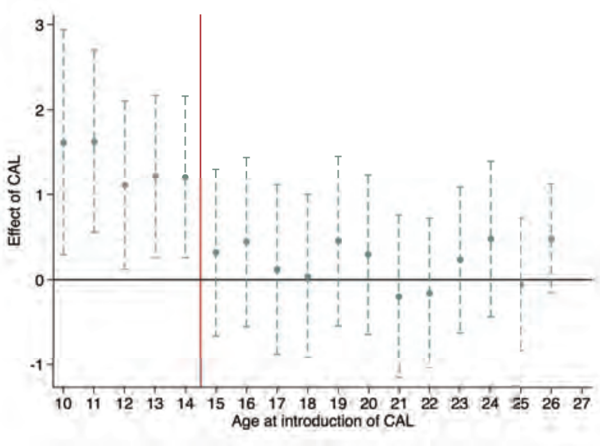
## Figures and Tables

**Figure 1:** Implementation of Computer-Aided Learning

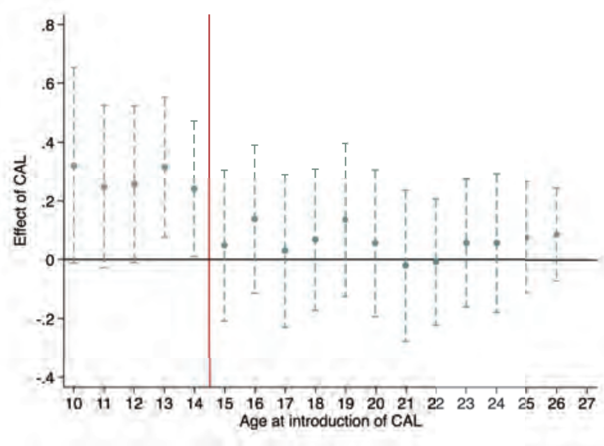



Notes: The map shows the implementation of computer-aided learning in different Chinese counties. Rural areas in different counties received computer-aided learning in 2004 (G1), 2005 (G2), 2006 (G3), and 2007 (G4). Some rural areas were not part of the program (G5). Sources: "Pilot work plan for modern distance education project in rural primary and secondary schools," Ministry of Education, National Development and Reform Commission, and Ministry of Finance, 2003, available at http://old.moe.gov.cn//publicfiles/business/htmlfiles/moe/moe_356/200409/3886.html. The full list of counties by implementation year is available in Appendix A.1.

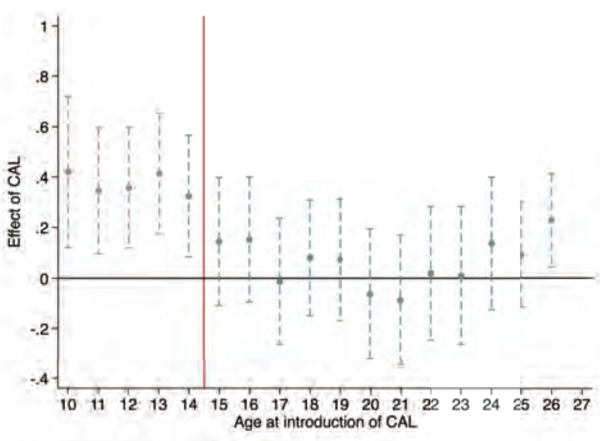
**Figure 2:** Leads and Lags in the Effect of Computed-Assisted Learning



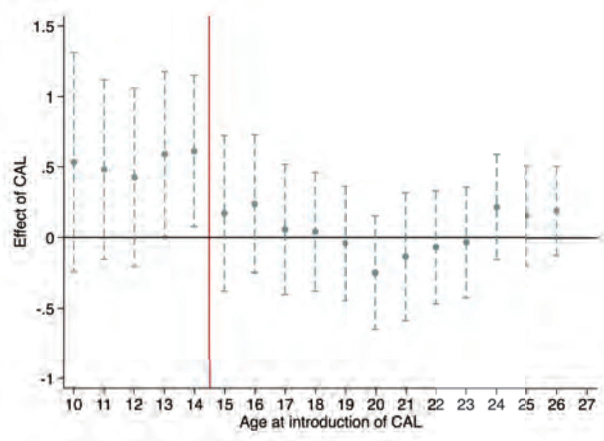

A. Years of completed education




B. Math skills




C. Chinese skills




D. Log earnings

Notes: These figures show differences between cohorts exposed to computer-aided learning (CAL=1) and cohorts not exposed (CAL=0). Each panel shows the coefficients $\beta_k$ from the following event study: $Y_{ibc} = \alpha + \sum_{k=-12}^{4} \beta_k \cdot D_k + W'_{ibc} \cdot \phi + \gamma_c + \eta_b + \varepsilon_{ibc}$. The variable $D_k$ is equal to 1 in areas with computer-assisted learning after the reform ($k \geq 0$), while is equal to 0 otherwise. The omitted birth cohort completed middle school 13 years before the reform (27 years old at the time of the reform). Individuals in areas that did not receive computer-aided learning are distributed across periods according to their age when the reform was first implemented. Figure E2 shows that this assumption does not affect the results. Vertical dashed bars are 95% confidence intervals computed from standard errors clustered at the county level. Source: CFPS, 2010 and 2014, individuals born from 1977.

**Table 1:** Summary Statistics

| | All observations | | No CAL | | CAL | |
|---|---|---|---|---|---|---|
| | Mean | Std. dev. | Mean | Std. dev. | Mean | Std. dev. |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Panel A: Demographics | | | | | | |
| Birth cohort | 1985.65 | 5.09 | 1983.94 | 4.34 | 1991.91 | 1.35 |
| Male | 0.50 | 0.50 | 0.50 | 0.50 | 0.51 | 0.50 |
| Minority | 0.11 | 0.32 | 0.12 | 0.32 | 0.09 | 0.29 |
| Siblings (dummy) | 0.87 | 0.34 | 0.87 | 0.34 | 0.87 | 0.34 |
| Father: no edu | 0.25 | 0.43 | 0.27 | 0.44 | 0.20 | 0.40 |
| Father: primary edu | 0.30 | 0.46 | 0.30 | 0.46 | 0.32 | 0.47 |
| Father: junior high edu | 0.31 | 0.46 | 0.30 | 0.46 | 0.37 | 0.48 |
| Father: high school edu | 0.12 | 0.33 | 0.13 | 0.33 | 0.10 | 0.30 |
| Father: college or more | 0.01 | 0.10 | 0.01 | 0.10 | 0.01 | 0.10 |
| Father: member of Communist party | 0.09 | 0.28 | 0.09 | 0.29 | 0.07 | 0.26 |
| Father: manager | 0.05 | 0.21 | 0.05 | 0.22 | 0.04 | 0.20 |
| Mother: no edu | 0.50 | 0.50 | 0.51 | 0.50 | 0.43 | 0.50 |
| Mother: primary edu | 0.26 | 0.44 | 0.25 | 0.43 | 0.29 | 0.46 |
| Mother: junior high edu | 0.19 | 0.39 | 0.18 | 0.39 | 0.23 | 0.42 |
| Mother: high school edu | 0.05 | 0.21 | 0.05 | 0.22 | 0.04 | 0.20 |
| Mother: college or more | 0.00 | 0.05 | 0.00 | 0.05 | 0.01 | 0.07 |
| Mother: member of Communist party | 0.01 | 0.12 | 0.01 | 0.12 | 0.01 | 0.12 |
| Mother: manager | 0.01 | 0.10 | 0.01 | 0.09 | 0.01 | 0.12 |
| Panel B: Education outcomes | | | | | | |
| Years of education | 9.34 | 4.01 | 9.07 | 4.16 | 10.34 | 3.21 |
| Middle school diploma | 0.71 | 0.46 | 0.68 | 0.47 | 0.79 | 0.41 |
| High school diploma | 0.34 | 0.47 | 0.33 | 0.47 | 0.40 | 0.49 |
| College degree | 0.14 | 0.35 | 0.15 | 0.36 | 0.09 | 0.29 |
| Informal education | 0.12 | 0.32 | 0.11 | 0.32 | 0.13 | 0.33 |
| Math score | -0.08 | 1.00 | -0.16 | 1.01 | 0.19 | 0.91 |
| Chinese score | -0.09 | 1.00 | -0.17 | 1.02 | 0.21 | 0.82 |
| Panel C: Labor market outcomes | | | | | | |
| Labor force participation | 0.58 | 0.49 | 0.56 | 0.50 | 0.65 | 0.48 |
| Log earnings | 9.04 | 1.39 | 9.12 | 1.36 | 8.68 | 1.47 |
| Cognitive skills | 0.00 | 1.00 | -0.04 | 1.00 | 0.25 | 0.99 |
| Manual skills | 0.00 | 1.00 | 0.03 | 1.01 | -0.16 | 0.95 |
| Farmer | 0.17 | 0.38 | 0.20 | 0.40 | 0.06 | 0.24 |
| Panel D: Internet usage | | | | | | |
| Internet use (dummy) | 0.58 | 0.49 | 0.54 | 0.50 | 0.80 | 0.40 |
| Frequency in using computer for work | -0.00 | 1.00 | -0.04 | 0.99 | 0.21 | 1.01 |
| Frequency in using computer for socializing | -0.00 | 1.00 | -0.10 | 0.99 | 0.51 | 0.89 |
| Panel E: Noncognitive skills | | | | | | |
| Satisfaction index | -0.00 | 0.82 | -0.01 | 0.83 | 0.06 | 0.77 |
| Popularity | 0.00 | 1.00 | -0.02 | 1.01 | 0.11 | 0.95 |
| Happiness | -0.00 | 1.00 | -0.01 | 1.01 | 0.04 | 0.93 |
| Getting along with others | -0.00 | 1.00 | -0.00 | 1.01 | 0.01 | 0.93 |
| Anxiety index | -0.00 | 0.81 | -0.00 | 0.83 | 0.02 | 0.76 |
| Depression | -0.00 | 1.00 | -0.00 | 1.02 | 0.02 | 0.92 |
| Nervousness | 0.00 | 1.00 | 0.00 | 1.01 | -0.02 | 0.94 |
| Difficulty in doing things | -0.00 | 1.00 | -0.01 | 1.02 | 0.05 | 0.91 |

Notes: Summary statistics on all birth cohorts in the sample (columns 1 and 2), on birth cohorts who did not benefit from computer-assisted learning (columns 3 and 4), and on birth cohorts who benefitted from computer-assisted learning (columns 5 and 6). Source: CFPS, 2010 and 2014, individuals born from 1977.

## **Table 2:** Baseline Differences Between Geographical Areas

| | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 | Diff. | Cond. Diff. |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | Panel A: Selection criteria | | | | | | |
| Midwest | 0.76 | 0.38 | 0.46 | 0.50 | 0.11 | 0.390*** | |
| | (0.44) | (0.49) | (0.51) | (0.51) | (0.31) | (0.069) | |
| Share of rural residents | 0.84 | 0.83 | 0.78 | 0.84 | 0.42 | 0.402*** | |
| | (0.10) | (0.14) | (0.24) | (0.11) | (0.38) | (0.065) | |
| Log number of cellphone users (/10k residents) | 6.07 | 6.18 | 6.28 | 6.19 | 8.00 | -1.819*** | |
| | (0.88) | (0.91) | (0.99) | (0.88) | (1.08) | (0.211) | |
| Log number of internet users (/10k residents) | 3.74 | 3.84 | 4.06 | 3.44 | 6.22 | -2.430*** | |
| | (1.11) | (1.30) | (1.64) | (2.17) | (1.59) | (0.307) | |
| Log value of postal services (10k CNY/10k residents) | 4.17 | 4.35 | 4.29 | 3.74 | 4.79 | -0.608** | |
| | (1.02) | (0.98) | (0.89) | (0.98) | (1.29) | (0.236) | |
| Log number of telephone users (/10k residents) | 6.74 | 6.90 | 6.95 | 6.55 | 7.92 | -1.113*** | |
| | (0.52) | (0.60) | (0.74) | (0.81) | (0.79) | (0.148) | |
| | Panel B: County characteristics | | | | | | |
| Log population (/10k residents) | 3.94 | 4.03 | 4.04 | 4.13 | 4.55 | -0.514*** | -0.178 |
| | (0.83) | (0.81) | (0.82) | (0.92) | (0.76) | (0.151) | (0.153) |
| Log GDP in primary sector (10k CNY/10k residents) | 6.92 | 7.11 | 6.89 | 6.69 | 6.92 | 0.011 | -0.046 |
| | (0.56) | (0.55) | (0.66) | (0.74) | (0.51) | (0.105) | (0.125) |
| Share of primary sector | 0.03 | 0.07 | 0.03 | 0.03 | 0.01 | 0.035*** | 0.020** |
| | (0.04) | (0.14) | (0.03) | (0.04) | (0.02) | (0.010) | (0.010) |
| Share of secondary sector | 0.32 | 0.31 | 0.30 | 0.30 | 0.46 | -0.149*** | -0.030 |
| | (0.19) | (0.18) | (0.13) | (0.18) | (0.12) | (0.026) | (0.031) |
| Share of tertiary sector | 0.64 | 0.62 | 0.66 | 0.67 | 0.53 | 0.114*** | 0.010 |
| | (0.17) | (0.17) | (0.12) | (0.18) | (0.13) | (0.026) | (0.031) |
| Log wage bill (10k CNY/10k residents) | 5.94 | 6.04 | 6.06 | 5.82 | 7.45 | -1.476*** | -0.055 |
| | (0.61) | (0.60) | (0.92) | (0.59) | (1.16) | (0.205) | (0.075) |
| Log yield of major crops (10k tons/10k residents) | 7.92 | 7.81 | 7.37 | 7.62 | 7.11 | 0.583** | -0.163 |
| | (0.75) | (1.16) | (1.17) | (1.07) | (1.51) | (0.274) | (0.227) |
| Log revenues of local government (10k CNY/10k residents) | 5.48 | 5.63 | 5.84 | 5.27 | 7.34 | -1.771*** | -0.189 |
| | (1.16) | (0.62) | (1.35) | (1.00) | (1.42) | (0.257) | (0.141) |
| Log expenses of local government (10k CNY/10k residents) | 6.11 | 6.17 | 6.25 | 6.02 | 7.51 | -1.366*** | -0.085 |
| | (0.37) | (0.40) | (0.87) | (0.65) | (1.30) | (0.225) | (0.164) |
| Log expenses for science (10k CNY/10k residents) | -0.71 | -0.25 | 0.29 | -0.37 | 2.27 | -2.516*** | -0.320 |
| | (1.18) | (0.94) | (1.50) | (1.60) | (1.92) | (0.346) | (0.268) |
| Log expenses for education (10k CNY/10k residents) | 4.66 | 4.74 | 4.80 | 4.44 | 5.63 | -0.955*** | -0.059 |
| | (0.40) | (0.44) | (0.74) | (0.69) | (1.19) | (0.207) | (0.174) |
| Log deposits (10k CNY/10k residents) | 8.07 | 8.26 | 8.34 | 8.07 | 10.23 | -2.029*** | -0.106 |
| | (0.80) | (0.78) | (1.19) | (0.94) | (1.43) | (0.255) | (0.091) |
| Log loans (10k CNY/10k residents) | 7.86 | 7.87 | 8.04 | 7.88 | 9.94 | -2.030*** | -0.147 |
| | (0.81) | (0.83) | (1.28) | (0.82) | (1.39) | (0.250) | (0.107) |
| Log number of tertiary schools (/100k residents) | 0.02 | 0.03 | 0.06 | 0.04 | 0.19 | -0.154*** | 0.023 |
| | (0.08) | (0.11) | (0.15) | (0.11) | (0.18) | (0.033) | (0.016) |
| Log number of secondary schools (/100k residents) | 1.70 | 1.66 | 1.67 | 1.30 | 1.49 | 0.110 | 0.104 |
| | (0.61) | (0.64) | (0.77) | (0.95) | (0.55) | (0.118) | (0.081) |
| Log number of primary schools (/100k residents) | 3.50 | 3.53 | 3.62 | 3.08 | 2.12 | 1.334*** | 0.383** |
| | (1.10) | (0.91) | (1.13) | (1.46) | (0.88) | (0.183) | (0.180) |
| Log number of students in tertiary schools (/10k residents) | 0.60 | 0.75 | 0.87 | 1.35 | 3.67 | -2.794*** | -0.078 |
| | (1.59) | (1.83) | (2.04) | (2.10) | (2.46) | (0.457) | (0.190) |
| Log number of students in secondary schools (/10k residents) | 6.22 | 6.23 | 6.21 | 5.87 | 6.14 | 0.007 | 0.054 |
| | (0.52) | (0.61) | (0.67) | (0.90) | (0.52) | (0.110) | (0.075) |
| Log number of students in primary schools (/10k residents) | 6.67 | 6.77 | 6.61 | 6.35 | 6.15 | 0.479*** | 0.187 |
| | (0.65) | (0.62) | (0.76) | (1.07) | (0.66) | (0.133) | (0.116) |
| Log number of teachers in tertiary schools (/10k residents) | 0.25 | 0.35 | 0.44 | 0.59 | 1.82 | -1.417*** | 0.039 |
| | (0.72) | (0.94) | (1.10) | (0.98) | (1.36) | (0.248) | (0.107) |
| Log number of teachers in secondary schools (/10k residents) | 3.25 | 3.32 | 3.34 | 3.01 | 3.37 | -0.124 | 0.040 |
| | (0.51) | (0.56) | (0.57) | (0.72) | (0.54) | (0.107) | (0.067) |
| Log number of teachers in primary schools (/10k residents) | 3.62 | 3.70 | 3.71 | 3.38 | 3.30 | 0.320*** | 0.142 |
| | (0.56) | (0.59) | (0.66) | (0.92) | (0.59) | (0.119) | (0.097) |
| Log number of hospitals beds (/100k residents) | 5.13 | 5.08 | 5.08 | 4.98 | 5.68 | -0.609*** | 0.084 |
| | (0.46) | (0.47) | (0.67) | (0.54) | (0.72) | (0.131) | (0.061) |

Notes: This table shows baseline differences between Chinese counties. Rural counties received computer-aided learning in 2004 (G1), 2005 (G2), 2006 (G3), 2007 (G4). More urban counties were not part of the program (G5). Columns 1 to 5 show averages of observable characteristics measured in 2002. Column 6 shows the difference between groups 1 to 4 and group 5. Column 7 shows the estimated difference between G1-G4 and G5 after controlling for selecting criteria. Standard deviations (columns 1 to 5) or robust standard errors (columns 6 and 7) in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Source: China County Statistical Yearbook, 2002.

**Table 3:** Trends Before the Implementation of Computer-Assisted Learning

| | Years of education | Math skills | Chinese skills | MS diploma | LM participation | Log earnings | Internet use | Anxiety index |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | | | | Panel A: Linear trends | | | | |
| G5 x Linear trend | 0.016 | -0.002 | 0.011 | -0.006 | -0.004 | 0.010 | -0.007 | -0.024 |
| | (0.041) | (0.009) | (0.010) | (0.005) | (0.006) | (0.016) | (0.006) | (0.019) |
| Observations | 3,246 | 3,246 | 3,246 | 3,246 | 3,246 | 2,762 | 2,202 | 2,200 |
| $R^2$ | 0.420 | 0.354 | 0.360 | 0.232 | 0.162 | 0.277 | 0.335 | 0.143 |
| | | | | Panel B: Quadratic trends | | | | |
| G5 x Linear trend | 0.014 | 0.023 | 0.084 | 0.007 | 0.014 | -0.026 | -0.008 | -0.137 |
| | (0.367) | (0.073) | (0.095) | (0.044) | (0.052) | (0.151) | (0.054) | (0.104) |
| G5 x Linear trend$^2$ | 0.000 | -0.001 | -0.003 | -0.001 | -0.001 | 0.001 | 0.000 | 0.004 |
| | (0.014) | (0.003) | (0.004) | (0.002) | (0.002) | (0.006) | (0.002) | (0.004) |
| Observations | 3,246 | 3,246 | 3,246 | 3,246 | 3,246 | 2,762 | 2,202 | 2,200 |
| $R^2$ | 0.420 | 0.354 | 0.360 | 0.232 | 0.162 | 0.277 | 0.335 | 0.143 |
| F-test | 0.92 | 0.90 | 0.45 | 0.32 | 0.76 | 0.77 | 0.49 | 0.19 |
| | | | | Panel C: Cubic trends | | | | |
| G5 x Linear trend | -0.550 | 0.138 | -0.266 | 0.147 | -0.501* | 0.502 | -0.177 | -0.805 |
| | (2.077) | (0.485) | (0.560) | (0.248) | (0.298) | (0.935) | (0.328) | (0.723) |
| G5 x Linear trend$^2$ | 0.047 | -0.011 | 0.026 | -0.012 | 0.043* | -0.043 | 0.014 | 0.061 |
| | (0.169) | (0.040) | (0.044) | (0.020) | (0.025) | (0.075) | (0.027) | (0.060) |
| G5 x Linear trend$^3$ | -0.001 | 0.000 | -0.001 | 0.000 | -0.001* | 0.001 | -0.000 | -0.002 |
| | (0.004) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) | (0.002) |
| Observations | 3,246 | 3,246 | 3,246 | 3,246 | 3,246 | 2,762 | 2,202 | 2,200 |
| $R^2$ | 0.420 | 0.354 | 0.360 | 0.232 | 0.162 | 0.277 | 0.335 | 0.144 |
| F-test | 0.97 | 0.97 | 0.31 | 0.48 | 0.34 | 0.84 | 0.57 | 0.28 |
| Mean | 8.77 | -0.24 | -0.23 | 0.66 | 0.54 | 9.19 | 0.50 | -0.02 |
| Std. dev. | 4.05 | 0.96 | 1.01 | 0.47 | 0.50 | 1.34 | 0.50 | 0.84 |

Notes: This table shows pre-reform trends in education and labor outcomes between individuals in treated counties (G1 to G4) and individuals in counties that did not receive computer-assisted learning (G5). Individuals are assigned to different counties based on their residence at age 12 . Panel A estimates linear pre-reform trends: $\mathrm{Y}_{ibc} = \alpha+\beta_1 \cdot \mathrm{t}_b \cdot \mathrm{G5}_c+\gamma_b+\delta_c+\mathrm{W}^{'}_{ibc} \cdot \phi+\varepsilon_{ibc}$. In this specification, $\gamma_b$ are birth cohort fixed effects, $\delta_c$ are counties fixed effects, $\mathrm{G5}_c$ is equal to 1 for individuals in untreated counties (G5), and $\mathrm{W}^{'}_{ibc}$ is a set of individual characteristics. Panel B estimates quadratic pre-reform trends: $\mathrm{Y}_{ibc} = \alpha+\beta_1 \cdot \mathrm{t}_b \cdot \mathrm{G5}_c+\beta_2 \cdot \mathrm{t}_b^2 \cdot \mathrm{G5}_c+\gamma_b+\delta_c+\mathrm{W}^{'}_{ibc} \cdot \phi+\varepsilon_{ibc}$. Panel C estimates cubic pre-reform trends: $\mathrm{Y}_{ibc} = \alpha+\beta_1 \cdot \mathrm{t}_b \cdot \mathrm{G5}_c+\beta_2 \cdot \mathrm{t}_b^2 \cdot \mathrm{G5}_c+\beta_3 \cdot \mathrm{t}_b^3 \cdot \mathrm{G5}_c+\gamma_b+\delta_c+\mathrm{W}^{'}_{ibc} \cdot \phi+\varepsilon_{ibc}$. Rural counties received computer-aided learning in 2004 (G1), 2005 (G2), 2006 (G3), and 2007 (G4). Some counties never received the program (G5). The dependent variables are: completed years of education (col. 1), math skills (col. 2), Chinese skills (col. 3), dummy for middle school diploma (col. 4), labor market participation (col. 5), log earnings (col. 6), frequency of internet use for work (col. 7), and an index for level of mental stress (col. 8). All regressions include individuals born between 1977 and 1988. Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Source: CFPS, 2010 and 2014, individuals born from 1977.

**Table 4:** Effects of Computer-Assisted Learning on Long-Term Outcomes

| | Full sample: G1-G5 | | | | Treated counties: G1-G4 | | | |
|---|---|---|---|---|---|---|---|---|
| | CAL | Obs. | $R^2$ | Mean outcome | CAL | Obs. | $R^2$ | Mean outcome |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: Education outcomes | | | | | | | | |
| Years of education | 0.848*** | 4,996 | 0.429 | 9.12 | 0.745** | 4,191 | 0.400 | 8.43 |
| | (0.304) | | | | (0.316) | | | |
| Middle school diploma | 0.072** | 4,996 | 0.241 | 0.69 | 0.074** | 4,191 | 0.219 | 0.63 |
| | (0.029) | | | | (0.033) | | | |
| Informal education | 0.066 | 2,841 | 0.180 | 0.11 | 0.037 | 2,347 | 0.163 | 0.09 |
| | (0.046) | | | | (0.050) | | | |
| Math skills | 0.183** | 4,996 | 0.368 | -0.15 | 0.183** | 4,191 | 0.337 | -0.30 |
| | (0.080) | | | | (0.088) | | | |
| Chinese skills | 0.227*** | 4,996 | 0.389 | -0.16 | 0.183*** | 4,191 | 0.381 | -0.30 |
| | (0.064) | | | | (0.066) | | | |
| Panel B: Labor market outcomes | | | | | | | | |
| Labor force participation | 0.063 | 4,996 | 0.161 | 0.56 | 0.096** | 4,191 | 0.150 | 0.52 |
| | (0.039) | | | | (0.045) | | | |
| Log earnings | 0.463*** | 3,889 | 0.281 | 9.13 | 0.379*** | 3,232 | 0.251 | 9.02 |
| | (0.120) | | | | (0.142) | | | |
| Cognitive skills | 0.279*** | 3,341 | 0.302 | -0.03 | 0.213* | 2,771 | 0.275 | -0.17 |
| | (0.107) | | | | (0.112) | | | |
| Manual skills | -0.270** | 3,341 | 0.268 | 0.02 | -0.235** | 2,771 | 0.225 | 0.16 |
| | (0.105) | | | | (0.118) | | | |
| Farmer | -0.048** | 4,996 | 0.279 | 0.20 | -0.057** | 4,191 | 0.268 | 0.24 |
| | (0.021) | | | | (0.023) | | | |
| Panel C: Internet usage | | | | | | | | |
| Internet use (dummy) | 0.082** | 3,109 | 0.404 | 0.54 | 0.071 | 2,554 | 0.394 | .47 |
| | (0.038) | | | | (0.047) | | | |
| Freq. in using computer for work | 0.276** | 3,109 | 0.285 | -0.04 | 0.199 | 2,554 | 0.246 | -.19 |
| | (0.138) | | | | (0.159) | | | |
| Freq. in using computer to socialize | 0.165** | 3,109 | 0.417 | -0.10 | 0.130 | 2,554 | 0.392 | -.25 |
| | (0.080) | | | | (0.089) | | | |
| Panel D: Noncognitive skills | | | | | | | | |
| Satisfaction index | -0.039 | 3,105 | 0.122 | -0.01 | -0.032 | 2,550 | 0.112 | -.05 |
| | (0.094) | | | | (0.115) | | | |
| Happiness | -0.184 | 3,106 | 0.142 | -0.01 | -0.218 | 2,551 | 0.139 | -0.06 |
| | (0.114) | | | | (0.141) | | | |
| Anxiety index | -0.172* | 3,107 | 0.164 | 0 | -0.182 | 2,324 | 0.155 | -0.02 |
| | (0.098) | | | | (0.115) | | | |
| Nervousness | -0.243* | 3,109 | 0.149 | 0 | -0.280* | 2,554 | 0.146 | 0 |
| | (0.135) | | | | (0.168) | | | |

Notes: This table shows differences between cohorts who were exposed to computer-aided learning (CAL=1) and cohorts who were not (CAL=0). Each row-column combination shows the coefficient $\beta$ from a different regression of exposure to computer-aided learning on several outcome variables: $\mathrm{Y}_{ibc} = \alpha + \beta \cdot \mathrm{CAL}_{bc} + \gamma_b + \delta_c + \mathrm{W}^{'}_{ibc} \cdot \phi + \mathrm{Pol}^{'}_{c} \cdot \mathrm{CAL}_{bc} \cdot \psi + \delta_c \cdot \mathrm{t}_b + \varepsilon_{ibc}$. In this specification, $\gamma_b$ are birth cohort fixed effects, $\delta_c$ are county fixed effects, $\mathrm{W}^{'}_{ibc}$ is a set of individual characteristics (an indicator variable for minority groups, the number of siblings, and dummy variables measuring the paternal schooling level), $\mathrm{Pol}^{'}_{c}$ is a set of variables describing other education policies (a bundle of policies to increase middle school completion in western counties, a reform of education finance in rural schools, the construction of rural boarding schools, and the consolidation of rural schools), and $\mathrm{t}_b$ is a linear trend in birth cohorts. Columns 1 to 4 include all geographical areas. Columns 5 and 8 restrict the sample to areas that received the program at some point (G1-G4). Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Source: CFPS, 2010 and 2014, individuals born from 1977.

## Table 5: Heterogeneous Effects

| | Years of education | Math skills | Chinese skills | MS diploma | LM participation | Log earnings | Internet use | Anxiety index |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | | | | Panel A: Average teacher education | | | | |
| CAL | 0.893** | 0.188** | 0.249*** | 0.071** | 0.084** | 0.441*** | 0.088** | -0.226** |
| | (0.343) | (0.092) | (0.073) | (0.032) | (0.042) | (0.134) | (0.042) | (0.109) |
| CAL*Teacher education | -0.187 | -0.022 | -0.090 | 0.003 | -0.091 | 0.090 | -0.027 | 0.231** |
| | (0.506) | (0.119) | (0.109) | (0.049) | (0.069) | (0.178) | (0.065) | (0.114) |
| | | | | Panel B: Average teacher-student ratio | | | | |
| CAL | 0.857** | 0.171* | 0.229*** | 0.065** | 0.096** | 0.395*** | 0.099** | -0.186* |
| | (0.342) | (0.091) | (0.075) | (0.029) | (0.042) | (0.136) | (0.042) | (0.104) |
| CAL*Teacher–student ratio | -0.431 | -0.011 | -0.065 | 0.018 | -0.120* | 0.233 | -0.090 | 0.086 |
| | (0.489) | (0.127) | (0.112) | (0.054) | (0.061) | (0.172) | (0.065) | (0.132) |
| | | | | Panel C: Internet proliferation | | | | |
| CAL | 0.856** | 0.175* | 0.237*** | 0.084*** | 0.096** | 0.501*** | 0.095** | -0.163 |
| | (0.334) | (0.091) | (0.073) | (0.029) | (0.043) | (0.130) | (0.042) | (0.103) |
| CAL*Internet proliferation | -0.438 | -0.025 | -0.096 | -0.058 | -0.122** | -0.198 | -0.087 | -0.010 |
| | (0.513) | (0.128) | (0.125) | (0.057) | (0.059) | (0.173) | (0.059) | (0.126) |
| | | | | Panel D: Geographic heterogeneity | | | | |
| CAL | 0.429 | 0.126 | 0.186** | 0.074** | 0.084* | 0.335** | 0.061 | -0.141 |
| | (0.345) | (0.101) | (0.081) | (0.037) | (0.050) | (0.134) | (0.048) | (0.107) |
| CAL*Midwest | 0.776 | 0.106 | 0.077 | -0.004 | -0.040 | 0.237 | 0.036 | -0.055 |
| | (0.473) | (0.122) | (0.112) | (0.046) | (0.057) | (0.153) | (0.057) | (0.106) |
| | | | | Panel E: Average wage | | | | |
| CAL | 0.897** | 0.162* | 0.198*** | 0.109*** | 0.110** | 0.393*** | 0.031 | -0.129 |
| | (0.357) | (0.085) | (0.075) | (0.034) | (0.049) | (0.143) | (0.047) | (0.119) |
| CAL*Above-median wage | -0.069 | 0.052 | 0.100 | -0.032 | -0.046 | -0.019 | 0.123** | 0.027 |
| | (0.523) | (0.134) | (0.119) | (0.046) | (0.058) | (0.174) | (0.059) | (0.106) |
| | | | | Panel F: Gender | | | | |
| CAL | 0.580* | 0.132 | 0.160** | 0.020 | 0.047 | 0.320** | 0.062 | -0.182 |
| | (0.349) | (0.091) | (0.076) | (0.032) | (0.044) | (0.152) | (0.046) | (0.115) |
| CAL*Female | 0.537** | 0.103 | 0.135* | 0.103*** | 0.031 | 0.292* | 0.038 | 0.020 |
| | (0.259) | (0.071) | (0.071) | (0.029) | (0.037) | (0.152) | (0.037) | (0.088) |
| | | | | Panel G: Paternal education | | | | |
| CAL | 0.407 | 0.082 | 0.171** | 0.054 | 0.072 | 0.385*** | 0.055 | -0.160 |
| | (0.294) | (0.082) | (0.066) | (0.036) | (0.045) | (0.130) | (0.041) | (0.098) |
| CAL*Primary edu. or less | 0.843*** | 0.197*** | 0.105* | 0.033 | -0.016 | 0.158 | 0.048 | -0.018 |
| | (0.251) | (0.073) | (0.061) | (0.038) | (0.033) | (0.125) | (0.043) | (0.077) |

Notes: This table shows how CAL education interacts with school inputs, as well as county-level and individual characteristics. It shows estimates from regressions that interact exposure to CAL with a dummy for counties with above-median teacher education in 2000 (panel A, China County Statistical Yearbook), a dummy for counties with above-median teacher–student ratio in 2000 (panel B, Census), a dummy for counties with above-median availability of the internet in 2002 (panel C, data from China County Statistical Yearbook), a dummy for counties in the midwest (panel D), a dummy for counties with above-median wage in 2002 (panel E, data from China County Statistical Yearbook), a dummy for female students (panel F), or a dummy for fathers with primary education or less (panel G). Standard errors clustered at the county level in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Source: CFPS, 2010 and 2014, individuals born from 1977.

# Online Appendix - Not For Publication

## A More Details on the CAL Program

### A.1 County-level Rollout

The list of counties by implementation year comes from the following official sources by the Chinese Ministry of Education:

- 2004: https://web.archive.org/web/20201107144943/http://www.moe.gov.cn/srcsite/A06/jcys_jyzb/200406/t20040607_82060.html
- 2005: https://web.archive.org/web/20201105225420/http://www.moe.gov.cn/srcsite/A06/jcys_jyzb/200510/t20051011_82044.html
- 2006: https://web.archive.org/web/20201105225730/http://www.moe.gov.cn/srcsite/A06/jcys_jyzb/200606/t20060621_82053.html; https://web.archive.org/web/20201105225830/http://www.moe.gov.cn/srcsite/A06/jcys_jyzb/200605/t20060523_82046.html
- 2007: https://web.archive.org/web/20201105225930/http://www.moe.gov.cn/srcsite/A06/jcys_jyzb/200707/t20070702_82048.html; https://web.archive.org/web/20201105230059/http://www.moe.gov.cn/srcsite/A06/jcys_jyzb/200705/t20070514_82057.html

### A.2 Implementation of the CAL Program

Although this paper focuses on middle schools exclusively, the Modern Distance Education Program was implemented in three types of education institutions: small-scale rural primary schools, which we will call rural teaching sites, rural primary schools, and rural middle schools. The implementation of the program in these three institutions varied to accommodate the different needs of their students and teachers.

First, rural teaching sites received DVD-player sets, including a TV, a DVD player, and teaching CDs prepared by the best teachers in the country (Figure A1, panel A). Second, in addition to the DVD-player sets, rural primary schools received satellite teaching receiving stations (Figure A1, panel B). These more complex setup included outdoor satellite antennas, TVs, satellite TV receivers, satellite data reception equipment (such as a modem compatible with satellite broadband internet), a broadband satellite internet connection, and other related equipment. In other words, the participating rural primary schools were connected to the internet through satellites (Figure A2). Third, in addition to DVD-player sets and satellite stations, rural middle schools received computer classrooms. This classroom included a projector, a central control station, a DVD-player set, a TV, a network of computers, and other related equipment (Figure A1, panel C).

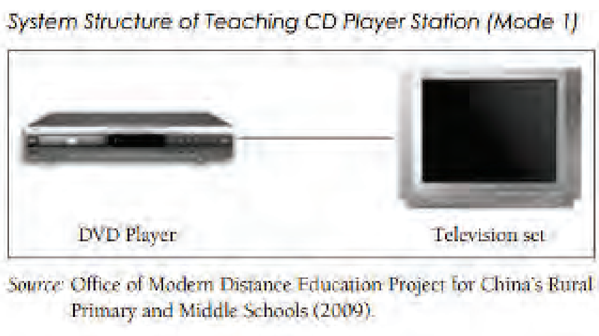
In rural middle schools, the availability of new technology introduced three new pedagogical approaches. First, in the regular classrooms, local teachers could use the DVD-player sets to play the teaching CDs prepared by some of the best teachers in the country (Figure A3, panel A). Moreover, local teachers could use the DVD-player sets to enhance their own lectures with audiovisual components. Second, the satellite receiving stations could be used to download and stream the lectures and related teaching materials prepared by the CAL program. Moreover, these stations could be used by local teachers to access the internet for teaching activities (Figure A3, panel

B). Third, computer rooms could be used to allow students to follow from their own device the lectures and teaching materials prepared by the CAL program, instead of following them from a single shared screen (Figure A3, panel C). Moreover, computers allowed students to take interactive quizzes and exercised based on the CAL lectures. Finally, computer classrooms could be used to introduce computer science in the curriculum of participating middle schools.

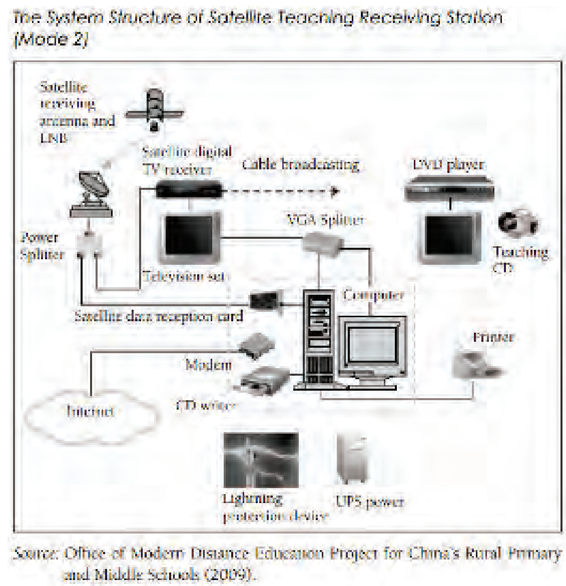
Office of Modern Distance Education Project for China's Rural Primary and Middle Schools (2009) reports data on the utilization of the CAL technology (Table A1). The share of schools using CAL equipment for more than 20 hours per week was 58% for computer rooms, 22% for satellite stations, and 33% for DVD-players sets. The share of schools using CAL equipment between 16 and 20 hours a week was 27% for computer rooms, 43% for satellite stations, and 36% for DVD-players sets. The share of schools using CAL equipment between 6 and 15 hours per week was 14% for computer rooms, 32% for satellite stations, and 29% for DVD-players sets. Finally, the share of schools using CAL equipment less than 5 hours per week was only 1% for computer rooms, 3% for satellite stations, and 2% for DVD-players sets.

We can use these statistics to compute a lower bound of the number of courses per week in which the average student was exposed to the equipment provided by the CAL program. Specifically, we use the center of these intervals, as well as the lowest bound of the top category (twenty hours), to compute for how many weekly hours the average participating middle school used CAL equipment. The estimate is equal to $(58\% * 20 + 27\% * 18 + 14\% * 10.5 + 1\% * 2.5) + (22\% * 20 + 43\% * 18 + 32\% * 10.5 + 3\% * 2.5) + (33\% * 20 + 36\% * 18 + 29\% * 10.5 + 2\% * 2.5) = 49.7$ total hours per week. Assuming that the mean number of classes per school is ten and that each school had only one computer room, one satellite set, and one DVD-player set, we can conclude that the average student was exposed to CAL equipment for at least $49.7/10 = 4.97$ hours, or 6.6 45-minute lectures per week.

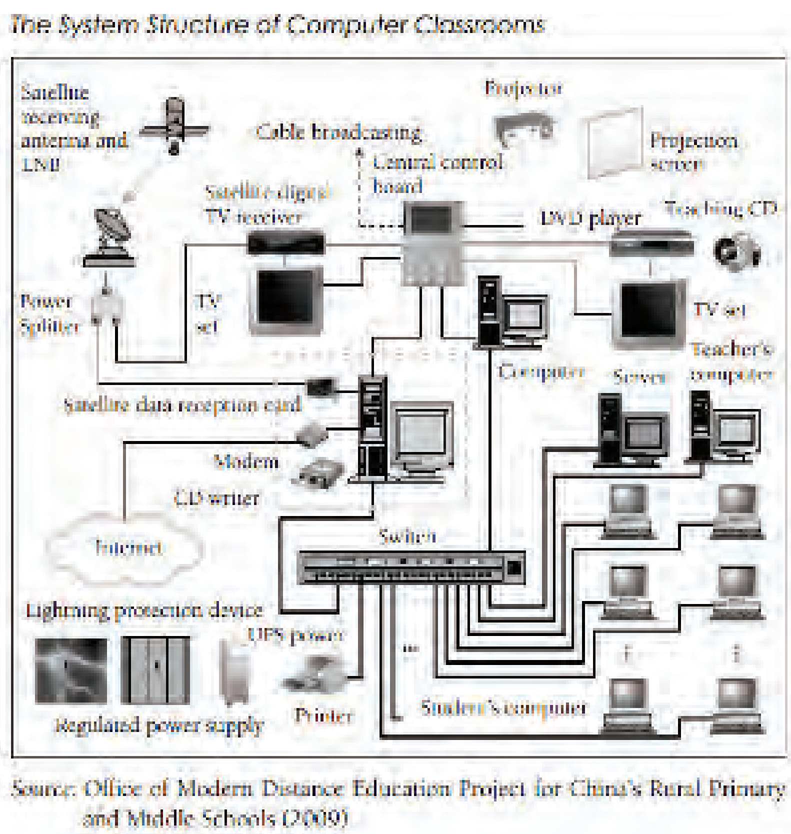
**Figure A1:** CAL in Middle Schools




Panel A: DVD player sets




Panel B: Satellite receiving stations




Panel C: Computer rooms

Notes: These pictures come from Office of Modern Distance Education Project for China's Rural Primary and Middle Schools (2009) and Wang, Zeng, and Wang (2015). In Wang, Zeng, and Wang (2015), they are Figure 2.2, 2.3, and 2.4, respectively.

**Figure A2:** Installation of Satellite Receiving Systems


Notes: The picture shows the installation of a satellite receiving system in a primary school in Yunlong County, Yunnan province. Source: `https://web.archive.org/web/20090107112617/http://www.dalidaily.com/tupian/20060809/035306.html`.

**Figure A3:** Use of CAL Equipment for Pedagogy


Panel A: CD-based teaching


Panel B: Distance education based on satellite stations


Panel C: Lectures in computer classrooms

Notes: Panel A shows CD-based teaching in a school in a minority region of Western China. Panel B shows distance education based on a satellite teaching receiving station in a rural primary school of Huining county in the Gansu Province. Panel C shows distance education in the computer room of a rural middle schools of Baokang county in the Hubei Province. In Wang, Zeng, and Wang (2015), they are Figure 2.11, 2.16, and 2.20, respectively.

**Figure A4:** Visits from MoE Inspectors

Notes: These pictures show the visits of inspectors from the Ministry of Education (MoE) in Luohe, Henan Province, in 2008. Source: https://web.archive.org/web/20201104211707/http://news.haedu.cn/dsjj/lh/633670300790718750.html.

**Table A1:** Utilization of CAL Equipment

| | DVD stations | Satellite stations | Computer rooms |
|---|---|---|---|
| | (1) | (2) | (3) |
| More than 20 hours | 33% | 22% | 58% |
| 16-20 hours | 36% | 43% | 27% |
| 6-15 hours | 29% | 32% | 14% |
| Less than 5 hours | 2% | 3% | 1% |

Notes: These data come from Office of Modern Distance Education Project for China's Rural Primary and Middle Schools (2009) and Wang, Zeng, and Wang (2015) (Figure 2.23).

## A.3 Anecdotal Evidence on Benefits of CAL Program

The following comments are from discussion and feedback about the CAL program by students, teachers, and their school principals.

> "The CAL program provides me with the opportunity to be instructed by the most excellent teachers. I always feel that now I am a student in an elite school in a modern city. I like their teaching styles a lot, which makes abstract and boring classes much more interesting and variegated."
> -A middle school student in a rural middle school in Guyuan city, Ningxia province.

> "I am 54 years old and less educated. It is difficult for me to keep my knowledge up to date. Previously, I felt it was extremely difficult for me to properly teach and motivate my students. Now, with the influx of modern education technology, everything has changed. With the help of a younger teacher in our school, I am now able to use a computer and multimedia content in class."

-A primary school teacher in Gansu province.

"The rural schools in our country face several common difficulties: outdated teaching style, old and less-educated teachers, and limited finances and information. This program is an effective way to solve these difficulties. Furthermore, the program connects the rural schools to the outside world and provides students in rural schools with the opportunity to enjoy high-quality teaching materials."
-Guo Jinchuan, a principal in a rural middle school in Guyuan city, Ningxia province.

"The CAL program was like a new paradigm for education. We noticed that the digital lectures have become the students' favorites. When students are instructed by the modern program, they are more focused and motivated. With the help of videos and multimedia materials, they show more interest and confidence in dealing with difficult questions. This program is extremely helpful for our rural schools that were lacking of information and knowledge. It makes students in rural schools enjoy the same educational materials that students in urban areas have available."
–A teacher in a rural school in Tongling county, Anhui province.

Reference: http://old.moe.gov.cn//publicfiles/business/htmlfiles/moe/moe_1851/200711/29185.html

# B More Details on the Data

## B.1 CFPS Cognitive Tests

The CFPS cognitive test includes a literacy test and a math test. The basis of the CFPS literacy and math tests is the Guttman scale. Specifically, all questions can be strictly arranged according to their difficulty. Answering a given question correctly implies that the respondent can answer all the easier questions. Similarly, answering one question incorrectly means that the respondent cannot move immediately to the harder questions. The major advantage of the Guttman scale design is to save data collection time and reduce the time commitment of respondents.

In the CFPS test, respondents start answering questions in ascending order of difficulty. The test ends either when the total number of questions is reached (34 literacy and 24 math questions) or when the respondent answers three subsequent questions incorrectly. In the latter case, the last question answered correctly determines the final score. In order to further improve the fairness and precision of the test, there are three different starting points based on the education level of the respondents. In other words, the first question of both the literacy and math test differs between respondents with at most primary education, respondent with middle school education, and respondents with at least high school education. If respondents answer the first question incorrectly, they are moved to the lower starting point (if a lower starting point exist) and restart the test.

In the data, the results of the literacy and math tests are highly and significantly correlated with years of completed education. Specifically, we regressed years of education on math and Chinese test scores, controlling for birth cohort and county fixed effects. This sample includes non-CAL individuals exclusively in order to exclude any influence of the reform on this relationship. The estimated coefficient of the math test score is 2.56, while the estimated coefficient of the Chinese test score is 0.63. Both coefficients are highly statistically significant.

## B.2 Noncognitive Outcomes

For ease of interpretation, we normalize each measurement to have a mean of zero and standard deviation of one.

Satisfaction Index

1. Popularity: Rate your popularity from 1-10, with 1 the lowest and 10 the highest
2. Happiness: Rate your happiness from 1-10, with 1 the lowest and 10 the highest
3. Getting along with others: Rate how well you are getting along with others, with 1 the lowest and 10 the highest

Anxiety Index

1. Depression: How frequently have you been feeling depressed in the past month? (1) Almost every day; (2) Always; (3) About half of the time; (4) Sometimes; (5) Never
2. Nervousness: How frequently have you been feeling nervous in the past month? (1) Almost every day; (2) Always; (3) About half of the time; (4) Sometimes; (5) Never
3. Difficulty in doing things: How frequently have you been feeling difficult in doing things in the past month? (1) Almost every day; (2) Always; (3) About half of the time; (4) Sometimes; (5) Never

# C Decomposition of the Earning Effect

Specifically, we decompose the overall effect on earnings using the following framework:

$$\begin{gathered}
E[Y \mid D=1] - E[Y \mid D=0] = \\
= [\tfrac{1}{N}\textstyle\sum_{i=1}^{N} Y_i \mid D=1] - [\tfrac{1}{N}\sum_{i=1}^{N} Y_i \mid D=0] \\
\\
= [\tfrac{1}{N}\textstyle\sum_{i=1}^{N}[(Y_i - \overline{Y}_o - \overline{Y}_m) + \overline{Y}_o + \overline{Y}_m] \mid D=1] \\
-[\tfrac{1}{N}\textstyle\sum_{i=1}^{N}[(Y_i - \overline{Y}_o - \overline{Y}_m) + \overline{Y}_o + \overline{Y}_m] \mid D=0] \\
\\
= \Big(E[\tilde{Y}_{om} \mid D=1] - E[\tilde{Y}_{om} \mid D=0]\Big) \\
+ \big(E[\overline{Y}_o \mid D=1] - E[\overline{Y}_o \mid D=0]\big) \\
+ \big(E[\overline{Y}_m \mid D=1] - E[\overline{Y}_m \mid D=0]\big)
\end{gathered} \tag{3}$$

The outcome variable $Y_i$ measures the earnings of individual $i$; the dummy $D$ indicates the treatment status; $N$ is the total number of workers employed; $\overline{Y}_o$ is the average wage for occupation $o$; and $\overline{Y}_m$ is the average wage for individuals with migration status $m$ (a dummy variable equal to 1 in case of migration from rural to urban areas after age 12). The variable $\tilde{Y}_{om}$ is the deviation of individual $i$'s earnings from occupation $o$'s and migration status $m$'s average earnings. The first component in the last three rows of equation (3) measures the "within-occupation-migration" earning premium as the individual deviation from the mean. The second component measures the "across-occupation" earning premium generated by computer-assisted learning. The third component measures the "across-migration" earning premium.

## D Cost-Benefit Analysis

Our results consistently show that computer-assisted learning improved students' long-term outcomes. Specifically, individual monetary returns from CAL are statistically and economically significant: an estimated increase in earnings of 59% and a shift towards occupations that focus more on cognitive skills and less on manual skills. In this section, we compare these higher earnings with the financial costs of implementing and maintaining the program.

**Life-cycle increase in earnings.** The CAL program increased individual earnings in adulthood for children who were treated in middle school by 59%, compared with the control group. Following the framework in Chetty, Hendren and Katz (2016), we employ this estimate for a cost-benefit analysis. We assume that: (1) this 59% increase in individual earnings remains constant over the life cycle; (2) the life cycle profile of earnings for the individuals exposed to CAL follows the average earnings profile of the Chinese population; (3) the discount rate is 5%. Moreover, we ignore real wage growth rate.

In the 2014 CFPS sample, the average earnings in rural counties for those not exposed to CAL were CNY 10,499. Therefore, the estimated undiscounted effect of CAL on earnings is 10,499*59% = CNY 6,194. Assuming that the number of working years is 30, the undiscounted total life-cycle increase in earnings is CNY 185,820 (6,194*30). Without taking into account the wage growth rate, its discounted present value is CNY 42,995 or USD 6,432 (185,820/(1+0.05)ˆ30).

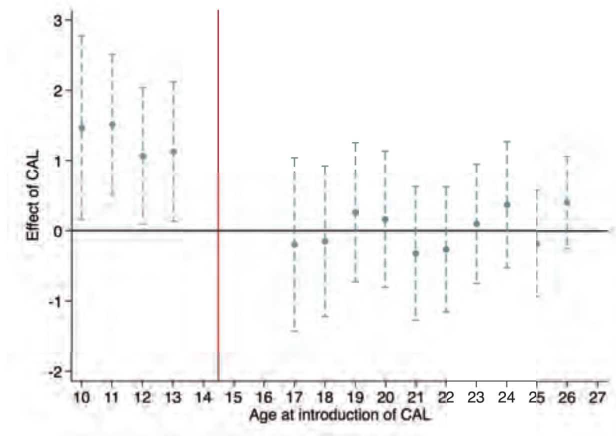
**Fiscal cost.** The total financial cost of implementing the CAL program was CNY 11.1 billion. The government reported that the program reached more than 100 million students in rural primary and secondary schools.[56] Since the exact number of students reached by the program is not available, we use 100 million students for our computations. Therefore, the per-student cost was CNY 111 or USD 17.

**Conclusions.** Overall, our cost-benefit analysis indicates that the cost per capita of the CAL program was far smaller than its per-capita earnings gains. It is worth noting that this simple analysis omits many factors that should be considered in a more comprehensive cost-benefit evaluation. First, our calculations do not account for the economic gains obtained from sources other than earnings. Second, widespread proficiency in using computers or the internet is an important driver of economic growth. Our computations, however, do not take into account the possibly large positive externalities generated by having a more technologically savvy population. Third, our calculations do not take into account wage growth. These three points make our estimated lifetime increase in earnings a "lower bound" of the true earnings increase. Fourth, we do not have data on the upkeep costs needed to maintain the CAL equipment in good working condition. Even though these maintenance costs could be large, it is implausible to assume that they would cancel the difference between the individual benefits and the direct implementation costs.

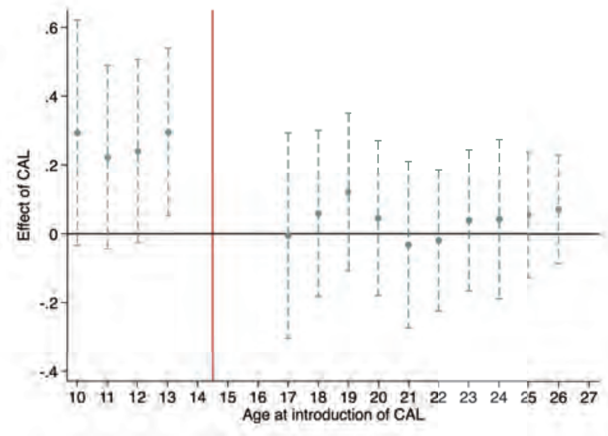
[56] https://web.archive.org/web/20201029160144/http://www.moe.gov.cn/jyb_xwfb/xw_fbh/moe_2069/moe_2095/moe_2100/moe_1851/tnull_29185.html.

# E Additional Figures and Tables

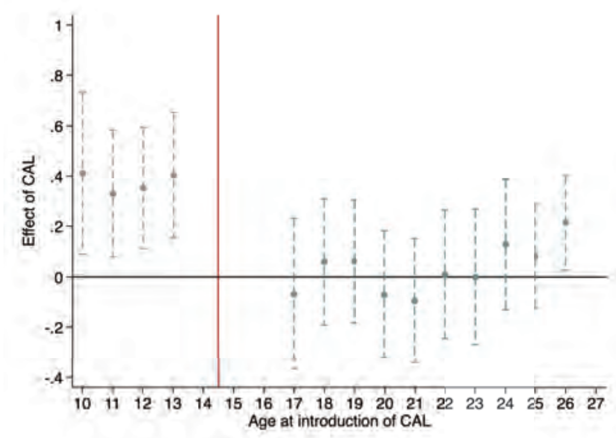
**Figure E1:** Leads and Lags Using Doughnut-Hole Approach



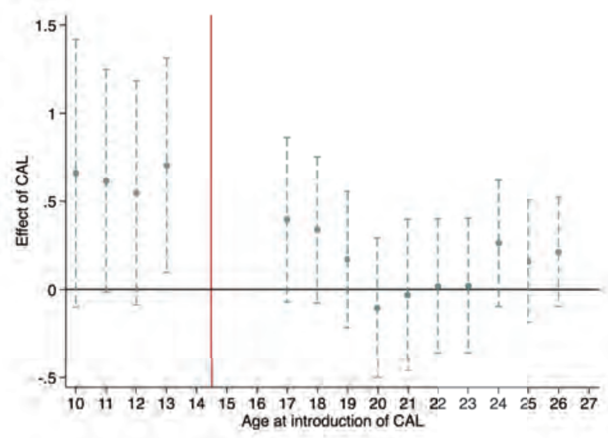

A. Years of completed education




B. Math skills



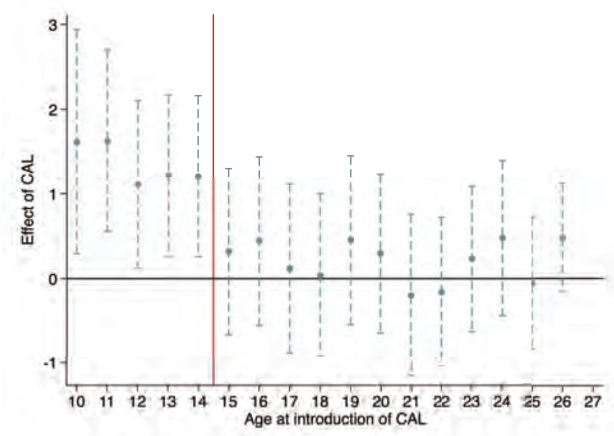

C. Chinese skills



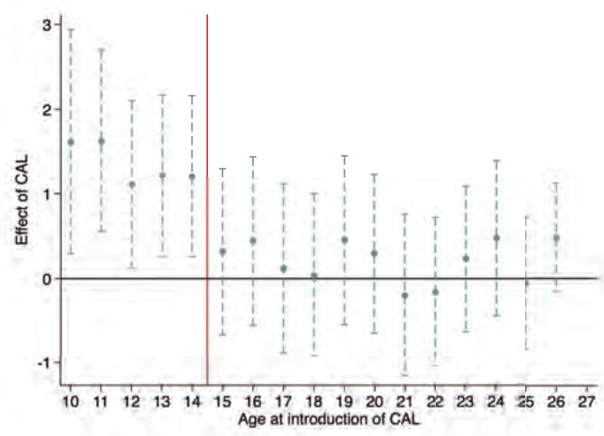

D. Log earnings

Notes: Each panel shows the coefficients $\beta_k$ from the following event study: $Y_{ibc} = \alpha + \sum_{k=-12}^{4} \beta_k \cdot D_k + W_{ibc}^{'} \cdot \phi + \gamma_c + \eta_b + \varepsilon_{ibc}$. The variable $\mathrm{D}_k$ is equal to 1 in areas with computer-assisted learning after the reform ($k \geq 0$). The omitted birth cohort completed middle school 13 years before the reform (27 years old at the time of the reform). The estimation drops cohorts who should have completed middle school either the year before or the same year of the policy implementation. These individuals, in fact, might have an incorrect exposure to the treatment due to grade retention or earlier-than-normal enrollment in school. Vertical dashed bars are 95% confidence intervals computed from standard errors clustered at the county level. Source: CFPS, 2010 and 2014, individuals born from 1977.

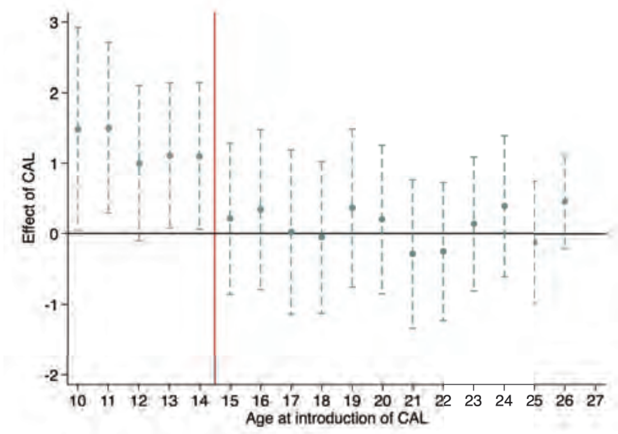
**Figure E2:** Years of Completed Education, Different Distributions of G5 Individuals



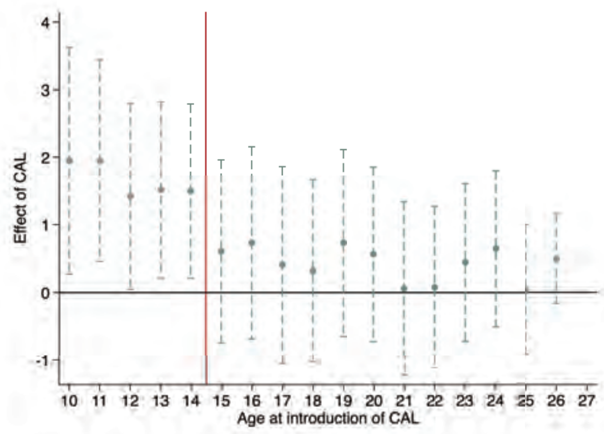

A. Using G1 distribution




B. Using G2 distribution



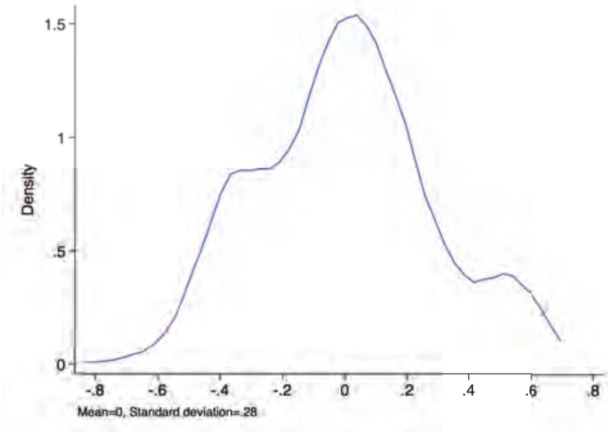

C. Using G3 distribution



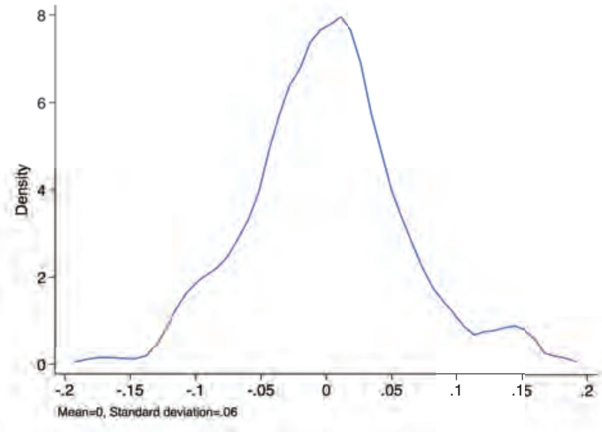

D. Using G4 distribution

Notes: Each panel shows the coefficients $\beta_k$ from the following event study: $Y_{ibc} = \alpha + \sum_{k=-12}^{4} \beta_k \cdot D_k + W'_{ibc} \cdot \phi + \gamma_c + \eta_b + \varepsilon_{ibc}$. The variable $D_k$ is equal to 1 in areas with computer-assisted learning after the reform ($k \geq 0$), and is equal to 0 otherwise. The omitted birth cohort completed middle school 13 years before the reform (27 years old at the time of the reform). Individuals in areas that did not receive computer-aided learning (G5) are distributed across periods according to their age when the reform was first implemented in G1 (panel A), G2 (panel B), G3 (panel C), and G4 (panel D). The dependent variable is completed years of education. Vertical dashed bars are 95% confidence intervals computed from standard errors clustered at the county level. Source: CFPS, 2010 and 2014, individuals born from 1977.

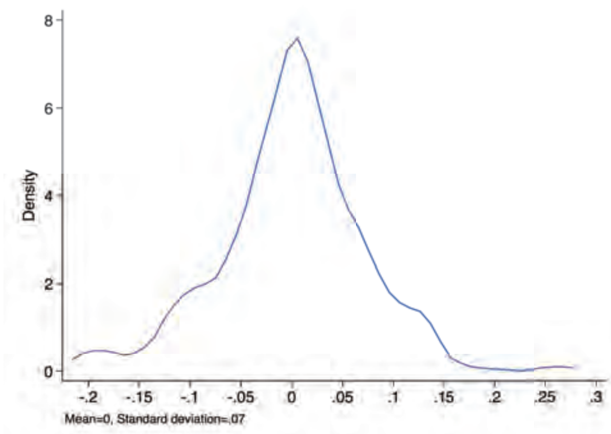
**Figure E3:** Placebo Test, Random CAL Among Pre-Reform Cohorts



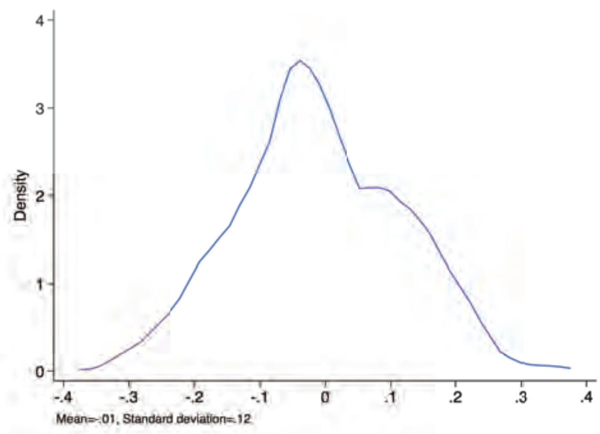

A. Years of completed education




B. Math skills



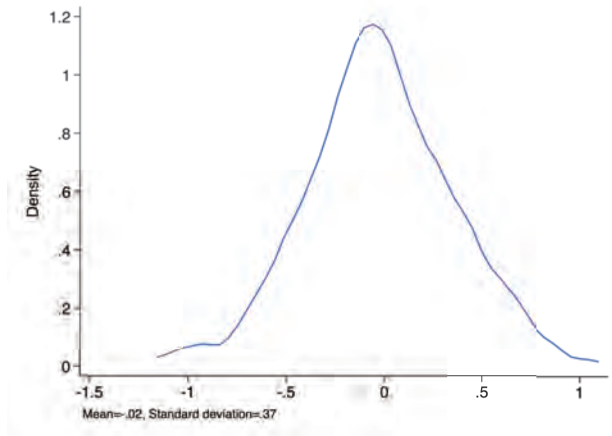

C. Chinese skills



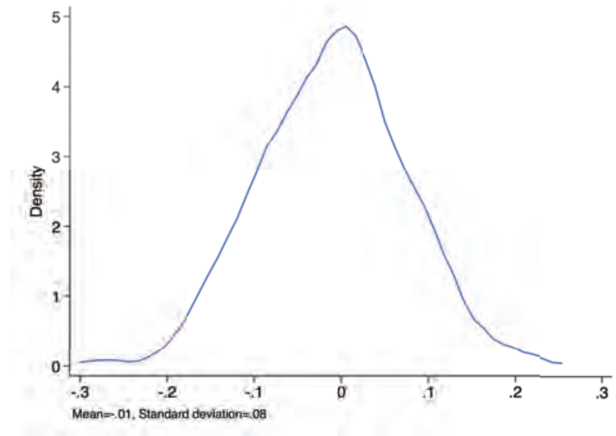

D. Log earnings

Notes: This placebo test randomizes the implementation of the reform among birth cohorts who completed middle school before the actual reform. The figures show the distribution of the coefficient of "false" CAL exposure for different long-term outcomes. The sample includes only individuals who were not actually exposed to CAL in middle school. Source: CFPS, 2010 and 2014, individuals born from 1977.

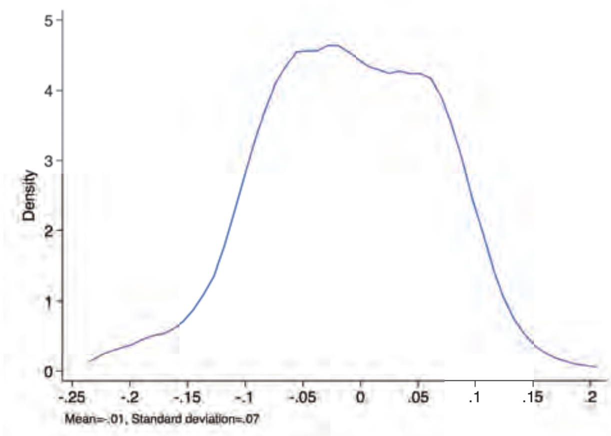
**Figure E4:** Placebo Test, Random CAL Among Different Counties



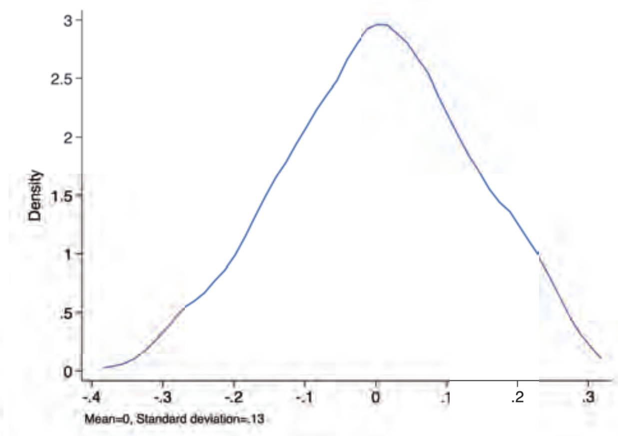

A. Years of completed education




B. Math skills




C. Chinese skills




D. Log earnings

Notes: This placebo test randomizes the implementation of the reform among different counties. The figures show the distribution of the coefficient of "false" CAL exposure for different long-term outcomes. Source: CFPS, 2010 and 2014, individuals born from 1977.

**Table E1:** Variable List

| | |
|---|---|
| Panel A: Education outcomes | |
| Years of education | 2014 wave, missing values filled in with 2010 wave |
| Middle school diploma | 2014 wave, missing values filled in with 2010 wave |
| High school diploma | 2014 wave, missing values filled in with 2010 wave |
| College degree | 2014 wave, missing values filled in with 2010 wave |
| Math score | 2014 wave, missing values filled in with 2010 wave |
| Chinese score | 2014 wave, missing values filled in with 2010 wave |
| Panel B: Labor market outcomes | |
| Labor force participation | 2014 wave, missing values filled in with 2010 wave |
| Log earnings | 2014 wave, missing values filled in with 2010 wave |
| Cognitive skills | 2014 wave, missing values filled in with 2010 wave |
| Manual skills | 2014 wave, missing values filled in with 2010 wave |
| Farmer | 2014 wave, missing values filled in with 2010 wave |
| Panel C: Internet usage | |
| Internet use (dummy) | 2014 wave |
| Frequency in using computer for work | 2014 wave |
| Frequency in using computer for socializing | 2014 wave |
| Panel D: Noncognitive skills | |
| Satisfaction index | 2014 wave |
| Popularity | 2014 wave |
| Happiness | 2014 wave |
| Getting along with others | 2014 wave |
| Anxiety index | 2014 wave |
| Depression | 2014 wave |
| Nervousness | 2014 wave |
| Difficulty in doing things | 2014 wave |

Notes: The CFPS is a survey with a panel design. Our analysis is based on the 2014 wave. We use observations from the 2010 wave only when observations are not available in 2010. We cannot carry out this procedure for variables measuring internet usage or noncognitive skills because the questionnaire is not consistent across waves.

## **Table E2:** Differences Between Treated Geographical Areas

| | Group 1 vs. G2-3-4 | Group 2 vs. G1-3-4 | Group 3 vs. G1-2-4 | Group 4 vs. G1-2-3 | Mean | Standard Deviation |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Panel A: Selection criteria | | | | | |
| Midwest | 0.329*** | -0.184* | -0.047 | 0.006 | 0.50 | 0.50 |
| | (0.108) | (0.097) | (0.116) | (0.116) | | |
| Share of rural residents | 0.023 | 0.016 | -0.059 | 0.017 | 0.82 | 0.16 |
| | (0.029) | (0.030) | (0.050) | (0.030) | | |
| Log number of cellphone users (/10,000 residents) | -0.143 | -0.006 | 0.128 | 0.009 | 6.18 | 0.91 |
| | (0.214) | (0.184) | (0.222) | (0.211) | | |
| Log number of internet users (/10,000 residents) | -0.063 | 0.077 | 0.355 | -0.437 | 3.79 | 1.55 |
| | (0.301) | (0.297) | (0.373) | (0.490) | | |
| Log value of postal services (10k CNY/10k residents) | -0.010 | 0.274 | 0.137 | -0.546** | 4.18 | 0.98 |
| | (0.243) | (0.195) | (0.211) | (0.234) | | |
| Log number of telephone users (/10,000 residents) | -0.081 | 0.152 | 0.176 | -0.327* | 6.81 | 0.67 |
| | (0.136) | (0.128) | (0.165) | (0.183) | | |
| Log population (/10,000 residents) | -0.119 | -0.006 | 0.005 | 0.119 | 4.03 | 0.83 |
| | (0.200) | (0.165) | (0.189) | (0.213) | | |
| Log GDP in primary sector (10k CNY/10,000 residents) | -0.020 | 0.272** | -0.062 | -0.305* | 6.94 | 0.63 |
| | (0.140) | (0.118) | (0.151) | (0.169) | | |
| Share of primary sector | -0.018 | 0.041* | -0.023* | -0.019 | 0.05 | 0.09 |
| | (0.014) | (0.022) | (0.013) | (0.014) | | |
| Share of secondary sector | 0.018 | 0.001 | -0.003 | -0.014 | 0.31 | 0.17 |
| | (0.045) | (0.034) | (0.033) | (0.041) | | |
| Share of tertiary sector | -0.000 | -0.042 | 0.026 | 0.034 | 0.64 | 0.16 |
| | (0.041) | (0.032) | (0.031) | (0.040) | | |
| Log wage bill (10k CNY/10,000 residents) | -0.049 | 0.094 | 0.100 | -0.194 | 5.98 | 0.68 |
| | (0.151) | (0.129) | (0.196) | (0.145) | | |
| Log yield of major crops (10,000 tons/10,000 residents) | 0.277 | 0.181 | -0.411 | -0.090 | 7.69 | 1.08 |
| | (0.203) | (0.222) | (0.262) | (0.253) | | |
| Log revenues of local government (10k CNY/10,000 residents) | -0.117 | 0.092 | 0.342 | -0.383 | 5.57 | 1.01 |
| | (0.271) | (0.175) | (0.290) | (0.236) | | |
| Log expenses of local government (10k CNY/10,000 residents) | -0.050 | 0.043 | 0.137 | -0.159 | 6.15 | 0.58 |
| | (0.105) | (0.104) | (0.184) | (0.149) | | |
| Log expenses for science (10k CNY/10,000 residents) | -0.584** | -0.014 | 0.691** | -0.157 | -0.24 | 1.30 |
| | (0.292) | (0.238) | (0.331) | (0.370) | | |
| Log expenses for education (10k CNY/10,000 residents) | -0.020 | 0.107 | 0.153 | -0.298* | 4.68 | 0.57 |
| | (0.109) | (0.105) | (0.159) | (0.155) | | |
| Log deposits (10k CNY/10,000 residents) | -0.159 | 0.093 | 0.177 | -0.168 | 8.20 | 0.92 |
| | (0.200) | (0.173) | (0.257) | (0.221) | | |
| Log loans (10k CNY/10,000 residents) | -0.061 | -0.060 | 0.167 | -0.032 | 7.91 | 0.93 |
| | (0.203) | (0.179) | (0.273) | (0.203) | | |
| Log number of tertiary schools (/100,000 residents) | -0.019 | -0.007 | 0.022 | 0.004 | 0.04 | 0.11 |
| | (0.022) | (0.023) | (0.033) | (0.026) | | |
| Log number of secondary schools (/100,000 residents) | 0.123 | 0.100 | 0.099 | -0.368* | 1.60 | 0.74 |
| | (0.156) | (0.141) | (0.175) | (0.212) | | |
| Log number of primary schools (/100,000 residents) | 0.053 | 0.129 | 0.214 | -0.465 | 3.45 | 1.13 |
| | (0.266) | (0.209) | (0.260) | (0.325) | | |
| Log number of students in tertiary schools (/10,000 residents) | -0.335 | -0.196 | -0.007 | 0.605 | 0.87 | 1.89 |
| | (0.404) | (0.379) | (0.461) | (0.485) | | |
| Log number of students in secondary schools (/10,000 residents) | 0.090 | 0.125 | 0.080 | -0.351* | 6.15 | 0.68 |
| | (0.137) | (0.131) | (0.155) | (0.200) | | |
| Log number of students in primary schools (/10,000 residents) | 0.052 | 0.232 | -0.031 | -0.351 | 6.63 | 0.77 |
| | (0.165) | (0.142) | (0.176) | (0.235) | | |
| Log number of teachers in tertiary schools (/10,000 residents) | -0.183 | -0.081 | 0.052 | 0.235 | 0.40 | 0.94 |
| | (0.189) | (0.192) | (0.243) | (0.230) | | |
| Log number of teachers in secondary schools (/10,000 residents) | 0.007 | 0.117 | 0.121 | -0.304* | 3.25 | 0.60 |
| | (0.128) | (0.116) | (0.133) | (0.163) | | |
| Log number of teachers in primary schools (/10,000 residents) | 0.000 | 0.121 | 0.119 | -0.300 | 3.62 | 0.68 |
| | (0.144) | (0.129) | (0.153) | (0.203) | | |
| Log number of hospitals beds (/100,000 residents) | 0.073 | 0.022 | 0.016 | -0.119 | 5.07 | 0.53 |
| | (0.114) | (0.101) | (0.145) | (0.128) | | |

Notes: This table shows baseline differences between the geographical areas that received computer-aided learning (G1 2004, G2 2005, G3 2006, G4 2007). Columns 1 to 4 show the estimated difference (and standard error) between different groups. Columns 5 and 6 shows the average and standard deviation of each dependent variable. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Source: China County Statistical Yearbook, 2002.

**Table E3:** Differences Between Treated Geographical Areas, Continued

| | Group 1 | Group 2 | Group 3 |
|---|---|---|---|
| | (1) | (2) | (3) |
| | Share of rural residents | | |
| Group 2 | -0.008 | - | - |
| | (0.032) | - | - |
| Group 3 | -0.064 | -0.056 | - |
| | (0.054) | (0.053) | - |
| Group 4 | -0.004 | 0.003 | 0.059 |
| | (0.033) | (0.033) | (0.054) |
| | Log number of cellphone users (/10,000 residents) | | |
| Group 2 | 0.111 | - | - |
| | (0.241) | - | - |
| Group 3 | 0.214 | 0.103 | - |
| | (0.279) | (0.249) | - |
| Group 4 | 0.122 | 0.011 | -0.092 |
| | (0.269) | (0.238) | (0.276) |
| | Log number of Internet users (/10,000 residents) | | |
| Group 2 | 0.100 | - | - |
| | (0.323) | - | - |
| Group 3 | 0.323 | 0.223 | - |
| | (0.413) | (0.396) | - |
| Group 4 | -0.297 | -0.397 | -0.620 |
| | (0.532) | (0.516) | (0.579) |
| | Log population (/10,000) | | |
| Group 2 | 0.092 | - | - |
| | (0.221) | - | - |
| Group 3 | 0.100 | 0.007 | - |
| | (0.247) | (0.210) | - |
| Group 4 | 0.191 | 0.099 | 0.091 |
| | (0.268) | (0.234) | (0.258) |
| | Log GDP (10k CNY/10,000 residents) | | |
| Group 2 | 0.187 | - | - |
| | (0.150) | - | - |
| Group 3 | -0.032 | -0.219 | - |
| | (0.183) | (0.160) | - |
| Group 4 | -0.226 | -0.413** | -0.194 |
| | (0.200) | (0.180) | (0.208) |

Notes: This table shows baseline differences between the geographical areas that received computer-aided learning (G1 2004, G2 2005, G3 2006, G4 2007) for few selected observable characteristics. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Source: China County Statistical Yearbook, 2002.

**Table E4:** Trends Before the Implementation of Computer-Aided Learning, Event Studies

| | Years of education | Math skills | Chinese skills | MS diploma | LM participation | Log earnings | Internet use | Anxiety index |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | | | | Panel A: Linear trends | | | | |
| Linear trend | 0.527 | -0.252 | -0.176 | 0.064 | 0.081 | -0.045 | -0.153 | 0.011 |
| | (0.627) | (0.174) | (0.143) | (0.073) | (0.146) | (0.266) | (0.092) | (0.381) |
| Observations | 2,970 | 2,970 | 2,970 | 2,970 | 2,970 | 2,454 | 1,926 | 1,924 |
| $R^2$ | 0.426 | 0.368 | 0.396 | 0.233 | 0.165 | 0.272 | 0.368 | 0.183 |
| | | | | Panel B: Quadratic trends | | | | |
| Linear trend | 0.429 | -0.085 | -0.029 | 0.066 | 0.083 | -0.052 | -0.093 | 0.096 |
| | (0.387) | (0.116) | (0.090) | (0.048) | (0.083) | (0.196) | (0.061) | (0.210) |
| Linear trend$^2$ | 0.098 | -0.167* | -0.147* | -0.002 | -0.002 | 0.006 | -0.060 | -0.086 |
| | (0.383) | (0.098) | (0.081) | (0.038) | (0.078) | (0.167) | (0.080) | (0.206) |
| Observations | 2,970 | 2,970 | 2,970 | 2,970 | 2,970 | 2,454 | 1,926 | 1,924 |
| $R^2$ | 0.426 | 0.368 | 0.396 | 0.233 | 0.165 | 0.272 | 0.368 | 0.183 |
| F-test | 0.54 | 0.23 | 0.18 | 0.33 | 0.39 | 0.96 | 0.19 | 0.55 |
| | | | | Panel C: Cubic trends | | | | |
| Linear trend | 0.320 | -0.098 | -0.008 | 0.039 | 0.110 | 0.120 | -0.038 | 0.162 |
| | (0.486) | (0.134) | (0.096) | (0.061) | (0.089) | (0.224) | (0.068) | (0.228) |
| Linear trend$^2$ | 0.079 | -0.170* | -0.143* | -0.007 | 0.002 | 0.033 | -0.048 | -0.072 |
| | (0.391) | (0.098) | (0.078) | (0.038) | (0.078) | (0.169) | (0.083) | (0.207) |
| Linear trend$^3$ | -0.001 | -0.000 | 0.000 | -0.000 | 0.000 | 0.002* | 0.001 | 0.001 |
| | (0.003) | (0.001) | (0.001) | (0.000) | (0.000) | (0.001) | (0.000) | (0.001) |
| Observations | 2,970 | 2,970 | 2,970 | 2,970 | 2,970 | 2,454 | 1,926 | 1,924 |
| $R^2$ | 0.426 | 0.368 | 0.396 | 0.234 | 0.165 | 0.273 | 0.369 | 0.184 |
| F-test | 0.65 | 0.39 | 0.32 | 0.36 | 0.44 | 0.26 | 0.06 | 0.62 |
| Mean | 8.51 | -0.28 | -0.28 | 0.64 | 0.53 | 9.02 | 0.49 | -0.02 |
| Std. dev. | 4.10 | 1.01 | 1.05 | 0.48 | 0.50 | 1.36 | 0.50 | 0.84 |

Notes: This table shows pre-reform trends in education and labor outcomes in treated counties (G1 to G4). The sample is organized as an event study in which period 0 is the first year with CAL education in each treated county. The pre-reform trends cover periods -13 to -1. Individuals are assigned to different counties based on their residence at age 12 . Panel A estimates linear pre-reform trends: $\mathrm{Y}_{ibc} = \alpha + \beta_1 \cdot \mathrm{CAL\ t}_b + \gamma_b + \delta_c + \mathrm{W}'_{ibc} \cdot \phi + \delta_c \cdot \mathrm{t}_b + \varepsilon_{ibc}$. In this specification, CAL $\mathrm{t}_b$ is a linear trend that measures the distance of birth cohorts to the implementation of the reform in their county, $\gamma_b$ are birth cohort fixed effects, $\delta_c$ are county fixed effects, $\mathrm{W}'_{ibc}$ is a set of individual characteristics, and $\mathrm{t}_b$ is a linear trend in the event periods. Panel B estimates quadratic pre-reform trends: $\mathrm{Y}_{ibc} = \alpha + \beta_1 \cdot \mathrm{CAL\ t}_b + \beta_2 \cdot \mathrm{CAL\ t}_b^2 + \gamma_b + \delta_c + \mathrm{W}'_{ibc} \cdot \phi + \delta_c \cdot \mathrm{t}_b + \varepsilon_{ibc}$. Panel C estimates cubic pre-reform trends: $\mathrm{Y}_{ibc} = \alpha + \beta_1 \cdot \mathrm{CAL\ t}_b + \beta_2 \cdot \mathrm{CAL\ t}_b^2 + \beta_3 \cdot \mathrm{CAL\ t}_b^3 + \gamma_b + \delta_c + \mathrm{W}'_{ibc} \cdot \phi + \delta_c \cdot \mathrm{t}_b + \varepsilon_{ibc}$. The dependent variables are: completed years of education (col. 1), math skills (col. 2), Chinese skills (col. 3), dummy for completed middle school education (col. 4), labor market participation (col. 5), log earnings (col. 6), frequency of internet use for work (col. 7), and an index for level of mental stress (col. 8). All regressions include individuals born between 1977 and 1988. Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Source: CFPS, 2010 and 2014, individuals born from 1977.

**Table E5:** Baseline Differences Between Cohorts

| | Full sample: G1-G5 | | | | Treated counties: G1-G4 | | | |
|---|---|---|---|---|---|---|---|---|
| | CAL | Obs. | $R^2$ | Mean outcome | CAL | Obs. | $R^2$ | Mean outcome |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Male | -0.006 | 5,176 | 0.051 | 0.50 | 0.001 | 4,357 | 0.024 | 0.49 |
| | (0.046) | | | | (0.053) | | | |
| Minority | -0.015 | 5,176 | 0.639 | 0.12 | -0.030* | 4,357 | 0.643 | 0.14 |
| | (0.015) | | | | (0.017) | | | |
| Number of siblings | 0.072 | 5,167 | 0.420 | 1.65 | 0.081 | 4,349 | 0.377 | 1.83 |
| | (0.070) | | | | (0.079) | | | |
| Father: no edu | -0.074** | 5,000 | 0.242 | 0.27 | -0.093** | 4,195 | 0.252 | .29 |
| | (0.034) | | | | (0.038) | | | |
| Father: primary edu | 0.061 | 5,000 | 0.100 | 0.30 | 0.052 | 4,195 | 0.096 | 0.30 |
| | (0.042) | | | | (0.045) | | | |
| Father: junior high edu | 0.030 | 5,000 | 0.140 | 0.30 | 0.056 | 4,195 | 0.136 | 0.28 |
| | (0.045) | | | | (0.051) | | | |
| Father: high school edu | -0.006 | 5,000 | 0.091 | 0.13 | -0.002 | 4,195 | 0.087 | 0.13 |
| | (0.028) | | | | (0.032) | | | |
| Father: college or more | -0.011 | 5,000 | 0.088 | 0.01 | -0.012** | 4,195 | 0.058 | 0.01 |
| | (0.007) | | | | (0.005) | | | |
| Father: member of Communist party | 0.021 | 4,734 | 0.086 | 0.09 | 0.017 | 3,964 | 0.083 | 0.10 |
| | (0.019) | | | | (0.020) | | | |
| Father: manager | 0.025 | 4,023 | 0.120 | 0.05 | 0.018 | 3,375 | 0.102 | 0.04 |
| | (0.020) | | | | (0.022) | | | |
| Mother: no edu | -0.089*** | 5,033 | 0.283 | 0.51 | -0.055 | 4,229 | 0.286 | 0.55 |
| | (0.033) | | | | (0.039) | | | |
| Mother: primary edu | 0.041 | 5,033 | 0.116 | 0.25 | 0.063** | 4,229 | 0.121 | 0.25 |
| | (0.029) | | | | (0.032) | | | |
| Mother: junior high edu | 0.006 | 5,033 | 0.226 | 0.18 | -0.036 | 4,229 | 0.201 | 0.16 |
| | (0.033) | | | | (0.034) | | | |
| Mother: high school edu | 0.045*** | 5,033 | 0.095 | 0.05 | 0.031* | 4,229 | 0.085 | 0.04 |
| | (0.015) | | | | (0.016) | | | |
| Mother: college or more | -0.003 | 5,033 | 0.115 | 0.00 | -0.003 | 4,229 | 0.073 | 0.00 |
| | (0.007) | | | | (0.007) | | | |
| Mother: member of Communist party | 0.004 | 4,757 | 0.099 | 0.01 | 0.009 | 3,991 | 0.096 | 0.01 |
| | (0.010) | | | | (0.012) | | | |
| Mother: manager | -0.007 | 3,641 | 0.144 | 0.01 | -0.001 | 3,094 | 0.135 | 0.00 |
| | (0.012) | | | | (0.014) | | | |

Notes: This table shows baseline differences between cohorts who could benefit from computer-aided learning (CAL=1) and cohorts who were too old to benefit (CAL=0). Each row-column combination shows the coefficient $\beta$ from a different regression of exposure to computer-aided learning in a county on baseline individual characteristics: $\text{Baseline}_{ibc} = \alpha + \beta \cdot \text{CAL}_{bc} + \gamma_b + \delta_c + \varepsilon_{ibc}$, where $\gamma_b$ are birth cohort fixed effects and $\delta_c$ are county fixed effects. Rural counties received computer-aided learning in 2004 (G1), 2005 (G2), 2006 (G3), 2007 (G4). Some counties never received the program (G5). Columns 1 to 4 include all geographical areas. Columns 5 and 8 restrict the sample to areas that received the program at some point (G1-G4). All regressions include individuals born between 1977 and 1994. Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Source: CFPS, 2014 wave, individuals born from 1977.

**Table E6:** Dropping Low-Wage Counties

| | Years of education | Math skills | Chinese skills | MS diploma | LM participation | Log earnings | Internet use | Anxiety index |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| CAL | 0.950*** | 0.221** | 0.261*** | 0.098*** | 0.074* | 0.310** | 0.099** | -0.064 |
| | (0.335) | (0.093) | (0.077) | (0.032) | (0.043) | (0.147) | (0.048) | (0.122) |
| Observations | 3,531 | 3,531 | 3,531 | 3,531 | 3,531 | 2,725 | 2,145 | 2,143 |
| $R^2$ | 0.426 | 0.372 | 0.412 | 0.233 | 0.139 | 0.271 | 0.387 | 0.146 |
| Mean | 8.65 | -0.25 | -0.26 | 0.66 | 0.54 | 9.06 | 0.50 | 0.00 |
| Std. dev. | 4.22 | 1.02 | 1.07 | 0.48 | 0.50 | 1.36 | 0.50 | 0.82 |

Notes: This table shows the results dropping from the estimating sample the counties in the bottom decile of average wage. The remaining counties are less likely to have residents who started schools after the standard age (and therefore possibly miscategorized by the ITT specification). Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Source: CFPS, 2010 and 2014, individuals born from 1977.

**Table E7:** P-values Adjusted for Multiple Hypothesis Tests

| | Years of education | Math skills | Chinese skills | MS diploma | LM participation | Log earnings | Internet use | Anxiety index |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| CAL | 0.848*** | 0.183** | 0.227*** | 0.072** | 0.063 | 0.463*** | 0.082** | -0.172* |
| | (0.304) | (0.080) | (0.064) | (0.029) | (0.039) | (0.120) | (0.038) | (0.098) |
| P-value (W-Y) | 0.015 | 0.040 | <0.001 | 0.040 | 0.125 | 0.005 | 0.090 | 0.110 |
| P-values (B-H) | 0.018 | 0.029 | 0.002 | 0.029 | 0.113 | <0.001 | 0.103 | 0.149 |
| P-values (S-H) | 0.018 | 0.029 | 0.002 | 0.029 | 0.113 | <0.001 | 0.099 | 0.144 |

Notes: This table computes adjusted p-values using three different methodologies: Westfall-Young (Westfall and Young, 1993), Bonferroni-Holm, and Sidak-Holm. The table uses the user-written Stata command `wyoung` (Jones, Molitor, and Reif, 2019). All specifications include birth cohort fixed effects, a set of individual characteristics (an indicator variable for minority groups, the number of siblings, and dummy variables measuring the paternal schooling level), and county-specific linear trends. Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Source: CFPS, 2010 and 2014, individuals born from 1977.

**Table E8:** Decomposition of the CAL Effect on Earnings

| | Across occupations: Log mean earnings (1) | Across migration: Log mean earnings (2) | Within occupation and migration: Log deviation from mean earnings (3) |
|---|---|---|---|
| CAL | 0.155*** | 0.013 | 0.295** |
| | (0.051) | (0.009) | (0.117) |
| Observations | 3,889 | 3,889 | 3,889 |
| $R^2$ | 0.255 | 0.367 | 0.193 |

Notes: This table shows the decomposition of the total effect of CAL on earnings. Column 1 shows the effect of CAL on the log average earnings in each occupation. It measures movements across occupations of individuals exposed to computer-assisted learning. Column 2 shows the effect of CAL on the log average earning in each migration status (a dummy equal 1 for individuals who migrated from rural to urban areas after age 12). Column 3 shows the effect of CAL on the distance between individual earnings and the average earnings in a given occupation and migration status. These specifications also include birth cohort fixed effects, county fixed effects, a set of individual characteristics (an indicator variable for minority groups, the number of siblings, and dummy variables measuring the paternal schooling level), and county-specific linear trends in birth cohorts. Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Source: CFPS, 2014 wave, individuals born from 1977.

**Table E9:** Effect of CAL on Urban-Rural Gap

| | Urban sample (1) | Rural sample (2) | Urban-rural gap (3) | Effect of CAL (4) | Reduction in urban-rural gap (5) |
|---|---|---|---|---|---|
| Years of education | 13.22 | 9.09 | 4.13 | 0.848 | 21% |
| Log earnings | 9.71 | 9.12 | 0.59 | 0.463 | 78% |
| Math score | 0.68 | -0.16 | 0.84 | 0.183 | 22% |
| Chinese score | 0.45 | -0.17 | 0.62 | 0.227 | 37% |

Notes: Column 1 and column 2 presents the average statistics for individuals living in urban and rural areas and not exposed to CAL. Column 3 computes the baseline urban-rural gap. Column 4 shows the estimated effect of CAL for each outcome (from Table 4). Column 5 is the estimated effect of CAL on the preexisting rural-urban gap. The percentages in column 5 are derived by dividing the estimated improvement in a given outcome for individuals living in rural areas by the baseline urban-rural gap.

**Table E10:** CAL Effect on Firm Performance

| | TFP | Profit | Value added |
|---|---|---|---|
| | (1) | (2) | (3) |
| CAL | 0.007 | -0.003 | 0.0004 |
| | (0.008) | (0.017) | (0.0093) |
| Mean dep. var. | 4.00 | 6.59 | 8.71 |
| Observations | 1,287,749 | 1,053,959 | 1,310,604 |
| $R^2$ | 0.780 | 0.806 | 0.839 |

Notes: This table shows the effect of CAL on the performance of Chinese firms. These specifications also include firm fixed effects, county fixed effect, and year fixed effect, as well as county-specific linear trends. For the construction of TFP, we follow the methodology used by Brandt, Van Biesebroeck, and Zhang (2012) on a sample of Chinese manufacturing firms (index number estimates of productivity). Profit and value added are expressed in thousands of CNY. Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Source: Annual Surveys of Industrial Firms (ASIF), 2002 to 2007.

**Table E11:** Robustness of ITT Estimates to Implementation of Reform

| | Years of education | Math skills | Chinese skills | MS diploma | LM participation | Log earnings | Internet use | Anxiety index |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: Treatment at prefecture level | | | | | | | | |
| CAL | 0.766** | 0.105 | 0.173** | 0.043 | 0.013 | 0.399*** | 0.076** | -0.221** |
| | (0.307) | (0.080) | (0.070) | (0.031) | (0.041) | (0.131) | (0.037) | (0.092) |
| Observations | 4,996 | 4,996 | 4,996 | 4,996 | 4,996 | 3,889 | 3,109 | 3,107 |
| $R^2$ | 0.408 | 0.348 | 0.369 | 0.222 | 0.148 | 0.267 | 0.381 | 0.149 |
| Panel B: Dropping counties that completed implementation early | | | | | | | | |
| CAL | 0.807** | 0.195** | 0.217*** | 0.063** | 0.067* | 0.495*** | 0.083** | -0.178* |
| | (0.309) | (0.080) | (0.065) | (0.029) | (0.040) | (0.121) | (0.039) | (0.097) |
| Observations | 4,834 | 4,834 | 4,834 | 4,834 | 4,834 | 3,755 | 3,035 | 3,034 |
| $R^2$ | 0.433 | 0.372 | 0.384 | 0.242 | 0.165 | 0.285 | 0.401 | 0.156 |
| Panel C: Dropping Shandong province | | | | | | | | |
| CAL | 0.916*** | 0.188** | 0.234*** | 0.067** | 0.060 | 0.483*** | 0.088** | -0.156 |
| | (0.308) | (0.081) | (0.064) | (0.029) | (0.041) | (0.124) | (0.038) | (0.097) |
| Observations | 4,783 | 4,783 | 4,783 | 4,783 | 4,783 | 3,721 | 2,954 | 2,952 |
| $R^2$ | 0.430 | 0.365 | 0.386 | 0.241 | 0.164 | 0.282 | 0.410 | 0.164 |

Notes: This table shows the robustness of the intent-to-treat results to the implementation of the reform. In panel A, the treatment variable is based on the original implementation plan at the prefecture level. Therefore, all counties within a prefecture receive the same treatment year, regardless of their actual first year of implementation. Panel B drops all counties in the Guizhou province. These areas might have completed the implementation of the reform in 2006, instead of in 2007 as originally planned. Panel C drops all counties in the Shandong province. Even though these areas were not supposed to receive the program, a report suggests that they implemented it. Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Source: CFPS, 2010 and 2014.

**Table E12:** Different Trends, Effects of Computer-Assisted Learning

| | Years of education | Math skills | Chinese skills | MS diploma | LM participation | Log earnings | Internet use | Anxiety index |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | | | | Panel A: County-level trends | | | | |
| CAL | 0.848*** | 0.183** | 0.227*** | 0.072** | 0.063 | 0.463*** | 0.082** | -0.172* |
| | (0.304) | (0.080) | (0.064) | (0.029) | (0.039) | (0.120) | (0.038) | (0.098) |
| Observations | 4,996 | 4,996 | 4,996 | 4,996 | 4,996 | 3,889 | 3,109 | 3,107 |
| $R^2$ | 0.429 | 0.368 | 0.389 | 0.241 | 0.161 | 0.281 | 0.404 | 0.164 |
| | | | | Panel B: Prefecture-level trends | | | | |
| CAL | 0.814*** | 0.173** | 0.222*** | 0.069** | 0.057 | 0.463*** | 0.084** | -0.179* |
| | (0.297) | (0.078) | (0.064) | (0.028) | (0.038) | (0.117) | (0.038) | (0.099) |
| Observations | 4,996 | 4,996 | 4,996 | 4,996 | 4,996 | 3,889 | 3,109 | 3,107 |
| $R^2$ | 0.426 | 0.365 | 0.387 | 0.235 | 0.157 | 0.278 | 0.398 | 0.157 |
| | | | | Panel C: Trends in selecting criteria | | | | |
| CAL | 0.525* | 0.119 | 0.163** | 0.049 | 0.064* | 0.397*** | 0.091** | -0.090 |
| | (0.305) | (0.082) | (0.070) | (0.032) | (0.033) | (0.105) | (0.039) | (0.072) |
| Observations | 4,858 | 4,858 | 4,858 | 4,858 | 4,858 | 3,778 | 3,018 | 3,016 |
| $R^2$ | 0.402 | 0.343 | 0.367 | 0.206 | 0.134 | 0.247 | 0.356 | 0.121 |
| | | | | Panel D: No trends | | | | |
| CAL | 0.730** | 0.163** | 0.181*** | 0.073*** | 0.061** | 0.437*** | 0.122*** | -0.073 |
| | (0.296) | (0.074) | (0.059) | (0.028) | (0.030) | (0.108) | (0.036) | (0.067) |
| Observations | 4,996 | 4,996 | 4,996 | 4,996 | 4,996 | 3,889 | 3,109 | 3,107 |
| $R^2$ | 0.400 | 0.341 | 0.363 | 0.205 | 0.134 | 0.245 | 0.357 | 0.121 |
| Mean | 9.12 | -0.15 | -0.16 | 0.69 | 0.56 | 9.13 | 0.50 | 0.00 |
| Std. dev. | 4.14 | 1.00 | 1.02 | 0.46 | 0.50 | 1.36 | 0.50 | 0.82 |

Notes: This table shows differences between cohorts who were exposed to computer-aided learning (CAL=1) and cohorts who were not (CAL=0). Each panel shows the coefficient $\beta$ from a different regression of exposure to computer-aided learning on several outcome variables: $\mathrm{Y}_{ibc} = \alpha + \beta \cdot \mathrm{CAL}_{bc} + \gamma_b + \delta_c + \mathrm{W}'_{ibc} \cdot \phi + \mathrm{Pol}'_c \cdot \mathrm{CAL}_{bc} \cdot \psi + \mathrm{trends}_{bc} + \varepsilon_{ibc}$. The trends are: interactions between county fixed effects and linear trends in birth cohorts (baseline, panel A); interactions between prefecture fixed effects and linear trends in birth cohorts (panel B); interactions between county characteristics measured in 2003 (share of rural residents, number of cellphone users, number of internet users, number of post offices, number of telephone users, a dummy for midwest regions) and linear trends in birth cohorts (panel C); no county-specific trends (panel D). Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Source: CFPS, 2010 and 2014, individuals born from 1977.

**Table E13:** Different Birth Cohorts, Effects of Computer-Assisted Learning

| | Years of education | Math skills | Chinese skills | MS diploma | LM participation | Log earnings | Internet use | Anxiety index |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: Baseline (1977-1994) | | | | | | | | |
| CAL | 0.848*** | 0.183** | 0.227*** | 0.072** | 0.063 | 0.463*** | 0.082** | -0.172* |
| | (0.304) | (0.080) | (0.064) | (0.029) | (0.039) | (0.120) | (0.038) | (0.098) |
| Observations | 4,996 | 4,996 | 4,996 | 4,996 | 4,996 | 3,889 | 3,109 | 3,107 |
| $R^2$ | 0.429 | 0.368 | 0.389 | 0.241 | 0.161 | 0.281 | 0.404 | 0.164 |
| Panel B: 1980-1994 | | | | | | | | |
| CAL | 0.872*** | 0.191** | 0.234*** | 0.079*** | 0.071* | 0.466*** | 0.079* | -0.120 |
| | (0.307) | (0.082) | (0.065) | (0.030) | (0.040) | (0.131) | (0.044) | (0.102) |
| Observations | 4,189 | 4,189 | 4,189 | 4,189 | 4,189 | 3,203 | 2,520 | 2,518 |
| $R^2$ | 0.428 | 0.357 | 0.391 | 0.238 | 0.161 | 0.289 | 0.395 | 0.181 |
| Panel C: 1985-1994 | | | | | | | | |
| CAL | 0.801** | 0.179** | 0.171** | 0.084** | 0.074* | 0.446*** | 0.033 | -0.133 |
| | (0.339) | (0.089) | (0.068) | (0.034) | (0.044) | (0.148) | (0.049) | (0.113) |
| Observations | 2,971 | 2,971 | 2,971 | 2,971 | 2,971 | 2,144 | 1,652 | 1,652 |
| $R^2$ | 0.404 | 0.333 | 0.368 | 0.224 | 0.173 | 0.310 | 0.409 | 0.235 |
| Panel D: 1970-1994 | | | | | | | | |
| CAL | 0.940*** | 0.206*** | 0.226*** | 0.078** | 0.063* | 0.457*** | 0.113*** | -0.132 |
| | (0.303) | (0.078) | (0.064) | (0.030) | (0.036) | (0.107) | (0.037) | (0.081) |
| Observations | 7,606 | 7,606 | 7,606 | 7,606 | 7,606 | 6,159 | 5,164 | 5,160 |
| $R^2$ | 0.436 | 0.394 | 0.401 | 0.241 | 0.150 | 0.268 | 0.408 | 0.132 |
| Mean | 9.12 | -0.15 | -0.16 | 0.69 | 0.56 | 9.13 | 0.50 | 0.00 |
| Std. dev. | 4.14 | 1.00 | 1.02 | 0.46 | 0.50 | 1.36 | 0.50 | 0.82 |

Notes: This table shows differences between cohorts who were exposed to computer-aided learning (CAL=1) and cohorts who were not (CAL=0). Each row-column combination shows the coefficient $\beta$ from a different regression of exposure to computer-aided learning on several outcome variables: $\mathrm{Y}_{ibc} = \alpha + \beta \cdot \mathrm{CAL}_{bc} + \gamma_b + \delta_c + \mathrm{W}'_{ibc} \cdot \phi + \mathrm{Pol}'_c \cdot \mathrm{CAL}_{bc} \cdot \psi + \delta_c \cdot \mathrm{t}_b + \varepsilon_{ibc}$. The estimating samples are: cohorts between 1977 and 1994 (baseline, panel A); cohorts between 1980 and 1994 (panel B); cohorts between 1985 and 1994 (panel C); cohorts between 1970 and 1994 (panel D). Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Source: CFPS, 2010 and 2014, individuals born from 1977.

**Table E14:** Different Age Groups, Effects of Computer-Assisted Learning

| | Years of education | Math skills | Chinese skills | MS diploma | LM participation | Log earnings | Internet use | Anxiety index |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | | | | Panel A: 10-27 | | | | |
| CAL | 0.903*** | 0.189** | 0.231*** | 0.075** | 0.058 | 0.473*** | 0.087** | -0.153 |
| | (0.307) | (0.079) | (0.064) | (0.030) | (0.038) | (0.119) | (0.039) | (0.096) |
| Observations | 4,964 | 4,964 | 4,964 | 4,964 | 4,964 | 3,870 | 3,095 | 3,093 |
| $R^2$ | 0.422 | 0.361 | 0.383 | 0.232 | 0.156 | 0.283 | 0.392 | 0.162 |
| | | | | Panel B: 10-24 | | | | |
| CAL | 0.909*** | 0.188** | 0.227*** | 0.081*** | 0.068* | 0.441*** | 0.073* | -0.138 |
| | (0.302) | (0.079) | (0.063) | (0.031) | (0.040) | (0.127) | (0.043) | (0.100) |
| Observations | 4,151 | 4,151 | 4,151 | 4,151 | 4,151 | 3,175 | 2,500 | 2,498 |
| $R^2$ | 0.416 | 0.349 | 0.377 | 0.234 | 0.163 | 0.290 | 0.393 | 0.182 |
| | | | | Panel C: 10-21 | | | | |
| CAL | 0.764** | 0.183** | 0.177*** | 0.077** | 0.058 | 0.395*** | 0.050 | -0.190* |
| | (0.326) | (0.084) | (0.067) | (0.031) | (0.043) | (0.135) | (0.048) | (0.112) |
| Observations | 3,404 | 3,404 | 3,404 | 3,404 | 3,404 | 2,521 | 1,950 | 1,949 |
| $R^2$ | 0.411 | 0.338 | 0.370 | 0.232 | 0.175 | 0.307 | 0.399 | 0.227 |
| Mean | 9.19 | -0.13 | -0.15 | 0.69 | 0.56 | 9.15 | 0.55 | 0.00 |
| Std. dev. | 4.11 | 1.00 | 1.01 | 0.46 | 0.50 | 1.36 | 0.50 | 0.82 |

Notes: This table shows differences between cohorts who were exposed to computer-aided learning (CAL=1) and cohorts who were not (CAL=0). Each row-column combination shows the coefficient $\beta$ from a different regression of exposure to computer-aided learning on several outcome variables: $\mathrm{Y}_{ibc} = \alpha + \beta \cdot \mathrm{CAL}_{bc} + \gamma_b + \delta_c + \mathrm{W}'_{ibc} \cdot \phi + \mathrm{Pol}'_c \cdot \mathrm{CAL}_{bc} \cdot \psi + \delta_c \cdot \mathrm{t}_b + \varepsilon_{ibc}$. The estimating samples are: individuals who were between 10 and 27 years old at the time of the policy implementation (panel A); individuals who were between 10 and 24 years old at the time of the policy implementation (panel B); individuals who were between 10 and 21 years old at the time of the policy implementation (panel C). Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Source: CFPS, 2010 and 2014.

**Table E15:** Middle School Graduates, Effects of Computer-Assisted Learning

| | Years of education | Math skills | Chinese skills | LM participation | Log earnings | Manual skills | Internet use | Anxiety index |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| CAL | -2.279*** | -0.614*** | -0.280*** | 0.159*** | 0.489*** | -0.023 | -0.084 | -0.174 |
| | (0.412) | (0.117) | (0.106) | (0.046) | (0.183) | (0.141) | (0.072) | (0.140) |
| CAL*Middle school | 3.786*** | 0.965*** | 0.614*** | -0.117*** | -0.032 | -0.294*** | 0.194*** | 0.002 |
| | (0.250) | (0.076) | (0.081) | (0.043) | (0.173) | (0.108) | (0.070) | (0.112) |
| Observations | 4,996 | 4,996 | 4,996 | 4,996 | 3,889 | 3,341 | 3,109 | 3,107 |
| $R^2$ | 0.458 | 0.398 | 0.401 | 0.163 | 0.281 | 0.269 | 0.407 | 0.164 |
| Mean | 9.12 | -0.15 | -0.16 | 0.56 | 9.13 | 0.02 | 0.54 | 0.00 |
| Std. dev. | 4.14 | 1.00 | 1.02 | 0.50 | 1.36 | 1.01 | 0.50 | 0.82 |
| Effect on MS grads | 1.507 | 0.351 | 0.334 | 0.042 | 0.457 | -0.317 | 0.110 | -0.171 |
| | (0.314) | (0.083) | (0.065) | (0.042) | (0.125) | (0.105) | (0.040) | (0.098) |

Notes: This table shows how the implementation of the reform in middle schools interacted with graduating middle school. Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Source: CFPS, 2010 and 2014, individuals born from 1977.

**Table E16:** Controlling for Concurrent Policies

| | Years of education | Math skills | Chinese skills | MS diploma | LM participation | Log earnings | Internet use | Anxiety index |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| CAL | 0.599* | 0.100 | 0.155** | 0.051** | 0.067 | 0.382*** | 0.035 | -0.151 |
| | (0.306) | (0.075) | (0.062) | (0.026) | (0.047) | (0.125) | (0.040) | (0.110) |
| Observations | 4,194 | 4,194 | 4,194 | 4,194 | 4,194 | 3,254 | 2,650 | 2,649 |
| $R^2$ | 0.352 | 0.311 | 0.263 | 0.234 | 0.172 | 0.267 | 0.390 | 0.166 |
| Mean | 9.71 | -0.02 | -0.01 | 0.72 | 0.57 | 9.21 | 0.58 | 0.03 |
| Std. dev. | 3.67 | 0.92 | 0.87 | 0.45 | 0.50 | 1.32 | 0.49 | 0.81 |

Notes: This table shows differences between cohorts who were exposed to computer-aided learning (CAL=1) and cohorts who were not (CAL=0). In addition to the controls for concurrent education policies, also included in all baseline regressions, these specifications include controls for the trade liberalization following WTO accession, which started in 2001, and for the expansion of college enrollment, which started in 1998. We control for these concurrent policy changes by interacting birth cohort fixed effects with two variables (pre-WTO prefecture-level import tariff, and prefecture-level number of college students) that describe the effect of these reforms on each Chinese prefecture. Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Source: CFPS, 2010 and 2014, individuals born from 1977.

**Table E17:** Matching Outcomes

| | Full sample: G1-G5 | | | | Matched sample: G1-G5 | | | |
|---|---|---|---|---|---|---|---|---|
| | G5 | Obs. | $R^2$ | Mean outcome | G5 | Obs. | $R^2$ | Mean outcome |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Male | 0.019 | 4,874 | 0.007 | 0.50 | 0.012 | 1,559 | 0.037 | 0.53 |
| | (0.031) | | | | (0.047) | | | |
| Minority | 0.033 | 4,874 | 0.123 | 0.13 | -0.012* | 1,559 | 0.029 | 0.01 |
| | (0.046) | | | | (0.007) | | | |
| Number of siblings | -0.372** | 4,865 | 0.163 | 1.72 | -0.118 | 1,559 | 0.154 | 1.21 |
| | (0.154) | | | | (0.100) | | | |
| Father: no edu | 0.056 | 4,710 | 0.064 | 0.27 | 0.028 | 1,559 | 0.096 | 0.25 |
| | (0.044) | | | | (0.039) | | | |
| Father: primary edu | -0.062** | 4,710 | 0.018 | 0.30 | -0.019 | 1,559 | 0.046 | 0.36 |
| | (0.031) | | | | (0.044) | | | |
| Father: junior high edu | -0.019 | 4,710 | 0.049 | 0.30 | -0.038 | 1,559 | 0.140 | 0.33 |
| | (0.039) | | | | (0.040) | | | |
| Father: high school edu | 0.008 | 4,710 | 0.015 | 0.12 | 0.028 | 1,559 | 0.028 | 0.06 |
| | (0.023) | | | | (0.020) | | | |
| Father: college or more | 0.017* | 4,710 | 0.008 | 0.01 | 0.001 | 1,559 | 0.013 | 0.00 |
| | (0.009) | | | | (0.001) | | | |
| Father: member of Communist party | 0.018 | 4,456 | 0.008 | 0.09 | 0.009 | 1,559 | 0.020 | 0.02 |
| | (0.017) | | | | (0.010) | | | |
| Father: manager | 0.040* | 3,762 | 0.016 | 0.04 | 0.027 | 1,243 | 0.029 | 0.03 |
| | (0.023) | | | | (0.024) | | | |
| Mother: no edu | 0.082 | 4,739 | 0.083 | 0.52 | 0.076 | 1,559 | 0.145 | 0.54 |
| | (0.050) | | | | (0.052) | | | |
| Mother: primary edu | -0.097*** | 4,739 | 0.014 | 0.26 | -0.058* | 1,559 | 0.045 | 0.26 |
| | (0.031) | | | | (0.033) | | | |
| Mother: junior high edu | 0.003 | 4,739 | 0.074 | 0.17 | -0.024 | 1,559 | 0.158 | 0.19 |
| | (0.042) | | | | (0.041) | | | |
| Mother: high school edu | 0.009 | 4,739 | 0.014 | 0.04 | 0.006 | 1,559 | 0.034 | 0.01 |
| | (0.016) | | | | (0.011) | | | |
| Mother: college or more | 0.002 | 4,739 | 0.006 | 0.00 | -0.001 | 1,559 | 0.013 | 0.00 |
| | (0.004) | | | | (0.001) | | | |
| Mother: member of Communist party | 0.009 | 4,478 | 0.004 | 0.01 | -0.001 | 1,559 | 0.022 | 0.00 |
| | (0.006) | | | | (0.001) | | | |
| Mother: manager | 0.019* | 3,417 | 0.017 | 0.01 | 0.006 | 1,112 | 0.028 | 0.01 |
| | (0.010) | | | | (0.009) | | | |

Notes: This table shows baseline differences between cohorts from areas that received the program at some point (G5=0) and cohorts from areas that never received the program (G5=1). Each row-column combination shows the coefficient $\beta$ from a different regression: $\text{Baseline}_{ibc} = \alpha + \beta \cdot \text{G5}_{bc} + \gamma_b + \sum_k \zeta_k \cdot \text{s}_k \cdot \text{t}_c + \varepsilon_{ibc}$, where $\gamma_b$ are birth cohort fixed effects, $\text{s}_k$ are county characteristics measured in 2003 (share of rural residents, number of cellphone users, number of internet users, number of post offices, number of telephone users, and a dummy for midwest regions), and $\text{t}_b$ is a linear trend in birth cohorts. Columns 1 to 4 include the whole sample. Columns 5 and 8 restrict the sample to individuals from areas that received the program at some point (G1-G4) matched to individuals from areas that never received the reform (G5). Matching was performed using the following individual variables: birth cohort fixed effects, paternal education, paternal affiliation to the Communist Party, gender, minority status, and number of siblings. Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Source: CFPS, 2010 and 2014, individuals born from 1977.

**Table E18:** Matching G1-4 to G5, Effects of Computer-Assisted Learning

| | Years of education | Math skills | Chinese skills | MS diploma | LM participation | Log earnings | Internet use | Anxiety index |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| CAL | 1.193* | 0.145 | 0.266* | 0.180** | -0.067 | 0.358 | 0.149 | -0.145 |
| | (0.664) | (0.121) | (0.135) | (0.074) | (0.097) | (0.300) | (0.111) | (0.281) |
| Observations | 1,685 | 1,685 | 1,685 | 1,685 | 1,685 | 1,307 | 1,103 | 1,103 |
| $R^2$ | 0.474 | 0.436 | 0.388 | 0.341 | 0.280 | 0.390 | 0.496 | 0.305 |
| Mean | 9.52 | -0.04 | -0.04 | 0.71 | 0.57 | 9.23 | 0.55 | 0.02 |
| Std. dev. | 3.75 | 0.89 | 0.90 | 0.46 | 0.49 | 1.31 | 0.50 | 0.83 |

Notes: The specifications match individuals who were born in areas that received computer-assisted learning to individuals who were born in areas that did not receive the reform. Matching was performed using the following individual variables: birth cohort fixed effects, paternal education, paternal affiliation to the Communist Party, gender, minority status, and number of siblings. Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Source: CFPS, 2010 and 2014, individuals born from 1977.