The Impact of Online Computer Assisted Learning for Disadvantaged Children in Taiwan: Evidence from a Randomized Experiment in Taiwan

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Abstract

The education of poor and disadvantaged populations has been a long-standing challenge for both developed and developing countries. In Taiwan, thousands of students from Yuanzhumin (aboriginal) families lag far behind their Han counterparts in academic achievement. When they fall behind, they often have no way to catch up. Many of their parents have neither the skills nor the money to provide remedial tutoring; whereas school teachers often lack the time to give students the individual attention they need.

Given this, both educators and policymakers are steadily growing interest in helping underperforming students catch up using computer-assisted learning (CAL). While in-school CAL interventions have been shown to be effective internationally and elsewhere in China, traditional software-based CAL programs are complex and costly to implement. An online version of CAL (OCAL), however, may be able to bypass many of offline CAL’s implementation problems and enhance the remedial tutoring experience. Unfortunately, there is little empirical evidence on whether OCAL programs can be equally effective in improving the learning outcomes of disadvantaged children.

The objective of this paper is to examine the impact of an in-home OCAL intervention on the academic performance of students using the program. To achieve these objectives, we carried out a randomized controlled trial (RCT) involving 1,539 fourth and fifth grade students in 84 Yuanzhumin schools across Taiwan. Among students who had computers at home, we randomly selected students into treatment and control groups. Students in the treatment group were instructed to attend in-home
OCAL sessions during each week for two semesters while the students in the control group did not receive any intervention.

According to our findings, in-home OCAL improved overall math scores of students in the treatment group relative to the control group by 0.08 to 0.20 standard deviations through intention-to-treat analysis (depending if the treatment was for one or two semesters). However, we found a low rate of compliance in our experiment. Results of an additional average treatment effect on treated analysis showed that in-home OCAL had an impact of 0.36 standard deviations on boosting student academic performance depending on their participation in OCAL at home. This study thus presents preliminary evidence that an in-home OCAL program has the potential to boost the learning outcomes of disadvantaged students.

**Keywords:** online computer assisted learning, randomized experiment, Yuanzhumin, in-home

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**Introduction**

Despite high levels of educational attainment and economic development in Taiwan, there is a “development gap” between aboriginal Taiwanese (primarily living in rural areas; henceforth Yuanzhumin) students and Han students (primarily living in urban areas). According to economics research, Yuanzhumin families are more likely than Han families to be under the official poverty line (Chen & Yin, 2008; Cheng & Chen, 1995; Hwu, Yeh, Wang, & Yeh, 1990). In terms of academic achievement, Yuanzhumin students score significantly lower than Han students, and evidence indicates that the gap in educational achievement is growing wider (Tsai & Wong, 2003; Chou & Wang, 2012).

The existing literature offers various explanations for the Yuanzhumin-Han achievement gap. First, rural Yuanzhumin students tend to have low-quality facilities and teachers. Recent economic growth and investments have improved Yuanzhumin’s living and educational standards to narrow the gap in quality of facilities and teachers, but there remains a clear disparity (Reid, Green, Cooper, Hastings, Lock, & White, 2010). Additionally, Yuanzhumin students are more likely to have a less-educated primary caregiver: 60.8% of Yuanzhumin students are left-behind children raised by their grandparents or relatives, many of whom have low levels of education (Hung, Young, and Lin, 2015). Even among children whose parents remain at home, their education levels are often too low to help with their children's classes and assignments. Third, worse health outcomes and higher rates of alcohol addiction and domestic violence continue to beset Yuanzhumin areas, issues that are likely related to the persistent poverty in those communities (Chen & Wei, 2013).

Yuanzhumin students who fall behind also lack access to some of the remedial resources that may help struggling students to get back on track. For example, when Han students fall behind academically they tend to employ one of several strategies to
improve their grades. For example, families can seek assistance for their child from teacher-provided tutoring; help from highly-educated parents (Huang and Du, 2007); and private cram schools (Kim and Chang, 2010). Unfortunately, these opportunities for remedial education are not readily available for Yuanzhumin students. First, both Yuanzhumin students and their teachers often live far away from school and leave immediately after the school day ends, thus removing the possibility of after-school tutoring. Next, a combination of high levels of parental out-migration and low levels of educational attainment for parents who remain at home leave Yuanzhumin students unable to rely on parental tutoring. Finally, persistent poverty in Yuanzhumin families render private remedial cram schools or commercial tutoring services unaffordable.

In light of these challenges, researchers around the world have explored other ways to deliver remedial tutoring to at-risk populations. In-school computer-assisted learning (CAL) interventions, which use educational software to enhance learning through computerized instruction, drills and exercises (Kirkpatrick and Cuban, 1998; President’s Committee of Advisors on Science and Technology, 1997) have been used as an alternative to traditional teaching in both developed and developing countries (for example, Banerjee et al. 2007; Barrow, Markman, and Rouse 2009; Linden 2008). CAL aims to enhance learning by turning regular class curriculum into engaging and interactive games (Inal and Cagiltay, 2007; Schaefer and Warren, 2004).

Results from in-school CAL interventions in developed countries as well as developing economies have been positive. Barrow, Markman, and Rouse (2008) found that a CAL intervention in Chicago schools improved math scores on state-administered standardized tests by 0.17 SD. A study in India found that the use of CAL had a positive impact on students' academic performance, with significant impacts shown to persist at least a year after the end of the program (Banerjee et al.,
Traditional CAL interventions have also been conducted in rural China, with evidence that CAL leads to significant, positive impacts in math, Chinese language, and English scores of students (Mo et al. 2016, 2015, 2014a, 2014b, 2013; Bai et al., 2016; and Lai et al., 2016, 2015a, 2015b, 2013). Further evidence in rural China shows that another method of delivering the CAL remedial tutoring—in particular, in-school Online CAL (OCAL)—is even more effective than traditional, offline CAL in improving student’s English scores (Bai et al., 2018).

While the evidence for the effectiveness of CAL and OCAL is strong, most of these programs have been implemented in-school. Implementing an OCAL program outside of school might be advantageous in poor communities for several reasons. First, in-school OCAL requires teachers to organize students to use computers at a fixed time in school. Because of this, in-school OCAL may displace other student activities—which could have negative effects on students. While students may improve their test scores with in-school OCAL interventions, it is unknown whether there are negative spillover effects on other subjects that ultimately receive less class time. It may also be that some rural schools may lack access to computers, which are required for OCAL.

One may consider in-home OCAL as a potential solution. Assuming that kids have access to computers at home and are allowed to use them, in-home OCAL may be an easier way for disadvantaged students to receive remedial tutoring. To our knowledge, the impact of OCAL in an in-home setting has never been empirically evaluated. In addition, there is little empirical evidence on whether an OCAL program may be effective in improving the quality of academic learning of primary students in the context of Taiwan. Finally, while the effectiveness of OCAL has been
demonstrated among Han populations, there has been very little research on ways to improve educational outcomes among the Yuanzhumin (Yang et al. 2013).

Thus, this paper examines whether in-home OCAL can improve the educational performance of Yuanzhumin students in Taiwan. To answer this question, we have four objectives. First, we utilize an intention-to-treat analysis (using a randomized controlled trial) to calculate the impact of an in-home OCAL intervention on the math performance of Yuanzhumin students. Second, we examine the nature of compliance at home. Are students taking advantage of the OCAL intervention? We also will examine what types of students use the services and what types do not. Third, we conduct analyses to investigate the impacts of OCAL when compliance is accounted for. Finally, heterogeneous effects are also analyzed as a way to assess who is benefiting and who is not.

To meet these objectives, we present the results of an RCT on an in-home OCAL intervention involving 1539 fourth and fifth grade students across 84 Yuanzhumin schools in Taiwan. Although there was a low compliance problem, when looking at the overall (average) impact (on both those that complied and those that did not), our results show that a remedial online CAL program at home improved standardized math scores by 0.08 standard deviations after one semester and 0.20 standard deviations after two semesters. When accounting for the level of compliance, we found that impacts were even higher (0.15 to 0.36 standard deviations).

The rest of the paper is organized as follows. The first section briefly lays out the context of the study, including the study’s research design, sampling, intervention, data collection, and statistical approach. The subsequent sections then present the results and discuss the findings.
Sampling, data and methods

To achieve our objectives, we implemented a clustered randomized experiment in more than 80 Yuanzhumin communities. A total of 1,539 fourth and fifth grade students in 84 elementary schools in Taiwan participated in our study. The program lasted for one academic year, from March 2016 to March 2017. In this section, we present the study’s sampling protocol, randomization procedure, intervention, data collection approach and statistical methods.

Sampling and randomization

We followed several steps to choose our sample. First, we restricted our sampling frame to Yuanzhumin communities, mostly poor rural areas. Yuanzhumin originally lived in the mountainous areas of Taiwan (especially in the central part of Taiwan) and formed tribes along the alluvial plain. The population of Taiwan Yuanzhumin was 504,531 (2.1% of Taiwan's total population) in 2009 and rose to 520,440 in 2012. Large shares of modern Yuanzhumin live in mountainous areas.

Second, we chose the sample counties. Four counties where Yuanzhumin extensively live: Hualien, Taitung, Pingtung, and Kaohsiung, were randomly selected to be included in our sampling frame.

Third, after choosing the counties, we chose the sample schools. Before selecting our sample schools, however, we needed to calculated the power to make sure our sample would be large enough to evaluate the impact of our program. For the power calculations, we assumed a standardized effect size for the outcome variable of 0.20, 0.80 power, a five percent significance level, an intra-cluster correlation (ICC) of 0.1, and a pre- and post-intervention correlation of 0.5. We also assumed that there were 20 observations in each cluster, on average. Based on these assumptions, we calculated that we needed a total of 84 schools to be included in our experiment.
To choose the sample schools, we followed a three-step process. We first obtained a comprehensive list of schools in the four counties from each county’s local education bureau. Next, we restricted our sample to schools that met the following criteria: that a majority of students were Yuanzhumin and that their school were mostly rural. We then selected 84 schools at random from the remaining pool of eligible schools to be a part of the program sample.

Within our sample schools, the intervention was focused on fourth and fifth graders. We chose sample students in fourth and fifth grades because research suggests that the true level of student’s performance can be reflected more easily and clearly through standardized math tests when students are in the middle stage of elementary school (Putnam, 1992; Cramer, Post, & Delmas, 2002). Moreover, we found in previous studies that students in grade four and five are old enough to reliably understand and answer the questions asked in the questionnaire, which allows for easier collection of accurate student and family characteristics. Choosing fourth and fifth grade students ensured that they would have already begun to learn math in school and that they would have the ability to answer the questions accurately.

We conducted a preliminary survey in February in Kaoshiung and Hualien in February of 2016, and in Taitung and Pingtung in March of 2016. We recruited enumerators from local colleges to conduct surveys and hold intensive training sessions for the enumerators to ensure high quality data collection. Based on the results of this survey, we determined that 727 students in our sample (47.2%) had computers at home and 812 students (52.8%) did not have computers at home. Those 727 students with home computers made up our final sample and were randomly assigned into the treatment and control groups. A total of 507 Yuanzhumin students
were assigned to the treatment group and 220 students were assigned to the control group.1

Our randomization process successfully created a balanced sample across the treatment and control groups. To show this, we use a set of student and school characteristics to look for significant differences between the groups. In doing so, we display mean and standard deviation of each variable of student’s characteristics in Table 1. The results show that none of the variables are significantly different between the groups except for father’s education level, but still we can reckon the control and treatment groups are balanced in the baseline (Table 1). Although the core sample at the baseline survey included a total of 727 students, there was some attrition by the end of the study. For various reasons (including school transfers, extended absences due to illness or injuries, unwillingness to continue the endline survey due to rejection from parents and teachers), by the time of the evaluation survey we were only be able to follow up with 452 students: 342 students in treatment group and 110 students in control group (Table 2, third column). In other words, 452 out of the initial 727 students were included in our evaluation survey and were part of the subsequent statistical analysis, implying a relatively large attrition rate of 37%. In order to check the balance between treatment group and control group in the endline, we conducted three kinds of regression on differences between attrited students and non-attrited students, between treatment students and control students before attrition and between treatment students and control students after attrition (Table 2). Compared with the non-attrited students, attrition students were more likely to be boys and those whose fathers were not Yuanzhumin. Fortunately, not only is there no significant difference

1 Because we were concerned about compliance, we decided to over-sample treatment students to ensure sufficient power, in case of high levels of attrition.
between baseline math test scores of attrited and non-attrited students, but it also appears to be unrelated to the assignment of the CAL intervention, and thus unlikely to either reduce the validity of our research design or bias our results. Therefore, we can say that there were no significant imbalances between the treatment and control groups among these variables at baseline as well as endline.

Experimental Intervention

After executing the baseline survey, we launched the intervention in February and March of 2016. All students in the treatment group participated in the same intervention. The intervention involved computer-assisted math remedial tutoring sessions designed to complement the regular in-class math curriculum for the Spring 2016 semester.

There were two general stages of the intervention. First, program teachers (who were trained by the study team) in each school trained treatment group students how to use OCAL at home. The trainings were organized hands-on sessions in the computer rooms at school where students could login to the software using private accounts. Using the training manual, they were taught how to use the OCAL software at home. The training sessions were mandatory with the teacher supervisors taking attendance. To avoid influence from teachers that might confound our estimation of the effect of OCAL intervention, teacher-supervisors were neither math teachers nor the homeroom teachers of the students.

Second, students were asked to log onto the OCAL software at home and complete one 60-min OCAL session per week. During each session at home, treatment students played animation-based math games designed to help students review and practice the basic math material taught in their regular school math
classes. The content—remedial questions and games—of each session was exactly same for every student in the treatment group and emphasized basic competencies in the local math curriculum in Taiwan. In short, the material was remedial in nature, based on the material that was in student textbooks, and reviewed the material taught in school in that same week. The teachers and families of students had no discretion on what was taught in the OCAL lessons.

When playing the games, the students first worked out the solutions with pencils/pens on scratch paper and then submitted the answers using the keyboards and mice of their home computers. As students used OCAL at home, if a student had a math-related question, he/she was unable to discuss the solutions with his/her classmates. The students were not supposed to consult their families or the teacher–supervisor. According to our protocol, the teachers were only allowed to remind students to use OCAL weekly, and to advise on Internet connectivity issues and software operations.

Students that were assigned to the control group did not receive any OCAL intervention. Following the protocol, they were not allowed to access the OCAL software. To our knowledge, no one in the control group used the OCAL software for any purpose.

Data collection

Our study included a total of three rounds of data collection in all 84 schools. The first-round survey was a baseline survey in March 2016 (at the beginning of the Spring semester) for all fourth and fifth graders in the 84 schools before any implementation of in-home OCAL program had begun. The second-round survey was a mid-line evaluation survey conducted in September 2016 after one semester of the OCAL intervention. The third-round survey was a final evaluation survey conducted
at the end of the program in March 2017, coinciding with the end of two semesters of the OCAL intervention.

In each round of data collection, the enumeration team visited each school and conducted a two-block survey. In the first block, students were given a standardized math test. The math test included 29–32 questions (tests in different rounds included slightly different numbers of questions), and test questions were pulled from official examination books and exercise books with the help of experts from Taiwan elementary schools (including university faculty and local teachers). Students were required to finish the test in math within 30 minutes. Our enumeration team proctored the test, strictly enforced the time limits, and patrolled the classroom to ensure there was no cheating. Student scores on these math tests were used in the analysis as our measures of student academic performance.

In the second block enumerators collected data on the characteristics of students and their families. The demographic and socioeconomic data included records of each student’s age (measured in years), gender (described by an indicator female, which is equal to one for girls, and zero for boys), whether their father or mother is Yuanzhumin, their father’s education level (whether their father has a college degree and whether the father has a high school degree), and their mother’s education level (whether their mother has a college degree and whether the mother has a high school degree). To create indicators of parental care, the students were also asked during the survey whether they lived with either of their parents for most of the time during the semester (living with father and/or living with mother). We also collected data on family asset value (collected via a checklist of high-value common household goods), whether the student is the only child in the family, whether any family member ever helps tutor the child in homework.
**Statistical methods**

To estimate the change in academic and non-academic outcomes in the treatment group relative to the control group, we ran an Ordinary Least Squares (OLS) model, regressing the outcome variables (i.e. post-program outcome value) on the baseline value of the outcome variable and a dummy variable of the treatment (OCAL intervention) status, controlling for a set of control variables. As randomization was conducted within schools, we also controlled for school fixed effects to disentangle the systematic within-school differences between the treatment and control classes in $y_{is}$ and to obtain an unbiased estimate of the genuine treatment effect of the OCAL intervention. We included control variables to improve the efficiency of the estimation. In all regressions, we constructed Huber-White standard errors (relaxing the assumption that disturbance terms were independent and identically distributed within schools) to account for the clustered nature of our sample.

To be specific, our model is:

$$y_{is} = \alpha + \beta \cdot \text{treatment} + s_s + \theta \cdot y_{0is} + X_{is} \gamma + \varepsilon_{is}$$

where $y_{is}$ is the endline (or midterm in some cases) outcome variable for child $i$ in school $s$, \text{treatment} is a dummy variable for whether the student was assigned to the treatment group (equal to one for students in the treatment group and zero otherwise), $s_s$ is the vector of school fixed effects, $y_{0is}$ is the pre-program (baseline) outcome value for student $i$ in school $s$, $X_{is}$ is a vector of additional control variables, and $\varepsilon_{is}$ is a random disturbance term.

The outcome variable of our analysis is student academic outcome, measured by student standardized math test score. The variables in $X_{is}$ are student and family
characteristics (female, age, whether father or mother is Yuanzhumin, father has a college/high school degree, mother has a college/high school degree, living with father and living with mother, family asset value, whether the student is the only child in the family, whether any family member helps tutor homework) and whether the student had access to a computer before the program started (ever used a computer). By construction, \( \beta \) equals the average within-school difference in \( y_{is} \) between the treatment and control groups conditional on \( y_{0is} \) (i.e. \( \beta \) measures the within-school difference in changes in the outcome variable between the treatment and control groups over the program period). As the OCAL intervention was randomly assigned within schools, \( \beta \) is an unbiased estimate of the effect of being assigned to the treatment group (i.e., the effect of the OCAL intervention, or the OCAL treatment effect). Because of the inclusion of \( X_{is} \) as additional control variables, \( \beta \) is an unbiased, efficient estimate of the OCAL treatment effect.

**Results**

*Impact of in-home OCAL intervention on student performance using intention-to-treat analysis*

An intention-to-treat (ITT) analysis of the results of an experiment is based on the initial treatment assignment and not on the treatment eventually received. ITT analysis is intended to avoid various misleading artifacts that can arise in intervention research such as non-random attrition of participants from the study or crossover. ITT is also simpler than other forms of study design and analysis because it does not require observation of compliance status for individuals assigned to different treatments or incorporation of compliance into the analysis.

The OLS regression analyses show that the estimated OCAL treatment effect after one semester on math test scores is equal to 0.08 standard deviations (Table 3,
Considering that the program only ran for one semester, the size of the OCAL program effect is comparable to the findings of other CAL evaluations that observed the beneficial effects of CAL on student performance (e.g., Banerjee et al., 2007; Barrow et al., 2008; Linden, 2008; Lai et al., 2015).

Furthermore, we find that the effect persisted over the two semesters. As shown in Table 3, row 2, column 6, the OCAL treatment has an impact after two semesters. In this case, the impact was 0.20 standard deviations on student’s math test scores at the significance level of 5%.

However, in ITT analysis, the treatment effect was measured on all students, whether or not they complied with the program’s requests (to use OCAL regularly). If a share of the students did not comply, the ITT results may be understating the effect of the in-home OCAL on students who complied with the program. If we want to understand the full potential effects of this treatment, it is necessary to analyze the program compliance and estimate the Average Treatment Effects on the Treated (ATT).

Compliance problems

There are a number of issues that may arise during the implementation of even the best-designed RCT. It is important, then, to be prepared and include plans to mitigate or control various risks. Uptake rates can sometimes be lower than expected, and this can have consequences on the effect size (and, following that, on the statistical power). It is worth noting that the relationship between uptake and power is exponential: a 50% drop in effect size will require a four-fold increase in sample size to achieve the same power. Another issue which can compromise an RCT’s estimates is non-compliance by program participants. That is, while individuals may be assigned to treatment or control groups, these assignments cannot always be
monitored or controlled. Non-compliance, then, can threaten the integrity of randomization if individuals are able to self-select into groups. While non-compliance can never be totally eliminated, it can be minimized.

Ensuring compliance may be particularly challenging in the case of in-home programs. In traditional in-school CAL programs, teachers manage student compliance by overseeing attendance and monitoring progress during each CAL session, which may lead to higher take-up rates and lower non-compliance rates. However, unlike in-school CAL, in-home OCAL is designed to be carried out by the students themselves, without supervision. Although the teachers were instructed to remind students to use OCAL every week, neither our program team nor the teachers had an effective way to monitor whether the students actually used OCAL or not.

In this experiment, we define compliance as following: if a particular student had logged onto OCAL in any of the 12 months of the program, we regard him/her as compliant, otherwise as non-compliant. In order to observe the student compliance rate, we used the administrative system built into the OCAL software to monitor student compliance with the program on a monthly basis. After calculation, the compliance rate started high, but decreased over the course of the program. In the 1st month after the implementation of OCAL, 74% of the students in the treatment group had logged onto the OCAL software. As shown in Table 4, 35.4% of the treatment group students (121 students) are classified as non-compliers and 64.5% (221 students) are regarded as compliers.

To examine some of the correlates of those that complied and those that did not comply, we compare the characteristics of the students who had complied and those who had not. Table 4 reveals the differences between compliant and not compliant student characteristics. First, we find that math test scores (including
baseline tests, midline tests and endline tests) have a positive relationship with compliance. This result indicates that students with higher math test scores were more likely to use the OCAL program than those with lower scores. Second, gender is an important factor affecting compliance, as girls showed a higher compliance rate than boys. Another factor that seems to influence compliance is whether the father is Yuanzhumin and the father’s education level. Compared to the students that did not comply, fathers of students using OCAL in the treatment group are more likely to be non-Yuanzhumin and have a lower education level (Table 4). Other student characteristics were neither found to influence compliance nor non-compliance, such as whether their parents are at home, whether the mother has relatively higher education levels, whether the students do not have siblings, and whether they have family members to help with their homework. In summary, then, the compliance correlates suggest that better female students whose fathers are not Yuanzhumin are the ones that are using OCAL the most.

*Impact of in-home OCAL intervention on student performance using Average Treatment Effects on the Treated analysis*

To examine the Average Treatment Effects on the Treated (ATE), ATE analysis has been adopted. The method of instrumental variables (IV) is used to estimate the impact as treatment is not successfully delivered to every unit in this randomized experiment. Two-stage least squares (2SLS) can be used as a computational method to calculate IV estimates. In this experiment, whether the student has logged onto OCAL is the endogenous variable and the assignment treatment is the IV. The first-stage regression equation is as follows:

\[ \log_{yesorno} = \gamma + \delta \cdot treatment + u \]
The fitting value $\hat{\log_{\text{yesorno}}}$ of regression in the first stage is exogenous, so $\hat{\log_{\text{yesorno}}}$ is replaced by $\log_{\text{yesorno}}$, and second stage regression of OLS can be used to get consistent estimation:

$$y_i = \alpha + \beta \cdot \log_{\text{yesorno}} + (\epsilon_i + \beta \cdot u_i) + \gamma \cdot X_{is}$$

According to the ATE analysis, we find there are significant impacts (Table 5). Based on the results produced by estimating these two equations, we find that the OCAL program is effective in raising test scores after one semester. Specifically, after one semester, the OCAL treatment is estimated to raise test scores by 0.16 standard deviations (column 1, row 1). After controlling for our set of specified control covariates, the impact is similar at 0.15 standard deviations (column 2, row 1).

Moreover, the results from estimating the ATE model finds that the OCAL program was consistently effective after two semesters. The coefficient on the OCAL treatment is positive (0.28 standard deviations) (columns 3, row 1.) The impact is also significant at the 5% level when controlling for covariates, showing 0.36 standard deviations.

These results are important because they clearly show that if more of the students could comply with the intervention, the impact of the intervention could increase. Indeed, the ATE estimate impacts are more than 50% to 100% or more higher than the ITT effects. Hence, in future programs, more effort should be made to improve compliance.

**Conclusion**

In this paper we present the results from a randomized field experiment on an in-home OCAL program involving 1,539 students in fourth and fifth grade. The main
intervention was a math OCAL remedial tutoring program that was used at the students’ home computers. Our results indicate that in-home OCAL has significant beneficial effects on academic outcomes. Weekly in-home OCAL math sessions increased student standardized test scores by 0.08 to 0.20 standard deviations. However, we found for a number of reasons, compliance with the in-home OCAL program was incomplete. Because of the low compliance, we conducted an ATE (average treatment effect on treated) analysis. When accounting for compliance, results showed that in-home OCAL had a higher impact, ranging from 0.15 to 0.36 standard deviations.

This paper contributes in several ways to our understanding of OCAL’s potential impact in Taiwan. First, we are the first to measure the effect of an in-home OCAL on learning outcomes among an underserved population in a developing economy. While the program appears to work, there are still serious compliance issues. More work, obviously, needs to go into figuring out why it is the compliance was so low. Still, it can be researched more on how to boost compliance rates in RCTs.

Our results also show that in-home OCAL may be a practical option (relative to traditional CAL) for policymakers looking to use computer technology to help narrow educational disparities. Based on our analysis, in-home OCAL is able to achieve almost the same impact as traditional offline CAL, even in spite of low compliance rates. Education policymakers in Taiwan (and in other developing countries, as well as underserved communities in developed countries) who are considering implementing large-scale CAL programs might consider in-home OCAL as a feasible alternative. Furthermore, this paper demonstrates that an OCAL program at home could be used as a complementary input to existing computer resources and
has the potential to narrow the academic achievement gap and help disadvantaged populations.
References


Kim, J. H., & Chang, J. (2010). Do governmental regulations for cram schools decrease the number of hours students spend on private tutoring?. KEDI Journal of Educational Policy, 7(1).


