The Impact of Vocational Schooling on Human Capital Development in Developing Countries: Evidence from China

Prashant Loyalka, Xiaoting Huang, Linxiu Zhang, Jianguo Wei, Hongmei Yi, Yingquan Song, Baoping Ren, Yaojiang Shi, James Chu, May Maani, and Scott Rozelle

Abstract

Background. A key question faced by developing countries is how to effectively build human capital to strengthen economic growth. Towards this end, a number of developing countries are currently promoting vocational education and training (VET). The primary aim of this study is to understand whether VET at the high school level in fact contributes to human capital development in developing countries. To fulfill that aim, we conduct two sets of analyses using longitudinal data on more than 10,000 vocational and academic high school students in China. First, we estimate the causal impacts of attending vocational versus academic high school on dropout, specific skills and general skills. Estimates from matching and instrumental variables analyses show that attending vocational high school (relative to academic high school) substantially reduces general skills and does not improve specific skills. Heterogeneous effect estimates also show that attending vocational high school increases dropout, especially among disadvantaged (low-income or low-ability) students. Second, we use vertically scaled (equated) baseline and follow-up test scores to measure gains in specific and general skills among the students. We find that students who attend vocational high school experience absolute reductions in their general skills. Taken together, our findings indicate that the rapid expansion of vocational schooling as a substitute for academic schooling may in fact be detrimental to building human capital in developing countries, such as China.

Keywords: human capital, specific and general skills, vocational education and training (VET), high school, coarsened exact matching, instrumental variables, developing countries, China

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A critical question faced by developing countries is how to effectively build human capital to promote and sustain economic growth. As the economies of developing countries shift from lower value-added to higher value-added industries and experience technological change, their need for human capital also increases (Heckman and Yi, 2012; Autor, Levy, and Murnane, 2003). Indeed, higher value-added jobs must be staffed with employees who are equipped with greater skills (Bresnahan et al., 2002; Bresnahan, 1999; Katz and Krueger, 1998). Without a labor force with sufficient skills, developing economies could ultimately stagnate (Hanushek and Woessman, 2012; Hanushek and Woessman, 2008; Mincer, 1984).

A number of developing countries currently identify vocational education and training (VET) as a key approach to building human capital. For example, the promotion of VET at the high school level (*"vocational high school",* which we use interchangeably with VET throughout the paper) has become a policy priority among emerging economies such as Brazil, Indonesia, Mexico and China (Newhouse and Suryadarma, 2011; National Congress of Brazil, 2011; Ministry of National Education of Indonesia, 2006; China State Council, 2010). Over the past decade, these countries have increased funding and enrollments in vocational high school (often in lieu of further increasing funding and enrollments for academic high school)**.** For example, the Brazilian government recently launched the National Program of Access to Technical Education and Employment (Pronatec), which will invest more than 600 million US dollars and expand vocational high school enrollments by 8 million students before 2014 (National Congress of Brazil, 2011). The Indonesian government aims to increase the share of vocational high school students to 70% of the high school-aged cohort (up from 30%) by 2015

(Ministry of National Education of Indonesia, 2006). The rationale underlying these policies is that increases in the proportion of vocational—as opposed to academic—high school enrollments can more effectively build human capital.

For VET to successfully build human capital in these countries, however, it must meet two prerequisites. The first prerequisite is that VET must help students learn specific (vocational) skills. Vocational high school, in particular, must help youth acquire specific, medium-level skills that can either directly be used in the labor market after graduation or serve as a foundation for vocational college (Kuczera et al., 2008).

Second, in addition to specific skills, for VET to be considered successful, it must help students acquire general skills (Kuczera et al., 2008; Chiswick, Lee and Miller, 2002). The international literature shows that a solid foundation of general or cognitive skills (for example, in math, reading and/or science) helps employees succeed in the workplace (Levy and Murnane, 2004). Similarly, the mastery of general skills has been shown to have a significant and long-term impact on the wages of high school graduates (Tyler, Murnane, and Willett, 1995). Labor markets are also prone to change, and job stability for individuals (as well as economic stability for countries) requires lifelong learning, which is contingent on a foundation in general skills (Kezdi, 2006). Indeed, for these reasons, almost all countries require (at least in theory) vocational high schools to teach general skills (Kuczera et al., 2008).

Despite the increasing interest in VET among policymakers, there is surprisingly little evidence from developing countries as to whether vocational high school, especially in comparison to academic high school, actually helps students acquire specific and general skills. Cross-national studies based on international tests such as the PISA do show that students in vocational high school have much lower levels of *general* skills (math, reading and science) than students in academic high school (by almost half a standard deviation among countries that take the PISA, see OECD, 2010). However, since the PISA data do not contain detailed information on student background characteristics (such as prior test scores) that are necessary to adjust for selection bias, the PISA data are not suitable for measuring the causal impacts of attending vocational versus academic high school. Furthermore, because the PISA data are cross-sectional and not longitudinal, they cannot show how much vocational high school contributes to gains in student learning.

In fact, we are only aware of one study that uses longitudinal data from a developing country to measure the impact of attending vocational versus academic high school. Using longitudinal data from Indonesia in the 1990s, Chen (2009) finds that attending vocational school has little impact on students' general skills. Unfortunately, limitations of the data used in the Chen study prevent the use of more rigorous causal methods that control for selection bias. Specifically, the Chen study relies on a relatively small sample of students (fewer than 1000). Because this sample does not have enough vocational and academic high school students that share a common set of characteristics (i.e., a common support) the OLS regressions used in the study may give biased results as they are based on linear extrapolations away from common support (King and Zeng, 2006). Similar to studies based on the PISA data, Chen (2009) also does not measure the impact of attending vocational high school on specific skills.

We aim to begin to fill what appears to be a gap in the literature on VET in developing countries by examining whether vocational high school students are, in fact, learning specific and/or general skills. Toward this overall aim, we seek to accomplish three goals. First, we seek to assess the impact of attending vocational versus academic high school on the dropout rates, specific skills and general skills of the *average* student that is attending academic and vocational high schools. Second, we seek to estimate the *heterogeneous impacts* of attending vocational versus academic high school on the dropout rates and skill levels of disadvantaged (low-income or low-ability) students. Third, we aim to establish whether vocational high school leads to any absolute gains in specific and general skills.

To accomplish these three specific goals, we draw on China as a case study. Like many other developing countries, policymakers in China have a strong interest in using VET to build human capital and drive economic growth (China State Council, 2010). The strong interest has resulted in the expansion of vocational high school enrollments from 11.7 million to 22.1 million students between 2001 and 2011 and annual investments of more than 21 billion dollars (NBS, various years; MOF and NBS, 2011). Policymakers in China also have a strong interest in using VET to help disadvantaged (low-income or low-ability) students gain employment (China State Council, 2010). It is for this reason that policymakers have provided financial aid to all vocational high school students and waived tuition for low-income (or poor) vocational high school students in particular (China State Council, 2010; MOF and MOE, 2006).

We conduct analyses using longitudinal data on more than 10,000 students in China. We first estimate the causal impacts of attending vocational versus academic high school on dropout, specific skills and general skills. Estimates from matching and instrumental variables analyses show that attending vocational (relative to academic high school) substantially reduces general skills without improving specific skills. Attending vocational high school also increases dropout, especially among disadvantaged (low-income and low-ability) students. We also use comparable (equated or scaled) baseline and follow-up test scores to measure absolute gains in specific and general skills among the students. We find that students who attend vocational high school experience absolute reductions in their general skills. That is, not only does vocational high school fail to teach any new general skills, it causes students to lose general skills they learned in the past. Taken together, our findings indicate that the promotion of vocational schooling as a substitute for academic schooling can in fact be detrimental to building human capital in developing countries such as China.

2. Research Design

2.1 Sampling

This paper draws on longitudinal survey data collected by the authors in October 2011 and May 2012. The sample for the longitudinal survey was chosen in several steps and covers vocational and academic high schools in different regions of China. First, we sampled two provinces in China: Shaanxi and Zhejiang. Shaanxi province is an inland province in Northwest China and ranks 15th out of 31 provinces in terms of GDP per capita (NBS, 2012). Zhejiang is a coastal province that ranks fifth in terms of GDP per capita (NBS, 2012). After selecting the two provinces, we sampled the most populous prefectures within each province (three in Shaanxi and four in Zhejiang).

We next sampled vocational high schools from the seven prefectures. According to administrative records, there were 204 and 285 vocational schools in the sample prefectures in Shaanxi and Zhejiang, respectively. Using administrative records, we included vocational high schools that offered a computer major in our sample. We selected schools based on whether they offered the computer major for two reasons. First, computing is studied in academic high schools (albeit to a lesser degree), which allows us to compare learning gains in specific skills (i.e. computers) across vocational and academic high schools. Second, the computer major is the most popular major in the two provinces (i.e., the major with the largest enrollments) among vocational high schools. Indeed, over half of all vocational high schools had computing majors, and we only had to exclude 101 schools in Shaanxi and 133 schools in Zhejiang due to the fact that they did not offer computer majors.

After selecting vocational high schools with computing majors, we then called these schools to ask how many new (grade 10) students enrolled in autumn 2011. Schools that reported fewer than 50 grade 10 students enrolled in the computer major were excluded from our sampling frame. We excluded these small schools because policymakers informed us that such schools were at high risk of being closed or merged during the school year. This criterion meant that we excluded 56 schools in Shaanxi and 78 schools in Zhejiang. Although the number of excluded schools was higher than we expected, these small schools comprised less than 15% of the share of computing students in Shaanxi and Zhejiang. We then enrolled the remaining 46 schools in Shaanxi and 55 schools in Zhejiang in our sample.

We concurrently sampled academic high schools in the seven prefectures. We found 104 and 155 academic high schools in the sample prefectures in Shaanxi and Zhejiang, respectively. Because we planned to match vocational and academic high school students, we needed a sample of academic high school students that might have considerable overlap in the basic characteristics of the students in the two types of high schools. To achieve this goal, we excluded elite academic high schools from our sample. In China, elite academic high schools select students of much higher ability than non-elite academic high schools. Few (if any) students that are eligible for elite academic high schools would ever consider going to vocational high school. In other words, the students in non-elite academic high schools are more similar in achievement to students in vocational high schools. In addition, students currently enrolled in non-elite academic high school were more likely to have considered attending vocational high schools. For these two reasons, we only sampled non-elite academic high schools.

Given these criteria for academic high school, we then selected our sample. Within the seven prefectures, there were 62 and 88 non-elite academic high schools in Shaanxi and Zhejiang (about 60% of all academic high schools). From these schools, we randomly sampled 15 eligible non-elite academic high schools from each province (30 schools in total).

The next step was to choose which students would be surveyed within the sample schools. In each vocational high school, we randomly sampled two first-year computer major classes (one class if the school only had one computer major class) and surveyed all students in these classes. In each non-elite academic high school, we randomly sampled two first-year classes and surveyed all students in these classes.

2.2 Data Collection

Our data collection started with a *baseline* (October 2011) survey. The baseline survey collected data from students, students' homeroom teachers and school principals. Among vocational high schools, 7,114 first-year students in 184 classes filled out the baseline survey. Among academic high schools, 2,957 students in 59 classes filled out the baseline survey.

We followed up with the sample vocational and academic high school students in May 2012 (hereafter known as the *endline* survey). The survey forms used in the endline survey were similar to those used in the baseline survey. Most importantly, our data allowed us to create three primary outcome variables: (a) student dropout (whether a student was enrolled in a high school as of May 2012); (b) student gains in specific (computer) skills (according to a standardized exam); and (c) student gains in general (mathematics) skills (according to a standardized exam).

Our first outcome was whether a student (who had started high school in September 2011) had dropped out by May 2012. To identify dropouts, our enumerators filled in a student-tracking form for each class during the endline survey. This form contained a list of all the students who completed our baseline survey. Our enumerators marked each student on the baseline list as present, absent, transferred, on temporary leave or dropped out, according to information provided by class monitors. Moreover, after the field survey was over, our enumerators called the parents or guardians of the students to further ascertain whether students marked dropped out on our tracking form had in fact dropped out.

A multi-step procedure was used to collect reliable and valid measures of specific and general skills and gains in those skills. First, we collected a large pool of computer and math exam items (questions) from official sources. The computer exam items were taken from past versions of national computer examinations (specifically, the National Computer Rank Examination and the National Applied Information Technology Certificate exam).[1] The math exam items were provided by the National Examination Center and closely matched the curricular requirements of high school students in China. Second, after piloting the large pool of exam items with more than 300 students, we designed vertically scaled (equated) baseline and endline exams using item response theory (IRT). By using the IRT procedure suggested by Kolen and Brennan (2004), we were able to ensure that baseline and endline exam scores could be compared on a common scale. Placing the baseline and endline exam scores on a common scale allows us to measure absolute gains (or losses) in learning from the start of grade 10 until the end of grade 10. Third, we administered and closely proctored the standardized computer and math exams during the baseline (October 2011) and endline surveys (May 2012). Fourth, the exam scores were normalized into z-scores (for computers and math separately and for the baseline and endline exams separately) by subtracting the mean and dividing by the standard deviation (SD) of the exam score distribution.

In addition to gathering data on our outcome variables, our survey included three blocks pertaining to student background characteristics. The first block asked students to report their gender, age, whether their household registration (*urban*) status was rural or urban, and whether they had migrated before. As a part of this block, we also asked students to report their high school entrance examination (*HSEE*) scores, the year they took the examination, and the prefecture where they took the examination.

The second block gathered information on students' families. This block included parents' education level (a dummy indicator equal to 1 if neither parent finished junior high and 0 otherwise), parental migration status (whether both parents stayed at home between January 2011 to August 2011), and whether the student had any siblings.

The third block was used to identify whether students were from low-income backgrounds. Students were asked to fill out a checklist of household durable assets. We used principal components analysis, adjusting for the fact that the variables are dichotomous and not continuous, to calculate a single metric of the "family asset value" for each student (see Kolenikov and Angeles, 2009).[2] *Low-income students* are defined as those students whose family asset value was in the bottom 33% of the sample.

The attrition rate in our survey was low. Of the 10,071 students we surveyed at the baseline, 361 students (3.5% of the sample) were absent or on long-term sick leave. While we do not show the tables for the sake of brevity, the attrited students are similar in baseline characteristics as the students who we followed up with in our sample. As such, we do not believe these missing observations will influence external validity. Another group of 891 students (or 9% of the sample) dropped out. For these students, we recorded their dropout status and thus include them in our analyses of the impacts of attending vocational (versus academic) high school on dropout. However, measures of the specific and general skills of dropouts are missing for such students.

As our study did not randomly assign students (to academic high school and vocational high school), we do not expect to see balance between the students that attended vocational high school and those that attended academic high school. Indeed, the groups differ substantially in terms of baseline characteristics (Table 1). Vocational high school students are less likely to be among students with the lowest incomes (row 4), tend to be older (row 6) and have parents that tend to have migrated in the past (row 8). Moreover, their parents are less likely to have completed junior high (row 11). Although their math scores are much lower than academic high students at the baseline (row 12), their computer scores are slightly higher (row 13). Because of these differences, outcomes such as dropout rates or learning in vocational high schools could be due to the kinds of students who attend rather than the low quality of vocational high schools compared to (non-elite) academic high schools. Our analytical approach focuses on addressing this problem of selection bias.

2.3 Analytical Approach

To assess the impact of attending vocational versus academic high school on student dropout rates, specific skills and general skills, we conduct three types of analyses: (a) ordinary least squares (OLS); (b) matching; and (c) instrumental variable (or IV) analysis.

Ordinary Least Squares (OLS)

Our first type of analysis uses OLS regression. We conduct the OLS analysis to examine the basic relationship between the treatment (attending vocational versus academic high school) and student outcomes, while controlling for observable covariates that may confound that relationship. The basic specification for the OLS analysis is:

(1)

where Y_{ij} represents the outcome variable of interest (dropout, specific skills, or general skills) of student i in school j. V_{ij} is a dummy variable for whether or not student *i* attended vocational high school at the time of the baseline survey. In the absence of omitted variables bias, *1* would be the treatment impact of attending vocational (versus academic) high school on $Y_{ij.}$

The term X_{ij} in equation (1) represents a vector of observable baseline covariates for student *i* in school *j.* It includes student and family covariates such as *male* (equals 1 if the student is male and 0 if female), *age* (in days), *urban* (equals 1 if the student has urban residential permit status and 0 if rural), *student migrated* (equals 1 if the student has migrated prior to the baseline survey and 0 otherwise), *siblings* (equals 1 if the student has siblings and 0 otherwise), *parents at home* (equals 1 if both parents stayed at home between January 2011 to August 2011 and 0 otherwise), *parents did not finish junior high* (equals 1 if neither parent finished junior high school and 0 otherwise) and *low-income* (equals 1 if students are in the bottom 33% of the distribution of our family asset value variable and 0 otherwise). Importantly, we also control for baseline computer and math scores. Finally, we control for social, economic, and political differences in local context by adding a fixed effect term to indicate the prefecture where the student went to high school.

Coarsened Exact Matching (CEM) Analyses

Despite controlling for a number of observable variables, the OLS analysis does not necessarily compare vocational and academic high school students who share common characteristics (i.e. who share a region of common support). Instead, the analytical sample may contain both vocational and academic high school students who overlap on their background characteristics as well as vocational and academic high school students who do not overlap on their background characteristics. If the analytical sample contains students that do not overlap on background characteristics, the assumption of linearity in our OLS analysis can produce biased estimates by extrapolating away from the region of common support (King and Zeng, 2006). To address the potential limitations of the OLS analysis in estimating the causal effects of attending vocational versus academic high school, we conduct a second analysis that relies on *only* comparing students who have similar (overlap on) baseline characteristics.

This second analysis isolates the sample of vocational and academic high school students that are similar on baseline characteristics by using coarsened exact matching or CEM (see Appendix A for a detailed explanation about CEM). The CEM procedure is comprised of three steps. In step one, each variable is recoded (or "coarsened") so that substantively similar values of the variable are grouped and assigned the same numerical value. In step two, students are matched "exactly" on the coarsened data. If either a vocational high school student or an academic high school student does not find one or more matches on the coarsened data, that student is dropped from the sample. In step three, the data are "uncoarsened" or returned to their original values for the students that were not dropped from the sample. The post-matching estimation procedure (see below for more information on the estimation, as opposed to the matching, procedure) is conducted on the data from step 3.

There are three major advantages of using CEM over other matching procedures (such as propensity score matching or Mahalanobis distance matching, see Iacus et al., 2012b for a full discussion). First, CEM allows the researcher to guarantee that the amount of imbalance in the distribution of baseline covariates (between the two groups of vocational and academic high school students) will not be larger than his/her predetermined and substantive choice. By choosing ex ante how much to bound the amount of imbalance, the researcher can bound the amount of model dependence as well as the bias in the estimation of treatment effects. Second, CEM automatically eliminates observations outside the common support and thus does not require a separate procedure by which to restrict the data to a common support (as in propensity score matching, for example). Third, unlike many other matching methods, CEM can be easily used on multiply imputed data.

Given our choice to apply CEM, we make two substantive choices. First, we choose to match students from vocational (treatment) and academic (control) high schools on the baseline covariates X_{ij} in equation (1). To ensure that we are comparing students who face similar educational choices within a similar local context, we also choose to match students (exactly) within the prefecture and year in which they took the high school entrance exam (HSEE). Since all of the academic high school students in our sample took the HSEE (to qualify for academic high school), the matching procedure automatically drops vocational high school students who did not take the HSEE (2,023 students).[3]

Second, we also had to choose how much to *coarsen* each covariate (see Appendix A for an explanation of *coarsening*). By way of example, we can choose to coarsen baseline math scores into quintiles, meaning that we can choose to create five equally sized bins of students based on the quintile of their baseline math score. It is by choosing how much to coarsen or bin each covariate (such as baseline math scores) that we can decide ex ante on the maximum amount of imbalance in covariates between the treatment and control groups. In our actual CEM analysis, we choose to coarsen the distributions of each of our baseline exam score variables (computers, math) into 6 equally spaced bins.[4] We next coarsen age by year (where a year is defined by the calendar of a typical school year, e.g. from Sept. 1, 1985 to Aug. 31 1986). We also configure the CEM procedure to match students within (and not across) prefectures. All of the other covariates in X_{ij} are dummy variables. As with exact matching, the CEM procedure uses the two values of each dummy variable to help create the bins on which we match treatment and control students.

The CEM procedure produces a high degree of balance across the observable covariates. Vocational and academic high schools students differed substantially in the distribution (e.g. means and various percentiles) of their baseline math scores, baseline computer scores, gender, and parent's education level before the matching procedure (Appendix A, Table 1). After applying the matching procedure, however, the two groups of students look similar on all of the baseline characteristics in equation 1 (Appendix A, Table 2). The balance in baseline covariates is not just at the mean but also at different parts of the distribution of each covariate (see Appendix A, Table 2). Furthermore, as explained above, the use of CEM automatically ensures that the matched data share common support. As such, we do not have to check to make sure that the matched data share a common support.

After matching the data using CEM, we run the same regression analyses as in equation (1) on the matched set of students. By running regression analyses on top of the matched student data, our causal estimators are *doubly-robust* in the sense that the estimators are unbiased if either the matching procedure *or* the regression specification is correctly specified (Ho et al., 2007; Bang and Robins, 2005). We call the regression analyses on the matched set of students our *CEM analyses*.

Instrumental Variables

For our third type of analysis, we conduct an instrumental variables (IV) analysis. We conduct the IV analysis because, in theory, it can produce causal estimates of the impact of vocational versus academic high school on student outcomes. The key condition that must be satisfied is whether the assumptions underlying the IV analysis hold. In particular, whereas both CEM and OLS fundamentally rely on the assumption of ignorability (that after controlling for observable pre-treatment covariates, treatment assignment is independent of the outcome of interest), the IV analysis relies on two different assumptions (Murnane and Willett, 2010). The first (untestable) assumption is that of exogeneity: the IV should influence student outcomes only through the treatment variable (attending vocational versus academic high school) and not through any other channel. The second (testable) assumption is that the IV should be strongly correlated with the treatment variable in order to produce consistent treatment effect estimates. We discuss how these two assumptions are likely met in our IV analysis immediately below.

Our IV analysis exploits variation in a student's HSEE score relative to an HSEE score cutoff. In China, HSEE scores determine entry into academic high school. Every county has a different cutoff for whether a student’s score makes him/her eligible to enter academic high school (more or less based on the number of positions in academic high school available that year). Students with HSEE scores that are equal to or higher than the HSEE score cutoff in their county can go to academic high school. By contrast, students with HSEE scores that are lower than the cutoff can only go to vocational high school (unless they choose to go into the labor market).

To apply the IV analysis, we first create an instrumental variable called *below cutoff*. Below cutoff equals 1 if a student scored below the HSEE cutoff in the county in which he/she took the HSEE and 0 if otherwise.[5] By using below cutoff as an instrument for V_{ij} in equation 1, we assume that whether a student is below or above the HSEE cutoff exclusively affects his/her outcomes (dropout, specific skills, general skills) through his/her decision to attend vocational or academic high school. This is the exogeneity assumption of IV analysis (see Murnane and Willett, 2010).

Although we only have one available IV and thus cannot test the exogeneity assumption directly, we provide justification for why below cutoff may be a valid IV. Figures 1a-1e map the relationship between each student's HSEE score (centered at the HSEE score cutoff in the county he/she took the HSEE, x-axis) and the probability of attending vocational versus academic high school (V_{ij}, y-axis). Figure 1a, in particular, shows that the probability of attending vocational high school drops by over 50% at the HSEE cutoff. By contrast, the probability of attending vocational high school only drops by 10% or less at 10 points to the right or left of the HSEE cutoff (Figures 1b and 1c respectively). The probability of attending vocational high school hardly drops at all at 20 points to the right or left of the HSEE cutoff (Figures 1d and 1e respectively). Figures 1a-1e, taken together with the fact that county officials set HSEE cutoffs after the HSEE is administered and scored, imply that the HSEE cutoff rule is likely exogenous. In other words, the HSEE cutoff variable should be uncorrelated with (observable and unobservable) factors that influence the relationship between vocational high school attendance (V_{ij}) and student outcomes. To further ensure that we control for possible sources of endogeneity, we control for X_{ij}, HSEE score, and county fixed effects in all of our IV analyses.

"Below cutoff" also fulfills the second important assumption of IV analyses (Murnane and Willett, 2010). Namely, the below cutoff variable is strongly correlated with V_{ij} in the first stage of the IV regression (results omitted for the sake of brevity). This is to be expected, given the high degree of compliance with the HSEE score cutoff rule in most counties.

We make two common statistical adjustments for all three types of analyses above. First, in all three types of analyses, we estimate Huber-White standard errors that correct for prefecture-level clustering. Second, we define our sample in two ways: (a) by excluding dropouts from analyses of the impact of vocational (versus academic) high school on skills; and (b) by using a multiple imputation procedure to fill in (or predict) the missing outcome values of the dropout students and include these students in our analyses. Our causal estimates are the substantively same whether we exclude dropouts or use multiple imputation (results omitted for the sake of brevity).

3. Results

3.1 What is the impact of attending vocational (versus academic) high school?

According to the results from the OLS analysis, students in vocational schools have different dropout rates and learn both specific skills and general skills at different rates than students from academic high schools. Specifically, students in vocational schools are 4 percentage points (or about 78 percent) more likely to drop out compared to students in academic high schools (Table 2, row 1, column 1). The difference is statistically significant at the 1% level. The OLS regressions also show that students attending vocational high school do not improve specific skills more than those attending academic high school (Table 2, row 1, column 2). Students in vocational high school scored only 0.02 SDs higher than academic high school students in specific skills. The effect, however, was not statistically different from zero. Finally, in terms of general skills, students in vocational high school score far lower (0.44 SDs) than students in academic high school (Table 2, row 1, column 3). The difference is significant at the 1% level. In summary, although we are looking at what best can be called correlations, students attending vocational versus academic high schools drop out more and learn less general skills. At the same time, attending vocational high school also yields no measurable gains in specific skills (which vocational high schools are supposed to be specializing in).

The results of the CEM analysis, the first part of our effort that seeks to assess causality, tell the same story (Table 3). According to the analysis, attending vocational high school increases dropout rates by 3 percentage points more than academic high school students (Table 3, row 1, column 1). This finding is significant at the 1% level. Moreover, similar to the OLS results, attending vocational high school also has a negligible effect on specific skills. Although vocational high school students appear to do slightly worse than their academic high school peers on the computer skills exams (by 0.05 SDs), the estimated coefficient is not statistically significant (Table 3, row 1, column 2). The CEM analysis—which matches similar students from vocational high school and academic high schools—demonstrates that vocational high school decreases general skills by 0.42 SDs (which is significant at the 1% level, Table 3, row 1, column 3).

The results from our IV analysis also generally support the story that vocational high schools do not build human capital (Table 4). Vocational high school students are 1.1 percentage points more likely to drop out (although this finding on differences in the dropout rate—unlike the OLS and CEM findings—is no longer statistically significant). However, like the findings from the OLS and CEM analyses, the effects of vocational schooling on specific and general skills remain the same. Vocational schooling reduces general skills by 0.30 SDs (a finding significant at the 1% level) without contributing any gains to student specific skills (an increase of 0.12 SDs that is not statistically significant).[6]

Taken together, our findings demonstrate that attending vocational high school actually hurts students relative to attending academic high school. First, vocational high school encourages drop out (or at least does not encourage students to stay in school). Second, vocational high schools are failing to equip students with specific skills even relative to academic high school (which spends little class time teaching specific skills like computing). Third, attending vocational versus academic high school results in the loss of general skills. Taken at face value, the results suggest that China's high school system would have been better off if all students would have taken the academic high school track instead of going through the vocational high school system.

3.2 The impact of vocational high schools on low-income and low-ability students

Although attending vocational high school hurts students on average (when compared to attending academic high school), the system, according to some policy documents (e.g. MOF and MOE, 2006), is meant to benefit low-income and low-ability students. Because low-income and low-ability students might still benefit from attending vocational (versus academic) high school, we examine the heterogeneous impacts of attending vocational (versus academic) high school on the dropout and skills by income (poverty) level and ability.

To examine the heterogeneous impacts of attending vocational high school on the dropout and skill levels of low-income students, we rerun two additional versions of the IV analyses (one with an additional treatment-low-income interaction term; and one with an additional treatment-low-ability interaction term. In fact, our results show that low-income students not only fail to benefit from attending vocational high school, they actually perform worse if they had attended vocational high school (Table 5). Low-income students who attend vocational versus academic high school are 5.9 percentage points more likely than higher income students to drop out (significant at the 10% level—column 1). Furthermore, like the average student (as shown in the subsection above), low-income students also make negligible gains in specific skills (column 2) while losing in general skills (column 3).

As with our results for low-income students, attending vocational high school has negative impacts on low-ability students. Low-ability students who attend vocational versus academic high school are more likely to dropout than higher ability students (the dropout rate increases by 2.5 percentage points for every 1 SD decrease in baseline computer scores—column 1). In addition, by attending vocational (versus academic) high school, low-ability students are even less likely to gain specific skills compared to higher ability students (the endline computer scores decrease by 0.13 SDs for every 1 SD decrease in baseline computer scores—column 2). Finally, by attending vocational (versus academic) high school, low-ability students see their general skills deteriorate more than higher ability students (by .06 SDs for every 1 SD decrease in baseline computer scores, although the result is not statistically significant at the 10% level—column 3).

Taken together, the findings indicate that attending vocational high school may hurt disadvantaged (low-income and low-ability) students even more than their advantaged counterparts. Low-income and low-ability students who attend vocational (rather than academic) high school drop out more than the higher income and ability students. There is also some evidence to indicate that low-income and low-ability students are even less likely to gain specific skills than higher income and higher ability students. Finally, by attending vocational high school, low-income and low-ability students are at least as likely to see a reduction in their general skills compared to higher income and higher ability students. These findings are true even though vocational schools are (by design) supposed to benefit such students. For this reason, according to our results, we conclude that (like the results above for students in general) low-income and low-ability students would have fared better in academic high schools.

3.3 IRT gains in general and specific skills

The results in the previous subsections demonstrate that the quality of vocational school is poor relative to the quality of academic high school. However, our analysis can go further. Because our standardized exams were vertically scaled using IRT, we are able to analyze the individual gains in general and specific skills for the sample vocational and academic high school students. This analysis will help us determine if vocational high school students are learning anything.

Surprisingly, the IRT-scaled gains show that vocational high school students are actually *losing* general skills (math skills—Figure 2).[7] The IRT-scaled math scores of students in vocational high school fell by 0.08 SDs from the beginning to the end of grade 10. By contrast, students in academic high schools gained 0.04 SDs in math over the same period. In other words, the results show that vocational high school students are not only falling behind academic high school students, they are actually losing skills they previously had.

There are somewhat more encouraging results in terms of specific skills. According the IRT-scaled test results, vocational high school students do make modest gains in learning computer skills (Figure 3). On average, the IRT-scaled computer scores of vocational high school students rose by 0.12 SDs. However, as would be expected (from the subsections above), vocational high school students make *fewer* gains in specific skills than academic high school students (who spend much less time in computer classes than their vocational counterparts). The computer scores of academic high school students (in non-elite academic high schools) rose by 0.23 SDs.

These results suggest that, in absolute terms, vocational high schools make only small contributions or perhaps can be said to detract from human capital development. While it is true that vocational high school students make modest gains in their specific skills, as a whole their gains are less than those in academic high school. More importantly, vocational high school students are actually *losing* in their general skills.

Conclusions

Overall, VET at the high school level is not meeting its mandate of equipping students with the human capital needed to succeed in China's future economy. Attending vocational high school appears to cause students to drop out of school, especially if they are of low-income and of low-ability. Our results show that attending vocational high school also has no significant effect on specific skills and a substantial, negative impact on general skills (relative to attending academic high school). This negative impact is also pronounced among both low-income students and low-ability students. These are the very students that vocational high school is supposed to benefit most. Finally, in absolute terms, vocational high school even detracts from students' general skills over the course of the first year (from the start to the end of grade 10). All in all, vocational high schools are failing to contribute to (and are even detracting from) human capital development in China.

In fact, there is reason to believe that these results are conservative. First, in our more robust models (the matching and IV estimates), we are actually comparing students around the HSEE cutoff. One implication of this method is that our results generalize to the "cream of the crop" in vocational high school. These are primarily students who scored high enough to be within reach of attending academic high school. If we were to use a counterfactual that allowed us to estimate the effect of attending vocational high school on all vocational high school students, the negative effects of vocational high school might be even larger.

Second, when selecting our sample, we chose schools with relatively large and stable enrollments in the computing major. If enrollments correlate with the quality of the school (as they do in academic schooling in China), our sample consists of higher-quality schools. If we estimated the effects of attending vocational high school among all vocational high schools, the negative impacts on dropout and skills would be even larger.

Why is VET at the high school level failing to generate human capital? While a full discussion of this question is beyond the scope of this study, one argument is that local governments (who are responsible for financing vocational high schools) are still failing to invest sufficient resources into vocational high schools. A related argument is that local governments favor academic over vocational high schools and deny appropriate resources like qualified teachers or finances to the latter (Xu, 2012; Yang, 2012). In fact, existing evidence suggests that this is not the case. In a study of inputs to vocational high schools, Yi et al. (2013) show that vocational high schools are meeting basic government benchmarks in terms of teacher qualifications, internships, and facilities.

A second possibility is a lack of coordination and oversight to ensure the transformation of inputs (e.g. financial investments) into outputs (e.g. student skills). Multiple ministries/departments/bureaus oversee vocational education. In addition, in none of these alternative systems (including the vocational system run by the education bureau), there is no agency that systematically monitors vocational high school quality. In fact, the actual situation is even less regulated (or monitored). During our time in the field, many principals would report that they had no set curricula or standards by which they were able to assess their students. As such, while we cannot be sure why vocational high schooling is failing, one possible reason is the absence of oversight.

If our findings on quality are generally true and if the reasons for this poor quality are as we surmise, policymakers in China may wish to cease the large, almost indiscriminate investment into the vocational high school system. Certainly our results pertain to the provinces in our study. However, there is no reason to believe that the results do not apply more broadly to other provinces in China. In spite of ambitious and rapid inputs toward vocational high school, the current system does not seem to be set up to build human capital. In fact, the vocational high school system is actually hurting students—both absolutely and relative to their counterparts that attend academic high school.

While policymakers are unlikely to consider dismantling vocational high school, substantial reforms should be considered before further financial and political resources are diverted to vocational high school. One approach would be to reduce the investment into vocational high schools and direct more resources toward the more effective approach to human capital development: academic high school.

Furthermore, the results of this study should give pause to policymakers seeking to promote VET in other developing countries. China is not alone in its new reliance on VET as a key driver of economic growth. The premise behind VET is simple: by training students with both specific and general skills, they can enter the labor market and contribute to growth more quickly than having them enter academic high school. As such, in China and elsewhere, policymakers have diverted resources away from academic high school toward vocational high school. Unfortunately, based on the results of this study, there is a good chance that this premise is flawed. Students may not actually learn any skills (and may even drop out) as a result of attending vocational high school. And, by diverting resources away from academic high school, developing countries like China reduce the number of students who can access a human-capital enhancing academic high school opportunity. Together, such a policy move would substantially hinder human capital production.

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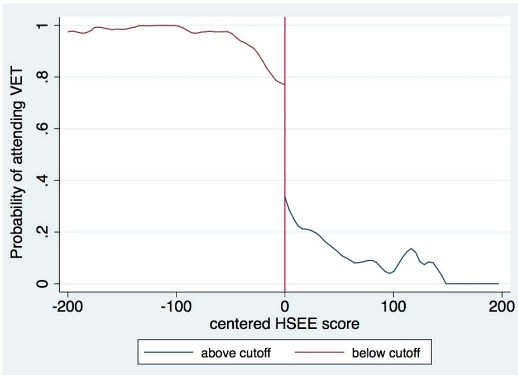
Figures 1a-1e: Graphs Showing the Discontinuity at the HSEE Cutoff (Between Attending Academic and Vocational High School)

Figure 1a: At the HSEE Cutoff



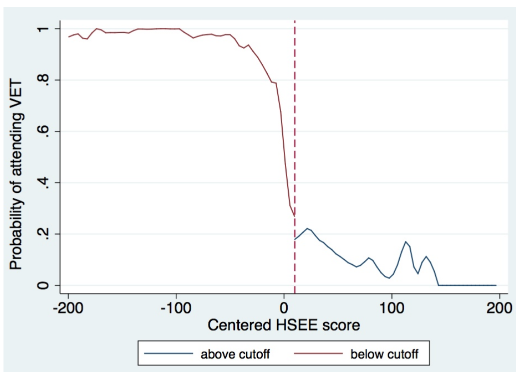


Figure 1b: 10 points above the cutoff

Figure 1c: 10 points below the cutoff

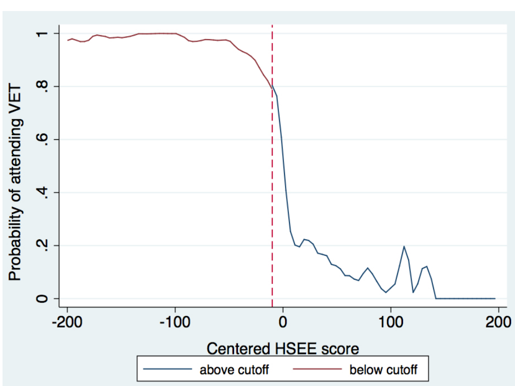


Figure 1d: 20 points above the cutoff

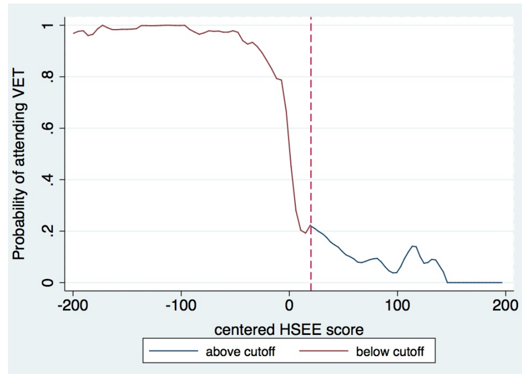


Figure 1e: 20 points below the cutoff

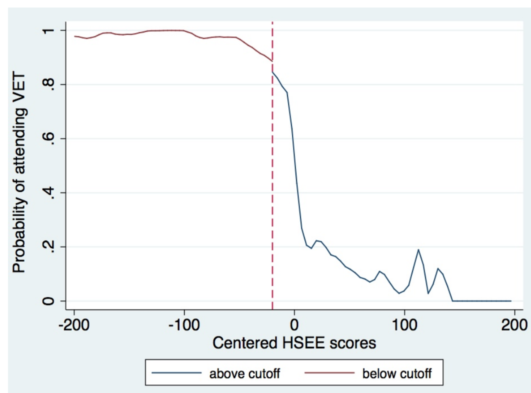


Figure 2: Gains in IRT-scaled math scores: academic vs. vocational high school

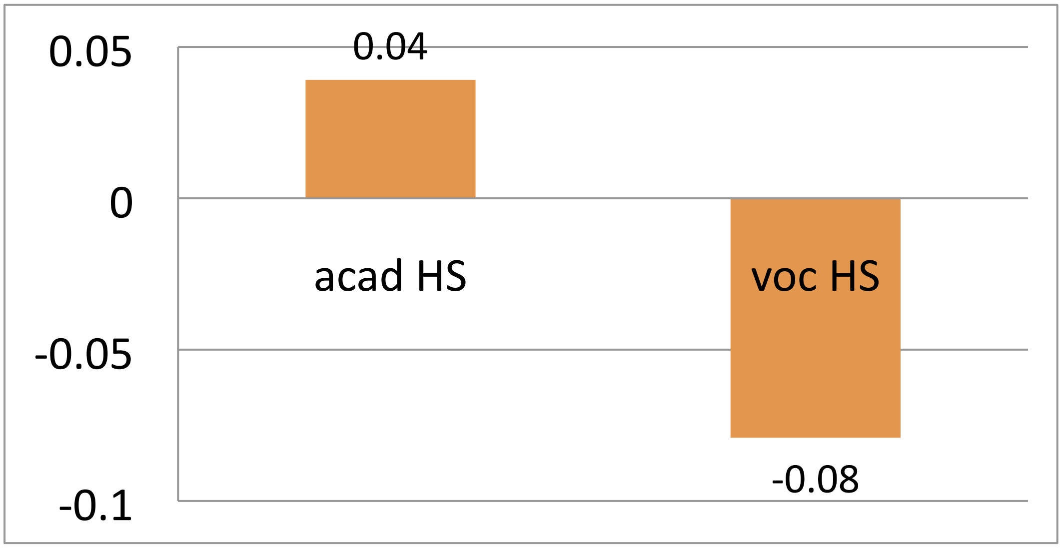


Figure 3: Gains in IRT-scaled computer scores: academic vs. vocational high school

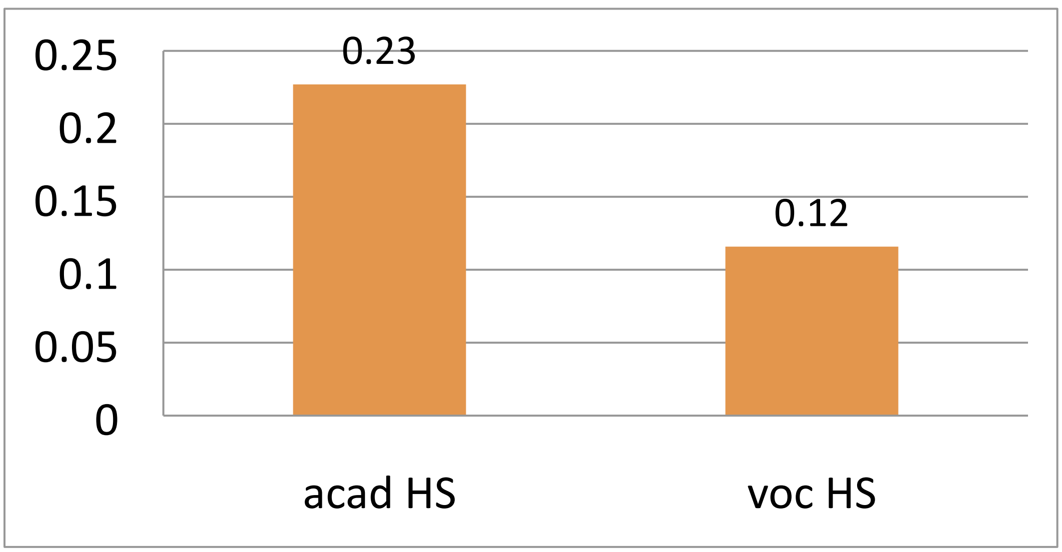


Table 1: Differences between Vocational High School and Academic High School Students

	(1)	(2)	(3) = (2) - (1)
	Academic high school	**Vocational high school**	**Difference**
Low-income	0.40	0.31	-0.09**
Male	0.50	0.57	0.06
Age	15.97	16.14	0.17***
Urban	0.88	0.90	0.01
Student migrated	0.14	0.17	0.04***
Siblings	0.72	0.68	-0.03
Parents home	0.87	0.89	0.02
Parents no junior high	0.29	0.40	0.11***
Math baseline (z-score)	2.13	1.16	-0.97***
Computer baseline (z-score)	-0.33	-0.13	0.19***

Cluster-robust SEs in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Impact of Attending Vocational High School (versus Academic High School) on Student Outcomes – OLS regressions with fixed effects (on unmatched data)

	(1) Dropout	(2) Computer endline	(3) Math endline
Went to VET	0.04***	0.02	-0.44***
	(0.01)	(0.05)	(0.08)
Low-income	0.00	0.01	0.05***
	(0.01)	(0.01)	(0.01)
Male	0.03***	0.01	-0.05**
	(0.01)	(0.02)	(0.02)
Age	0.01***	-0.02***	-0.05***
	(0.00)	(0.00)	(0.01)
Urban	0.01	-0.03	0.01
	(0.01)	(0.04)	(0.04)
Student migrated	0.01	0.02	0.06*
	(0.01)	(0.02)	(0.04)
Siblings	0.01***	-0.01	-0.02
	(0.00)	(0.02)	(0.03)
Parents home	-0.04***	0.02	-0.01
	(0.01)	(0.02)	(0.04)
Parents no junior high school	0.02***	-0.01	0.03
	(0.01)	(0.01)	(0.03)
Math baseline	-0.01***	0.05***	0.26***
	(0.00)	(0.01)	(0.02)
Computer baseline	0.00	0.33***	0.19***
	(0.01)	(0.03)	(0.04)
Observations	7,299	6,395	6,395

Cluster-robust SEs in parentheses
*** p<0.01,** p<0.05,*p<0.1

Table 3: Impact of Attending Vocational High School (versus Academic High School) on Student Outcomes – OLS regressions on matched data

	(1) Dropout	(2) Computer endline	(3) Math endline
Went to VET	0.03***	-0.05	-0.42***
	(0.01)	(0.08)	(0.09)
Low-income	-0.00	0.05	-0.01
	(0.01)	(0.03)	(0.04)
Male	0.04***	0.05	-0.07**
	(0.01)	(0.06)	(0.03)
Age	0.01	-0.04	-0.07**
	(0.01)	(0.03)	(0.03)
Urban	0.02**	-0.12	0.03
	(0.01)	(0.15)	(0.09)
Student migrated	0.04**	-0.02	0.24***
	(0.02)	(0.02)	(0.08)
Siblings	0.01	0.10***	-0.11**
	(0.01)	(0.04)	(0.05)
Parents home	-0.03	-0.03	-0.05
	(0.05)	(0.05)	(0.10)
Parents no junior high school	0.03***	-0.06	-0.00
	(0.01)	(0.06)	(0.09)
Math baseline	-0.01**	0.04***	0.22***
	(0.01)	(0.01)	(0.02)
Computer baseline	-0.01	0.33***	0.19***
	(0.01)	(0.03)	(0.05)
Observations	2,122	1,927	1,927

Cluster-robust SEs in parentheses
***p<0.01,**p<0.05,*p<0.1

Table 4: Impact of Attending Vocational High School (versus Academic High School) on Student Outcomes (IV analyses, 2011 HSEE takers from 21 counties)

	(1) Dropout	(2) Computer Endline	(3) Math endline
Went to VET	0.01	0.12	-0.30***
	(0.03)	(0.08)	(0.11)
Low-income	0.01	-0.01	0.02
	(0.01)	(0.02)	(0.03)
Male	0.01	0.06***	0.09***
	(0.01)	(0.02)	(0.04)
Age	0.01**	-0.01	-0.08***
	(0.00)	(0.02)	(0.02)
Urban	-0.003	-0.07**	0.005
	(0.01)	(0.03)	(0.06)
Student migrated	0.01	0.02	0.01
	(0.01)	(0.03)	(0.05)
Siblings	0.01	0.03	0.04
	(0.01)	(0.03)	(0.04)
Parents home	-0.03***	0.02	-0.04
	(0.01)	(0.02)	(0.05)
Parents no junior high school	0.00	-0.02	0.01
	(0.01)	(0.02)	(0.02)
Math baseline	0.00	0.02**	0.17***
	(0.00)	(0.01)	(0.01)
Computer baseline	0.01	0.30***	0.13***
	(0.01)	(0.04)	(0.03)
Centered HSEE score	-0.00**	0.00***	0.00***
	(0.00)	(0.00)	(0.00)
Observations	3,600	3,303	3,303

Cluster-robust SEs in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Heterogeneous Impacts of Attending Vocational High School (versus Academic High School) on Low-income Student Outcomes (IV analyses, 2011 HSEE takers from 21 counties)

	(1) Dropout	(2) Computer endline	(3) Math endline
Went to VET	0.00	0.12	-0.30**
	(0.03)	(0.08)	(0.12)
VET*Low-income	0.06*	-0.05	0.00
	(0.03)	(0.05)	(0.09)
Low-income	-0.02	0.01	0.02
	(0.02)	(0.03)	(0.05)
Male	0.01	0.06***	0.09**
	(0.01)	(0.02)	(0.04)
Age	0.01**	-0.01	-0.08***
	(0.00)	(0.02)	(0.02)
Urban	0.00	-0.07**	0.00
	(0.01)	(0.03)	(0.06)
Student migrated	0.01	0.02	0.01
	(0.01)	(0.03)	(0.05)
Siblings	0.01	0.03	0.04
	(0.01)	(0.03)	(0.04)
Parents home	-0.03***	0.02	-0.04
	(0.01)	(0.02)	(0.05)
Parents no junior high school	0.00	-0.02	0.01
	(0.01)	(0.02)	(0.02)
Math baseline	0.00	0.02**	0.17***
	(0.00)	(0.01)	(0.01)
Computer baseline	0.00	0.30***	0.13***
	(0.01)	(0.04)	(0.03)
Centered HSEE score	-0.00**	0.00***	0.00***
	(0.00)	(0.00)	(0.00)
Observations	3,600	3,303	3,303

Cluster-robust SEs in parentheses
*** p<0.01, ** p<0.05, *p<0.1

Table 6: Heterogeneous Impacts of Attending Vocational High School (versus Academic High School) on Low-Ability Student Outcomes (IV analyses, 2011 HSEE takers from 21 counties)

	(1) Dropout	(2) Computer Endline	(3) Math endline
Went to VET	0.02	0.09	-0.31***
	(0.03)	(0.08)	(0.11)
VET*computer_baseline	-0.03*	0.13***	0.06
	(0.02)	(0.04)	(0.06)
Male	0.01	0.06***	0.09**
	(0.01)	(0.02)	(0.04)
Age	0.01**	-0.01	-0.08***
	(0.00)	(0.02)	(0.02)
Urban	0.00	-0.07**	0.00
	(0.01)	(0.03)	(0.06)
Student migrated	0.01	0.02	0.01
	(0.01)	(0.03)	(0.05)
Siblings	0.01	0.03	0.04
	(0.01)	(0.03)	(0.04)
Parents home	-0.03***	0.02	-0.04
	(0.01)	(0.02)	(0.05)
Parents no junior high school	0.00	-0.02	0.01
	(0.01)	(0.02)	(0.02)
Low-income	0.01	-0.01	0.02
	(0.01)	(0.02)	(0.03)
Math baseline	0.00	0.02**	0.17***
	(0.00)	(0.01)	(0.01)
Computer baseline	0.02**	0.24***	0.10*
	(0.01)	(0.04)	(0.06)
Centered HSEE score	-0.00*	0.02***	0.03***
	(0.00)	(0.00)	(0.00)
Observations	3,600	3,303	3,303

Cluster-robust SEs in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix A
Coarsened exact matching (CEM) is one of a number of matching methods used by researchers to identify causal treatment estimates. All matching methods, including CEM, rely on the assumption of ignorability (that after controlling for observable pre-treatment covariates, treatment assignment is independent of the outcome of interest). The distinguishing feature of CEM, however, is that the researcher chooses or bounds the maximum amount of imbalance (for each covariate and for the multivariate distribution of the covariates) ex ante (Iacus et al., 2012a). By bounding imbalance ex ante, the researcher obviates the need to check and re-check for balance after different iterations of matching. In other words, CEM stands in contrast to the majority of matching methods in which the researcher (a) matches the data; (b) checks for imbalance between treatment and control groups after matching; and then (c) repeats (a) and (b) until acceptable balance is achieved.

When applying CEM, the researcher not only chooses which covariates on which to match on (which is standard in most matching methods), but also chooses how much to *coarsen* each covariate. By way of example (see Iacus et al., 2012a), *years of education* could be coarsened into the categories of primary school (years = 1 to 6), junior high school (years = 7 to 9), high school (years 10-12), and college or higher (years = 12+). It is in fact by choosing how much to coarsen each covariate, that the researcher ex ante decides the maximum amount of imbalance in covariates between the treatment and control groups.

After the researcher chooses (a) the vector of covariates on which to match (X) and (b) how much to coarsen each covariate in X, the CEM algorithm proceeds in three steps (Iacus et al., 2012a). In the first step, each covariate in X is *temporarily* coarsened (again according to the researcher's pre-determined choice). In the second step, all of the observations in the dataset that have the same value of the coarsened X are sorted into strata. In the third step, observations that fall into strata that do not have at least one treatment and one control observation are dropped from the sample. The remaining data is the matched sample of treatment and control students.

The researcher can then apply any statistical method (e.g. linear regression) on top of the matched data to estimate causal effects. When applying a statistical method, the researcher should also use weights to equalize the number of matched treatment and control units across strata (Iacus et al., 2012a).

Compared to other matching methods, CEM has a number of desirable features (see Iacus et al., 2012b). First, the researcher's choice of how to coarsen the pre-treatment covariates ex ante bounds the degree of model dependence and the error in the estimation of average treatment effects. Second, CEM automatically eliminates the "extrapolation region" and thus does not require a separate procedure by which to restrict the data to a common support. Third, CEM is robust to measurement error. Four, CEM works with multiply imputed data. A detailed explanation of these and other advantages of using CEM over other matching methods is provided in Iacus et al. (2012b).

Appendix A, Table 1: Pre-matching balance diagnostics

Academic high school students: 2778
Vocational high school students: 4830

Univariate imbalance:

	Mean	25%	50%	75%
HSEE-city-year	27129	20000	80000	50000
Math baseline	-0.90	-0.71	-1.21	-1.29
Computer baseline	0.20	0.30	0.19	0.15
Male (y/n)	0.09	0.00	0.00	0.00
Age	0.04	0.05	0.01	0.01
Student migrated (y/n)	0.04	0.00	0.00	0.00
Urban (y/n)	0.02	0.00	0.00	0.00
Siblings (y/n)	-0.05	0.00	0.00	0.00
Parent home (y/n)	0.02	0.00	0.00	0.00
Parent no junior high (y/n)	0.11	0.00	0.00	0.00
Low-income (y/n)	-0.13	0.00	0.00	0.00

Appendix A, Table 2: Coarsened Exact Matching (CEM), post-matching balance diagnostics

All: 2778 (acad HS); 4830 (voc HS)
Matched: 943 (acad HS); 1286 (voc HS)
Unmatched: 1835 (acad HS); 3544 (voc HS)

Univariate imbalance:

	Mean	25%	50%	75%
HSEE-city-year	0.00	0.00	0.00	0.00
Math baseline	-0.07	0.00	0.00	0.00
Computer baseline	0.03	0.00	0.07	0.00
Male (y/n)	0.00	0.00	0.00	0.00
Age	0.03	0.03	0.05	-0.01
Student migrated (y/n)	0.00	0.00	0.00	0.00
Urban (y/n)	0.00	0.00	0.00	0.00
Siblings (y/n)	0.00	0.00	0.00	0.00
Parent home (y/n)	0.00	0.00	0.00	0.00
Parent no junior high (y/n)	0.00	0.00	0.00	0.00
Low-income (y/n)	0.00	0.00	0.00	0.00

Endnotes

[1] We also asked a number of vocational high school teachers to serve as content experts and make sure that the items had a high degree of content validity (i.e. that the test items were relevant to what computer majors would actually be learning in vocational high school).

[2] We conduct standard robustness tests to see whether the use of polychoric PCA results in a viable family wealth metric. First, we find that the first principal component explains a large proportion of the variance in the family asset variables. The second and remaining principal components explain little of the variance. This indicates that the poverty metric reflects a common relationship underlying the inputs (wealth). Second, the scoring coefficients on the first principal component for each asset indicator all run in the anticipated directions. This means that the possession of assets indicates a higher first principal component score (wealth). Third, we find no evidence of clumping or truncation in our family wealth metric.

[3] Before we run our CEM analysis, we also trim outliers from our analytical sample. By trimming outliers, we are more likely to compare vocational and academic high school students who share a common support. First, we trim 247 students who score in the bottom and top 1% of the baseline math and computer score distributions. Second, we trim away another 141 students whose age is outside the normal range for high school (roughly 14.5 to 18.5 years old). We apply the same trimming rules in our IV analyses below.

[4] As shown in Appendix A, Tables 1 and 2, we achieve good balance after coarsening the baseline math exam score distribution and baseline computer exam score distributions into 6 equally spaced bins (each). As a robustness check, we also coarsen the baseline math and computer exam distributions into finer bins (from 6 up to 15 bins each). Although the size of the matched sample decreases with the finer coarsening, we obtain similar results across the various matching specifications.

[5] We attempted to collect information on HSEE scores cutoffs from each county in our sample prefectures for 2011 (the year in which the vast majority of students in our sample took the HSEE). In the end, we were able to collect HSEE score cutoffs from 21 sample counties.

[6] One possible concern may be that the sample from the IV estimates, which are exclusively from 21 counties that had proper cutoffs, differs substantially with the sample from the other two analytic models (OLS and matching). In fact, when we compare the sample of students in the three analyses, there are no substantial differences in terms of baseline standard characteristics like gender, age, and family background. Tables are available upon request.

[7] In fact, this graph only examines the IRT-scaled math gains among the lowest scoring 50% of students at the baseline. We make this adjustment because our baseline results were right-censored (a ceiling effect). Including these students would have biased the estimate of gains upward, as students scoring full marks at the baseline actually could have scored higher. In spite of this adjustment and ceiling effect, our main analytic models which compare the impact of vocational versus academic high school are unaffected.