The Impact of Vocational Schooling on Human Capital Development in Developing Countries

Evidence from China

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Abstract

A number of developing countries are currently promoting vocational education and training (VET) as a way to build human capital and strengthen economic growth. The primary aim of this study is to understand whether VET at the high school level contributes to human capital development in one of those countries—China. To fulfill this aim, a longitudinal data on more than 10,000 students in vocational high school (in the most popular major, computing) and academic high school from two provinces of China are used. First, estimates from instrumental variables and matching analyses show that attending vocational high school (relative to academic high school) substantially reduces math skills and does not improve computing skills. Second, heterogeneous effect estimates also show that attending vocational high school increases dropout, especially among disadvantaged (low-income or low-ability) students. Third, vertically scaled (equated) baseline and follow-up test scores are used to measure gains in math and computing skills among the students. The results show that students who attend vocational high school experience absolute reductions in math skills. Taken together, the findings suggest that the rapid expansion of vocational schooling as a substitute for academic schooling can have detrimental consequences for building human capital in developing countries such as China.

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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). Higher value-added jobs must be staffed with employees who are equipped with greater skills (Bresnahan et al. 2002). Without a labor force with sufficient skills, developing economies could ultimately stagnate (Hanushek and Woessman 2012).

A number of developing countries 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 (or “vocational high school”) has become a policy priority among emerging economies such as Brazil, Indonesia, and China (Newhouse and Suryadarma 2011; National Congress of Brazil 2011; China State Council 2010). Over the past decade, these countries have increased funding and enrollments in vocational high school (often in lieu of academic high school—e.g., Indonesia, see Newhouse and Suryadarma 2011). 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 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, VET must help students acquire general skills (e.g., in math, reading, and/or science—Chiswick, Lee, and Miller 2003). The international literature shows that a
solid foundation of general skills has a significant and long-term impact on the wages of high school graduates (Levy and Murnane 2004). Research also suggests that 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). For these reasons, almost all countries require vocational high schools to teach general skills (Kuczera et al. 2008).

Surprisingly, there is little evidence from developing countries as to whether vocational high school helps students acquire specific and general skills, especially in comparison to academic high school. Cross-national studies based on international tests such as the PISA show that students in vocational high school have lower levels of general skills than students in academic high school (by almost half a standard deviation, see Altinok 2011). 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.

One exception uses longitudinal data from Indonesia in the 1990s to show that attending vocational school has little impact on students’ general skills (Chen 2009). Unfortunately, the Chen study relies on a sample of students smaller than 1,000. Because this sample does not have sufficient vocational and academic high school students that share a common set of characteristics, the OLS regressions used in the
study may give biased results (as they are based on linear extrapolations away from a common support—King and Zeng 2006).

In this paper, we examine whether vocational high school students are learning specific and/or general skills. We seek to accomplish three goals. First, we seek to assess the impact of attending vocational versus academic high school on the dropout rates, math, and computing skills of the average student. 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 math and computing skills.

To accomplish these aims, we conduct analyses using longitudinal data on more than 10,000 students in China. Estimates from instrumental variables and matching analyses show that attending the most popular major in Chinese vocational schools (computers) relative to attending academic high school substantially reduces math skills without improving computing 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 students’ absolute gains in math and computing skills. We find that computing major students who attend vocational high school experience absolute reductions in math. Taken together, our findings indicate that the promotion of vocational schooling as a substitute for academic schooling may be detrimental to building human capital in developing countries such as China.
I. BACKGROUND

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). This interest has resulted in the expansion of vocational high school enrollments from 11.7 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 hope to use 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 vocational high school students in particular (China State Council 2010; MOF and MOE 2006).

What are vocational high schools supposed to accomplish? Vocational high school students are trained to become mid-level skilled workers. By policy design, the computer major in China is set up to train workers for entry level jobs in database management, website administration, software engineering, advertising (layout, photo-editing), or computer animation (Chinese Ministry of Education 2008). This differs from academic high school, which trains students in academic or general skills, mainly for entry into higher education.

In terms of curriculum, vocational high school students in the first year of the computing major are supposed to spend roughly equal amounts of time on academic
and computing skills. In their second year, students spend the majority of their time on computing skills. Students spend the third year in internships.

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1 All VET curricula are based on national standards (such as those from the Ministry of Education, which publishes a detailed list of standards for all facilities, textbooks, and software required for instruction—Chinese Ministry of Education 2008).
Academic high schools, by contrast, are focused on academic subjects tested on the college entrance examination, with roughly only 10% of time spent on subjects like music, computers, or physical exercise.

How do students choose to attend vocational high school? After graduating from junior high, students decide between entering the labor market, vocational high school, or academic high school. In China, the level of a student’s high school entrance examination (HSEE) score is the primary determinant for entry into academic high school. Every county ostensibly has a cutoff for whether a student’s score makes him/her eligible to enter academic high school (based on the number of positions in academic high school available that year). Those who test below the cutoff are unable to attend academic high school and must choose whether to enter the labor market or vocational high school. Those students that test just above the cutoff sometimes waver between whether to attend vocational or academic high school. Those who test far above the cutoff almost always attend academic high school.

II. 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 fifteenth out of thirty-one 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) and all the counties in those prefectures. In sum, we sampled two provinces, seven prefectures in those provinces, and the seventy-five counties in those prefectures.

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 all vocational high schools that offered a computer major in our sample. We focused on 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 major with the largest number of enrollments in the two provinces. 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 called these schools to ask how many new (grade ten) students enrolled in autumn 2011. Schools that reported fewer than fifty grade ten students enrolled in the computer major were excluded from our sampling.

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2 In contemporary China each province is split into multiple prefectures, which are in turn split into counties.
3 Note that the seven prefectures in our sample contain seventy-five counties. Since not every one of these counties had a vocational school or a vocational school with the computing major, the schools in our sample were distributed in thirty-five of the seventy-five total counties.
frame. This criterion meant that we excluded fifty-six schools in Shaanxi and seventy-eight 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 forty-six schools in Shaanxi and fifty-five 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 basic student characteristics across 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 nonelite academic high schools. Few (if any) students that are eligible for elite academic high schools would ever consider going to vocational high school. Because students currently enrolled in nonelite academic high school were more likely to have considered attending vocational high schools, we only sampled nonelite academic high schools.

Given these criteria for academic high school, we then selected our sample. Within the seven prefectures, there were sixty-two and eighty-eight nonelite academic high schools in Shaanxi and Zhejiang (about 60% of all academic high schools). From these schools, we

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4 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.
randomly sampled fifteen eligible nonelite academic high schools from each province (thirty 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 nonelite 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 fifty-nine classes filled out the baseline survey.\(^5\) In total, we surveyed 10,071 students (7114+2957).

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 computing skills (according to a standardized exam); and (c) student gains in math skills (according to a standardized exam).

\(^5\) Because of low enrollments, there was one academic high school (out of the 30) that only had one class (instead of 2). This explains why there are fifty-nine classes as opposed to sixty.
Our first outcome was whether a student (who had started high school in October 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 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 the students marked as dropped out on our tracking form had in fact dropped out.

A multi-step procedure was used to ensure that the computing and math tests were valid (and represented the types of skills that students were expected to acquire in high schools in China). First, we collected a pool of over 200 computer and math exam items (questions) from official sources. Because the test items were based on national standards, they are (according to policy) supposed to be reflected in the content actually taught in school. Second, to further verify the content validity of the items, we asked vocational high school teachers to ensure that the items were relevant to what computer majors would actually be learning in vocational high school. Third, 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

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6 Specifically, the computer exam items were taken from the previous year’s National Computer Rank Examination and the National Applied Information Technology Certificate exams. The math exam items were provided by the National Examination Center and closely matched the current curricular requirements of high school students in China.
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 ten until the end of grade ten.

We administered and closely proctored the standardized computer and math exams during the baseline (October 2011) and endline surveys (May 2012). The exam scores were then 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.\(^7\)

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 HSEE scores, the year they took the examination, and the prefecture where they took the examination.\(^8\)

The second block gathered information on students’ families. This block included parental education level (a dummy indicator equal to 1 if neither parent finished junior high and

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\(^7\) Although it is standard in education studies, we did not implement a reading test because principals and local education administrators were concerned that the time of the survey would be too long. Likewise, our Institutional Review Board was concerned that we would take too much instructional time away from our respondents by adding a third test.

\(^8\) Students are unlikely to suffer from recall bias when reporting on their HSEE scores because they received their scores only two months before the time of the survey. Granted, it is possible that vocational students remembered their scores as being lower than they actually were precisely because they ended up in vocational school. However, this would bias the results toward finding a positive effect of vocational school. As such, it would not challenge the findings of the paper.
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). Low-income students are defined as those students whose family asset value was in the bottom 33% of the sample.

Before conducting any analyses, we trim observations that, for substantive reasons, clearly lie outside the common support shared by academic and vocational high school students. As detailed in our analysis section below, students with extreme ages and test scores or that did not take the HSEE are dropped from the analyses. Thus, of the original 10,071 students, we first trimmed 263 students who scored in the bottom and top 1% of the baseline math and computer score distributions. Second, we trimmed away another 137 students whose age is outside the normal range for high school (roughly fourteen to nineteen years old). We further trimmed students that did not take the HSEE (1,279 students) or those who took the HSEE in years other

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9 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.
than 2010 or 2011 (748 students). These students made schooling choices (whether or not to take the HSEE and thus apply for academic high school; whether or not to take the HSEE “on time” like “regular” students aspiring to go to academic high school) that were clearly different from academic high school students. By trimming away these students, we effectively controlled for school choice (between vocational and academic high school) before conducting our matching analyses. In total, there were 7,644 students remaining after our trimming procedure.

The attrition rate in our analytical sample was low. Of the 7,644 in our analytical sample, 367 students (4.8% of the sample) were absent (305) or on long-term sick leave (sixty-two). Another group of 583 students (or roughly 8% of the analytical sample) dropped out. For the students who dropped out, 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 computing and math skills of dropouts are missing for such students.

We also test for attrition in appendix table S1 (appendix table S1 in the supplemental appendix). From appendix table S1, we can see that the attriting students (the majority of which are dropouts) differ from non-attribiting students in baseline characteristics. Specifically, attritors were more likely to be male (column 2, significant at the 10% level), older (column 3, significant at the 5% level), have parents who are not at home (column 7, significant at the 1% level), have lower math scores (column 9, significant at the 1% level), and have lower computer scores (column 10, significant at the 10% level). Although there is imbalance between attriting and non-attribiting students, the imbalance does not appear to bias our results. In particular, we estimate
Lee Bounds (that account for problematic attrition) for the endline math and endline computer achievement outcomes (see our robustness check subsection 3.1.2 below).

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 (nonelite) academic high schools. Our analytical approach focuses on addressing this type of selection bias.

2.3 Analytical Approach

To assess the impact of attending vocational versus academic high school on student dropout rates, computing skills and math skills, we conduct three types of analyses: (a) ordinary least squares (OLS); (b) instrumental variable (or IV); and (c) matching analyses. Note that, in
all three types of analyses, we estimate Huber-White standard errors that correct for prefecture-level clustering.\textsuperscript{10}

2.3.1 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:

\[
Y_{ij} = \alpha_0 + \alpha_1 V_{ij} + X_{ij}\alpha + \tau_p + \varepsilon_{ij}
\]

where $Y_{ij}$ represents the outcome variable of interest (dropout, computing, or math 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, $\alpha_1$ 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

\textsuperscript{10} Although it would be most appropriate to adjust standard errors for clustering at the school level, we conservatively adjust for clustering at the higher levels of aggregation. In particular, we adjust for clustering at the prefecture level for the OLS and matching analyses (and the county level for the IV analyses) because we add in prefecture (county) fixed effects when estimating differences across treatment and control groups. In fact, the results of the paper are substantively the same whether we adjust the standard errors for clustering at the school level (without prefecture/county fixed effects) or prefecture/county level (with prefecture/county fixed effects). Results are available from the authors on request.
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 $\tau_p$ to indicate the prefecture where the student went to high school.\(^{11}\)

2.3.2 Instrumental Variables

For our second type of analysis, we conduct an instrumental variables (IV) analysis. We conduct the IV analysis because, in contrast to OLS, it can in theory produce causal estimates of the impact of vocational versus academic high school on student outcomes. In particular, whereas OLS fundamentally relies on the assumption of ignorability (that after controlling for observable pretreatment covariates, treatment assignment is independent of the outcome of interest), the IV analysis relies on two different assumptions (Murnane and Willett 2010). The first 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 assumption is that the IV should be strongly correlated with the treatment

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\(^{11}\) The estimates of the impact of attending vocational schools on dropout in tables 2 and 3 are from a linear probability (OLS) model. Since dropout is a binary outcome, as a robustness check, we also estimated the impact using a logit model. The results from the logit model are substantively identical to the OLS results and are available upon request.
variable in order to produce consistent treatment effect estimates. We discuss whether these two assumptions are met in our IV analysis immediately below.

Our IV analysis exploits variation in student HSEE scores 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. 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 (or enter the labor market).

Significantly, while our approach is similar in spirit to a regression discontinuity design, we apply an IV strategy because standard sensitivity tests show that the typical RD design is not valid for our situation. In particular, due to the fact that we sampled (academic and vocational) high school students, the density of students that score just below the HSEE cutoff (to enter academic high school) is significantly less than the density of students that score just above the HSEE cutoff. This difference is not due to students’ ability to manipulate their HSEE scores. Rather, the difference arises because a large proportion of students that scored under the HSEE cutoff and did not get into academic high school chose to enter the unskilled labor market (where wages are relatively high—see Cai et al. 2008) instead of vocational high school. Since our sample does not include students that chose to enter the unskilled labor market, the RD design is not strictly valid for our situation.

We instead rely on an IV estimation strategy that still leverages the HSEE cutoff for academic (versus vocational) high school. Namely, our IV estimation strategy takes advantage of
the strict assignment rule associated with the HSEE cutoff and yet controls for a number of important baseline covariates that, because of sample selection bias, may be correlated with the treatment and the outcome variables of interest (see appendix S1 for a full discussion, appendix S1 in the supplemental appendix, available at http://wber.oxfordjournals.org/). We further check the robustness of our IV results to sample selection bias (see subsection 3.1.2).

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. We attempted to collect information on HSEE score 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 twenty-one of the seventy-five total sample counties, and the IV analysis is only among these twenty-one counties.\textsuperscript{12} Note that the HSEE test scores are not comparable across different prefectures because each prefecture administers a different test. In addition, although students within the same prefecture take the same HSEE, different counties within the same prefecture may use slightly different rules for grading the (same) HSEE test forms. For this reason, we always control for county fixed effects (using the county that each student took the HSEE in) when using our instrumental variable. By using below cutoff as an instrument for $V_{ij}$ in equation

\textsuperscript{12} To attempt to keep information from the other counties, we did in fact try to infer the cutoff points by looking at the distribution of HSEE scores and vocational versus academic high school entrants in each county. Unfortunately, we were unable to identify large jumps in entry at particular HSEE score values. Failing to identify these jumps, we surmise that these other counties did not use a strict cutoff rule to determine entry into academic high school. This may be the reason why officials in these counties did not publicly publish their HSEE cutoffs (and the reason that we could not obtain information about these cutoffs from the county officials themselves).
1, we assume that, conditional on baseline covariates, 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.

We provide justification for why below cutoff may be an appropriate IV. Figures 1 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 (Vij, y-axis). Figure 1a 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 ten 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 twenty points to the right or left of the HSEE cutoff (figures 1d and 1e respectively). Figures 1, taken together with the fact that county officials set HSEE cutoffs after the HSEE is administered and scored, lend support to the idea that (in the absence of sample selection bias), the HSEE cutoff rule is likely exogenous. If controlling for baseline covariates can appropriately adjust for sample bias, the HSEE cutoff variable should be uncorrelated with (observable and unobservable) factors that influence the relationship between vocational high school attendance (Vij) and student outcomes. In an attempt to control for possible sources of endogeneity, we control for Xij, HSEE score, and county fixed effects in all of our IV analyses.13

13 It is true that a small number of students (eighty-six out of 1754 or less than 5% of students) scored below the cutoff and yet managed to enter academic high school. This small number of students may have (unofficially) paid high fees
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 (see appendix table S2 and appendix table S2 in the supplemental appendix, available at http://wber.oxfordjournals.org/). Specifically, the first stage results show that the instrument has a strong and statistically significant (at the 1% level) relationship with the endogenous regressor. The weak identification tests (using the Craig-Donald Wald F Statistic) all reject the null hypotheses that the equations are weakly identified (with a p-value < 0.01).

2.3.3 Coarsened Exact Matching (CEM) Analyses

As a robustness check on our IV analyses and also to see whether our IV analyses hold over a broader range of data (i.e., because the IV analyses were only for students from twenty-one counties with HSEE cutoff data), our third analysis is a matching exercise. This third analysis isolates the sample of vocational and academic high school students that are similar on baseline characteristics by using coarsened exact matching or 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”

to enter academic high school. Nevertheless, this is the exception and not the rule. As such, this phenomenon should not substantively change our analyses.
or returned to their original values for the students that were not dropped from the sample. The post-matching estimation procedure is conducted on the data from step three.

Why do we choose CEM over traditional matching methods like propensity score matching? First and most importantly, compared to propensity score and Mahalanobis distance matching (which belong to the Equal Percent Bias Reducing or EPBR class of matching methods—Rosenbaum and Rubin 1985), CEM can obtain unbiased estimates with fewer restrictions on the data (see appendix S2 for a detailed discussion and appendix S2 in the supplemental appendix, available at http://wber.oxfordjournals.org/). As a result and as shown across a wide variety of datasets (see Iacus et al. 2011), CEM typically finds better balance in baseline characteristics across treatment and control groups than matching methods from the EPBR class. Second, CEM automatically eliminates the extrapolation region and thus (unlike matching methods in the EPBR class) does not require a separate procedure by which to restrict the data to a common support. Third, CEM is robust to measurement error. Fourth, CEM works with multiply imputed data. Fifth, CEM is computationally fast. A full discussion for how CEM outperforms propensity score and Mahalanobis distance matching is in appendix S2.

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).
Second, we also had to choose how much to coarsen each covariate (see appendix S2 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 (computing, math) into six equally spaced bins. 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 balance across the observable covariates. After applying the matching procedure, the vocational and academic high school students look similar on all of the baseline characteristics in equation 1 (appendix table S3 versus appendix table S4, and appendix table S3 and S4 in the supplemental appendix, available at http://wber.oxfordjournals.org/). As a robustness check, we also coarsen the baseline math and computer exam distributions into finer bins (from six up to fifteen bins each). Although the size of the matched sample decreases with the finer coarsening, we obtain similar results across the various matching specifications. The balance in baseline covariates is not just at the mean but
also at different parts of the distribution of each covariate (see appendix table S2). Furthermore, as explained above, the use of CEM automatically ensures that the matched data share a 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. Like Iacus et al. (2011), we use doubly robust methods to estimate the causal effects: we use linear regressions (that adjust for baseline covariates) to estimate the impacts of attending vocational high school on student outcomes after matching the 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). We call the regression analyses on the matched set of students our CEM analyses.

Granted, matching methods like CEM rely on the assumption of ignorability. That is, after controlling for observable covariates, no unobservable covariate is significantly correlated with both the treatment and outcome(s) of interest. While we cannot claim that CEM accounts for all possible confounding covariates, we believe that the CEM model presented here controls for the main confounding influences for why students attend vocational high school even when they are eligible to attend academic high school (see appendix S2 for more details).
III. RESULTS

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

3.1.1 Main Results

According to the results from the OLS analysis, students in vocational schools have different dropout rates and learn both computing and math 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 computing skills more than students attending academic high school (row 1, column 2). Students in vocational high school scored only 0.02 SDs higher than academic high school students in computing skills (not statistically different from zero). Finally, in terms of math skills, students in vocational high school score far lower (0.44 SDs) than students in academic high school (row 1, column 3). The difference is significant at the 1% level. In summary, students attending vocational versus academic high schools drop out more, learn fewer general skills, and have no measurable advantage in learning specific skills.

The results from our IV analysis generally support the story that vocational high schools do not build human capital (table 3). 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 finding—is no longer statistically significant). The IV estimates of vocational schooling on computing and math skills remain consistent with the findings from the OLS analysis. Vocational
schooling reduces math skills by 0.30 SDs (a finding significant at the 1% level). Moreover, there is no statistically significant evidence that attending VET improves computing skills (an increase of 0.12 SDs, p=0.16). The magnitude of the point estimate, even if it were statistically significant, is not large given the much greater number of class hours spent on learning computing in vocational schools compared to academic schools.

The results of the CEM analysis also tell the same story (table 4). Attending vocational high school increases dropout rates by 3 percentage points (over academic high school students—row 1, column 1). This finding is significant at the 1% level. Attending vocational high school has a negligible effect on computing 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 (row 1, column 2). The CEM analysis—which matches similar students from vocational high school and academic high schools—demonstrates that attending vocational high school decreases math skills by 0.42 SDs (significant at the 1% level—row 1, column 3).

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 computing skills relative to academic high schools (which spend little class time teaching computing). Third, attending vocational versus academic high school results in a loss of math skills.
3.1.2 Robustness Checks

To test the sensitivity of our estimates, we conduct six sets of robustness checks. Our first set of robustness checks tests whether our IV analyses are robust when we adjust our IV estimation strategy in four ways: (a) add nonlinear controls of the running variable; (b) allow slopes to be different on either side of the cutoff; (c) limit the sample to students that are closer to (on either side of) the cutoff; and (d) relax the assumption of linearity by using a probit model. Our second set of robustness checks involves defining our sample differently: (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 thereafter including these students in our analyses. A third set of checks involves ascertaining whether our estimates are sensitive to attrition, which we test for using Lee Bounds. A fourth set of robustness checks involves checking whether defining our variables differently (as continuous rather than binary variables, for example) would change our results. A fifth set of robustness checks tests whether sample selection could bias our IV estimates. Sixth (and related to the sample selection issue), we use a procedure suggested by Conley et al. (2012) to test the sensitivity of our IV estimates to deviations from the exogeneity assumption. In all cases, the results are not substantively different from the results from the models presented in the paper. While we do not display these results in the body of the text for the sake of brevity, they are presented in the appendixes (appendix S3, appendix table S5, and appendix table S6 in the supplemental appendix, available at http://wber.oxfordjournals.org/).
3.2 The impact of vocational high schools on low-income and low-ability students

According to some policy documents (e.g., MOF and MOE 2006), vocational high schools are meant to benefit low-income and low-ability students. In this section, we examine the heterogeneous impacts of attending vocational (versus academic) high school on dropout rates and skills by income (poverty) level and ability. To do so, 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).

Our results show that low-income students not only fail to benefit from attending vocational high school, they actually perform worse (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 make negligible gains in computing skills (column 2) while losing in math 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—table 6, column 1). In addition, by attending vocational (versus academic) high school, low-ability students are even less likely to gain computing 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 may see their math 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 computing skills than higher income and higher ability students and at least as likely to see a reduction in their math 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 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 attending vocational high school has a negative impact on student outcomes. 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.
Surprisingly, the IRT-scaled gains show that vocational high school students are actually losing math skills (figure 2). 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 make modest gains in 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 made fewer gains in specific skills than academic high school students, even as they spend much less time in computer classes than their vocational counterparts. The computer scores of academic high school students (in nonelite academic high schools) rose by 0.23 SDs.

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14 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.

15 What explains the surprising result that academic high school students are learning so little math and vocational high school students are learning so little in computers? One reason to suspect that academic high school students learned so little mathematics is that our schools are nonelite academic high schools, where the quality of schooling is not always high. Another reason for the low mathematics gains for academic high school students is that they were entering a new school (their first year of high school). As is common in the United States, for example, students entering a new schooling environment may have muted learning gains as they adjust to their new environment (e.g., see Roderick and Camburn 1999).

16 Why did academic high school students appear to make higher gains in computers even compared to mathematics? Students have a minimum exposure to computers in junior high school. As such, their first real exposure to computers
These results suggest that, in absolute terms, vocational high schools make only small contributions to or may even detract from human capital development. While it is true that vocational high school students make modest gains in their computing skills, as a whole their gains are less than those in academic high school. More importantly, vocational high school students are actually losing math skills.

IV. Conclusion

Overall, VET at the high school level does appear to be meeting its mandate of equipping students with the human capital needed to succeed in China’s future economy. Specifically, attending vocational high school appears to cause students (in the computer major) to drop out of school if they are of low-income and of low-ability. Our results also show that attending vocational high school 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 pronounced among both low-income students and low-ability students. Finally, in absolute terms, vocational high school even detracts from students’ math skills over the course of the first year (from the start to the end of grade ten). If our results generalize to other provinces and majors, vocational high schools are failing to contribute to human capital development in China.17

comes at the high school level. Hence, even though academic high schools only reserve one course for computers per week, the first systematic exposure to computers may have resulted in higher gains compared to mathematics. In addition, although it may appear peculiar that vocational high school students were learning fewer computer skills than academic high school students, the fact that the tests were constructed to match national standards suggests that vocational high schools were simply not teaching well (or students were not learning well).

17 It is conceivable that the students were performing poorly in vocational school because they were still adjusting to
There are reasons to believe that these results are conservative. First, in our more robust models (the IV and matching 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.

Overall, the lack of value-added in math or computing skills is likely to mute or decrease future labor market payoffs. Granted, it could be that vocational high schools produce value-
added in noncognitive (or social and behavioral) skills, such that there is still a net labor market return even without value-added in general or specific (cognitive) skills. In fact, Kim (2013) finds positive labor market returns on vocational education in Korea. However, the fact that Chinese computer major students are losing their math skills and barely learning any computing skills suggests that they also may not be acquiring social or behavioral skills either.\(^{19}\)

Why does VET at the high school level appear to fail at generating 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 (Yang 2012).

In fact, evidence suggests that this is not the case. We compare the vocational and academic high schools across a set of inputs—including the percentage of teachers with a college degree; the percentage of teachers with professional experience; computers per student; total school area (in square meters) per student; whether the school has laboratories; libraries or multimedia rooms; and expenditures per student (in RMB). We find that, with one exception,
there are no substantial or statistically significant differences between vocational high schools and academic high schools (appendix table S7). The exception is that vocational high schools have more computers per student. As such, vocational high schools appear to be on equal (if not marginally better) footing with academic high schools in terms of basic inputs.

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, thus reducing coordination and sharing of best practices between schools. Moreover, none of the ministries/departments/bureaus have developed protocols to systematically monitor vocational high school quality in a standard fashion. As such, there is almost no oversight over the quality of these schools.

A limitation of our study is that we focus only on students in the computer major and only test their math and computer skills. Ideally, our study would have included students in other majors and tested a wider set of skills. Therefore, strictly speaking, our results do not apply to other majors and other types of skills in vocational schooling in China. However, 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. Instead they may wish to direct more resources toward the apparently 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. Our results show that, at the margin, students in the most popular major in vocational school in two Chinese provinces lose general skills without any
apparent gain in specific skills. While our results do not strictly apply to other developing countries, the fact that our findings are consistent with results from Indonesia (Chen 2009) and Romania (Malamud and Pop-Eleches 2008) suggests that other developing countries with substantial investments in vocational secondary education may also fail to enjoy significant returns to their investment. By diverting resources away from academic high school, developing countries may be reducing the number of students who can access a human-capital enhancing opportunity to attend academic high school. Together, such a policy could substantially hinder human capital production.
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FIGURE 1. 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 HSEE Cutoff Figure 1c. 10 Points below the HSEE Cutoff Figure 1d. 20 Points above the HSEE Cutoff Figure 1e. 20 Points below the HSEE Cutoff

Source: Authors’ analysis based on data described in the text.
FIGURE 1. Continued

(c)

(d)
FIGURE 1. Continued

(e)
Figure 2. Gains in IRT-scaled Math Scores: Academic vs. Vocational High School

Note: Figure 2 shows the raw difference before controlling for any background characteristics

Source: Authors’ analysis based on data described in the text.
FIGURE 3. Gains in IRT-scaled Computer Scores: Academic vs. Vocational High School

Note: Figure 3 shows the raw difference before controlling for any background characteristics.

Source: Authors’ analysis based on data described in the text.
Table 1. Differences between Vocational High School and Academic High School Students

|                                | (1) Academic high school | (2) Vocational high school | (3) = (2) - (1) |
|--------------------------------|--------------------------|----------------------------|-----------------|
| Low-income\(^1\)              | 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***         |

\(^1\) The academic high school students appear to be economically poorer than the vocational high school students in our sample. This is likely because we sampled second tier, nonelite academic high schools that enrolled students with characteristics more comparable to those in vocational high schools. In addition, students who do not qualify for academic high schools have two choices: they may enter the labor market or attend vocational high schools. Students entering the labor market are typically from poorer backgrounds than those going into vocational high (Song et al. 2013). That is, a number of vocational high school students were children who were unable to test well enough to enter academic high schools but came from richer families that did not need to send their children to the labor market.

*Note:* Cluster-robust SEs in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

*Source:* Authors’ analysis based on data described in the text.
|                                       | (1)     | (2)     | (3)     |
|---------------------------------------|---------|---------|---------|
|                                       | Dropout | Computer endline | Math endline |
| Went to VET                           | 0.04*** | 0.02    | -0.44***|
| Low-income                            | 0.00    | 0.01    | 0.05*** |
| Male                                  | 0.03*** | 0.01    | -0.05** |
| Age                                   | 0.01*** | -0.02***| -0.05***|
| Urban                                 | 0.01    | -0.03   | 0.01    |
| Student migrated                      | 0.01    | 0.02    | 0.06*   |
| Siblings                              | 0.01*** | -0.01   | -0.02   |
| Parents home                          | -0.04***| 0.02    | -0.01   |
| Parents no junior high school         | 0.02*** | -0.01   | 0.03    |
| Math baseline                         | -0.01***| 0.05*** | 0.26*** |
| Computer baseline                     | 0.00    | 0.33*** | 0.19*** |
| Observations                          | 7,299   | 6,395   | 6,395   |

Note: Cluster-robust SEs in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors’ analysis based on data described in the text.
### TABLE 3. 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            |

*Note: Cluster-robust SEs in parentheses; *** p<0.01, ** p<0.05, * p<0.1.*

*Source: Authors’ analysis based on data described in the text.*
### Table 4. 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           |

*Note:* Cluster-robust SEs in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

*Source:* Authors’ analysis based on data described in the text.
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

Note: Cluster-robust SEs in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors’ analysis based on data described in the text.
### 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)   | (2)    | (3)    |
|------------------------|-------|--------|--------|
|                        | Dropout | Computer Endline | 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  |

*Note:* Cluster-robust SEs in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

*Source:* Authors’ analysis based on data described in the text.
Appendix S1. Rationale for using IV estimation strategy over an RD design

Standard sensitivity tests show that the typical RD design is not valid for our situation. For example, after conducting the McCrary density test, the density of students that score just below the HSEE cutoff (to enter academic high school) is significantly less than the density of students that score just above the HSEE cutoff (see the Figure below). This difference is not due to students’ ability to manipulate their HSEE scores. Rather, the difference arises because a large proportion of students that do not get into academic high school choose to enter the unskilled labor market (where wages are relatively high—see Cai et al., 2008) instead of vocational high school (Song et al., 2013).

Put differently, since we sampled students that were already at vocational and academic high schools (and not students that did not attend one of these two types of high schools), we under-sampled students on the left side of the HSEE cutoff. As such, we under-sampled students that did not qualify for academic high school and that entered the labor market. This under-sampling not only resulted in a significant jump in the density of the running variable across the cutoff, but also resulted in significant jumps in important baseline covariates (for example, baseline computer achievement).

Because the RD design is not strictly valid for our situation, we instead relied on an IV estimation strategy that still leverages the HSEE cutoff for academic (versus vocational) high
school. Namely, our IV estimation strategy takes advantage of the strict assignment rule associated with the HSEE cutoff, and yet controls for a number of important baseline covariates that, because of sample selection bias, may be correlated with the treatment and the outcome variables of interest. We note that by doing so, our estimation strategy is similar in spirit to situations in which researchers have adjusted their RD regressions with covariates (Frölich, 2007).
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).

Why did we use CEM instead of other matching procedures (such as propensity score matching or Mahalanobis distance matching)? Namely, CEM belongs to a new class of matching methods called the Monotonic Imbalance Balance (MIB) class (Iacus et al., 2011). The MIB class generalizes the previously (and only) existing class of matching methods (including propensity score matching or Mahalanobis distance matching) called the Equally Percent Bias Reducing (EPBR) class. As such, matching methods from the MIB class have several advantages over matching methods from the EPBR class.

The EPBR property (of the EPBR class), introduced and discussed by Rubin (1976), has at least two fundamental limitations. The first limitation of the EPBR property is that it attempts to
improve mean imbalance in baseline characteristics (covariates) and ignores other moments, interactions, or nonlinear relationships (unless they are explicitly included as baseline characteristics in the matching method). The second limitation of the EPBR property is that it assumes that improving the balance in the difference in means for one baseline characteristic also improves it for all the other baseline characteristics (and their linear combinations) by a (single) proportional constant.

Given the limitations associated with the EPBR property, Rosenbaum and Rubin (1985) offered special conditions under which controlling for mean characteristics would allow the researcher to also control for all expected differences between the multivariate treated and control distributions. When these restrictions on the data are in place, balancing the mean in one baseline characteristic (across treatment and control groups) balances the entire multivariate distribution of baseline characteristics (the latter of which is the ultimate goal of matching—Iacus et al., 2011; Rosenbaum and Rubin, 1985). Two important restrictions on the data (required by propensity score matching, for example) are that (a) the baseline characteristics must be randomly drawn from a specified population; and (b) the population distribution of the baseline characteristics must be an ellipsoidally symmetric density (Rubin and Thomas, 1992) or a discriminant mixture of such densities (Rubin and Stuart, 2006). Unfortunately, such data restrictions often do not hold (and the second limitation rarely holds) for observational data (Iacus et al., 2011).

By contrast, matching methods in the MIB class differ from those of the EPBR class in several important ways (see Iacus et al., 2011 for a detailed, technical discussion of the way that the MIB class generalizes and modifies the definition of the EPBR class). First, matching methods in the MIB class do not require data restrictions (the advantages of which have been explained in the previous paragraph). Second, matching methods in the MIB class focus on increasing in-sample balance rather than balance in expectation. This avoids seemingly paradoxical results (such as when the estimated propensity score is more efficient than the true score—see Hirano et al., 2003). Third, matching methods in the MIB class focus on reducing distributional differences in baseline characteristics (across treatment and control groups) variable by variable (rather than all at once and just for means of baseline characteristics like matching methods in the EPBR class). As previously explained, this is done by using a vector of tuning parameters (one for each baseline characteristic or covariate) that are chosen by the researcher ex ante. As a result (and in contrast to matching methods in the EPBR class), the numbers of matched treatment and control observations are not chosen ex ante by matching methods in the MIB class.

The theoretical advantages of matching methods in the MIB class (such as CEM) over matching methods in the EPBR class (such as propensity score matching and Mahalanobis distance matching) are apparent when working in practice with observational data. As shown across a number of different datasets (see Iacus et al., 2011), CEM typically “outperforms” matching methods from the EPBR class (i.e. CEM finds better balance in baseline characteristics across
treatment and control groups than matching methods from the EPBR class). This is true even when “ideal” datasets (datasets that have the necessary restrictions for the EPBR property to hold) are used. CEM considerably outperforms matching methods from the EPBR class when regular observational datasets (that do not have the necessary restrictions for the EPBR property to hold) are used.

In addition to typically outperforming the matching methods in the EPBR class, CEM has functional advantages that may be appealing to researchers (Iacus et al, 2012b). First, CEM automatically eliminates the “extrapolation region” and thus does not require a separate procedure by which to restrict the data to a common support. Second, CEM is robust to measurement error. Third, CEM works with multiply imputed data. Fourth, CEM is computationally fast. A detailed explanation of these advantages of using CEM over other matching methods is provided in Iacus et al. (2012b).

Granted, matching methods like CEM rely on the assumption of ignorability (that after controlling for observable covariates, no unobservable covariate is significantly correlated with both the treatment and outcome(s) of interest). Even though we match on a diverse set of observable covariates, we cannot guarantee that our CEM analyses control for all unobservable, confounding covariates.

Because of this, we cannot claim that CEM accounts for all possible confounding covariates. However, we believe that the current model controls for the main confounding influences for why students attend vocational high schools when they are eligible to attend academic high schools. For example, one reason students who are eligible to attend academic high school still choose vocational high school over academic high school is cost. Studies have shown that attending academic high school can be expensive—as much as 10 times the per capita income of those in poor, rural areas (Liu et al., 2009). By contrast, the government has instituted financial aid policies to encourage vocational high school attendance. To account for this possibility, we have controlled for student wealth and family background.

As another example, students may be more interested in learning vocational skills than traditional academic skills. Students may find academic learning routine or theoretical and desire more practical skills. However, the fact that all students in our sample took the high school entrance examination suggests that our sample students all thought they had a chance at academic high school. Students who are only interested in vocational schooling are able to go directly into the schools without having to take the high school entrance examination.

As a third example, students may be better equipped to succeed in vocational versus academic schools. Some students are more skilled in math or computing skills. It may be that students chose into vocational or academic high school because of their comparative advantages. However, we control for this possibility by including baseline mathematics and computer scores in our matching model.
Appendix S3: Robustness Checks

Our first set of robustness checks tests whether our IV analyses are robust when we adjust our IV estimation strategy in four ways: (a) add nonlinear controls of the running variable; (b) allow slopes to be different on either side of the cutoff; (c) limit the sample to students that are closer to (and on either side of) the cutoff; (d) relax the assumption of linearity of the treatment and outcome variables. In all cases, the results are not substantively different from the results from the models presented in the paper.

First, instead of only using one linear control of the running variable (the HSEE score) in the IV regressions, we (in line with the recommendations in Lee and Lemieux, 2010) run specifications with nonlinear controls of the running variable. When we add a quadratic control to our IV model (a model which generally fits as well or better than the linear model), the results are not substantively different from the results from the linear model (Appendix Table S5).

Second, the magnitude and significance of the IV results hardly changes even after we add an interaction term between the running variable and the IV/treatment to the linear model. As shown in Appendix Table S5, attending vocational as opposed to academic high school does not affect dropout (Column 3), does not increase endline computer scores (Column 6), and decreases math scores (Column 9).

Third, narrowing the analysis to only include students that have HSEE scores within 150 points on either side of the cutoff (as opposed to 200 points on either side of the cutoff) does not substantively change the results. Attending vocational as opposed to academic high school decreases math skills, but has little impact on dropout or computer skills (the results are omitted for the sake of brevity but are available from the authors upon request).

Fourth, we also check the robustness of the instrumental variable model results by relaxing the assumption of linearity. Specifically, we run a bivariate probit model in which we instrument for the endogenous binary treatment variable (attending vocational high school) and examine the impacts of the treatment variable on the binary outcome (dropout). The results from the bivariate probit model are substantively the same as the results from the linear model: attending vocational high school has no statistically significant impact on dropout. The results are not included for brevity but are available from the authors upon request.

Our second set of robustness checks involves defining 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).
A third set of checks involves ascertaining whether our estimates are sensitive to attrition. Because of dropout and other types of attrition, we test how sensitive our estimates of the impact of attending vocational high school on math and computer endline scores are to attrition. We do this by estimating Lee Bounds (Lee, 2009) for the OLS specification (the OLS regression on the unmatched dataset) and the CEM specification (the OLS regression on the matched dataset). For the OLS specification, the Lee Bounds estimates (that control for prefecture) are [-0.839, -0.419] for endline math achievement and [-0.140, 0.088] for endline computer achievement. For the CEM specification, Lee Bounds estimates are [-0.524, -0.313] for endline math achievement and [-0.109, 0.021] for endline computer achievement. In both cases the estimated bounds and point estimates (on the matched sample) agree: attending vocational school appears to significantly reduce math achievement and has no significant impact on computer achievement. To the best of our knowledge, the published literature does not provide a way to estimate Lee-type bounds for the IV regression estimates.

A fourth set of robustness checks involves checking whether defining our variables differently would change our results. In particular, we note that several of the explanatory variables used in our analyses have been transformed into categorical variables (whereas originally they were continuous variables). We did this for the sake of consistency. Namely, we initially transformed the explanatory variables such as number of siblings, education level, and wealth variables into dummy variables for the analyses based on coarsened exact matching (CEM). The transformation effectively helped to create coarser bins inside which treatment and control observations could be compared. Nonetheless, we reran all the regression analyses (OLS, IV, CEM) using the (original) continuous explanatory variables to check if the results would be substantively similar to those using the transformed categorical variables. The regression analyses using the (original) continuous explanatory variables give us the same substantive results as those using the categorical variables. We do not display these results for the sake of brevity but they are also available upon request.

A fifth set of robustness checks aims to test whether (and what direction) sample selection could bias our IV estimates. We acknowledge that our estimates could be biased downwards if students to the left of the cutoff that directly entered the labor market had a higher ability to gain skills than other students to the left of the cutoff that actually did enroll in vocational high school. That is, our estimates may have been biased downward if, even after conditioning on student and family background variables and skill levels, students that directly entered the labor market actually had a higher ability to gain skills than students that actually did enter vocational high school.

On the other hand, sample selection may work in the opposite direction (that is, in a positive direction). Among students that scored below the cutoff, those that directly entered the labor market may have had a lower ability to gain skills than those that actually entered vocational
This may be due to the fact that students that perceived lower returns to entering vocational high school (perhaps due to lower potential skill gains) may have been more likely to directly enter the labor market (instead of enrolling in vocational high school). By contrast, students that perceived higher returns (and higher potential skill gains) to entering vocational high school may have been more likely to enter vocational school. Moreover, because of the high opportunity costs of going to high school in China (due to a relatively high and rising unskilled wage), students that directly entered the labor market may also have been more likely to be of lower social and economic class (as measured by family wealth and parental education background) than students that entered vocational high school. Thus, students that entered the labor market may have been among those with fewer resources with which to make skill gains in vocational high school (had they even attended).

We present empirical evidence that lends support to the second possibility. Our evidence comes from, as far as we know, the only survey in China that follows up students from junior high school into either a.) high school; or b.) the labor market (see Yi et al., 2015). The survey tracks approximately 2,000 students in Shaanxi and Hebei provinces from the start of junior high school into high school (or the labor market). Using the data from the study, we find that among students with HSEE scores below the academic high school cutoff, those that directly entered the labor market (group A) demonstrate significantly lower skill gains in math (both from the start of grade 7 to the start of grade 9 and from the start of grade 9 until the time that they take China’s HSEE—which is at the end of grade 9) than students that entered vocational high school (group B—see Appendix Table S6, Rows 6-7 below). Those that directly entered the labor market (group A) are also of lower social and economic status than those that entered vocational high school (group B), as reflected by lower levels of family wealth and parental education (Appendix Table S6, Rows 3-5). Differences in skill gains and social and economic status increase when we examine students that score closer to but still below the cutoff.

Because the students that directly enter the labor market (group A) have lower skill gains and are of a lower social and economic class, the data suggest that group A students would have lower skill gains if they entered vocational school compared to students that already entered vocational high school (group B). Thus, failing to account for students that directly entered the labor market likely creates an upward bias in our IV estimates of the impacts of attending vocational school on skill gains. In other words, as suggested by the OLS and matching estimates that we are able to compute given our sample (which does not include those students that directly enter the labor market), the impacts of attending vocational high school on skills gains are at best negative for the academic skill (math) and unlikely to be statistically different from zero for the vocational skill (computers).

Sixth (and related to the sample selection bias issue discussed immediately above), we use a procedure suggested by Conley et al. (2012) to test the sensitivity of our IV estimates to deviations from the exogeneity assumption. Since the statistical consistency of our IV estimates depends on
whether our instrument variable is exogeneous, both in the presence and absence of sample selection, we believe that this is also the most direct test of the sensitivity of our IV estimates to sample selection.

The bounding procedure proposed by Conley et al. (2012) is based on the following equation:

\[ Y = \beta T + \lambda Z + \alpha X + \epsilon \]

Where \( Y \) is the outcome, \( T \) is the treatment variable, \( Z \) is the instrumental variable, \( X \) is a vector of control variables, and \( \epsilon \) is the error term (reflecting unobservable factors). Under the exclusion restriction underlying IV – that \( \lambda \) equals zero – the above equation can consistently estimate the treatment effect (\( \beta \)). The bounding procedure proposed by Conley et al. (2012), however, examines the degree to which deviations from the exogeneity assumption – that \( \lambda \) does not equal zero – changes the treatment effect estimates. For more details on how the bounding procedure is conducted, we refer the reader to Conley et al. (2012) directly.

How do we specifically apply the bounding procedure to our situation? As noted earlier, it is most likely that students who score below the HSEE cutoff and enter vocational high school (the students that are in our sample) will make greater skill gains than students who score below the HSEE cutoff and enter the labor market (the students that are not in our sample). It is thus most plausible to assume that \( \lambda \) (the relationship between skill gains and being just below as opposed to just above the cutoff in our sample) is greater than 0.

Under this assumption and using the most conservative “union of confidence intervals” approach of Conley et al. (2012), we find that the impacts of attending vocational high school on student skill gains are most likely zero or negative. Specifically, when \( \lambda \) goes from 0 to 0.1, the impact of attending vocational high school on math skills remains negative, large (-0.46), and statistically significant at the 1% level. The impact of attending vocational high school on computer skills is essentially zero (-0.001) and not statistically different from zero.

Thus, failing to account for students that directly enter the labor market likely upwardly biases our IV estimates of the impacts of attending vocational school on skill gains. In other words, as suggested by our OLS and matching estimates, the impacts of attending vocational high school on skills gains are at best negative for the academic skill (math) and likely to be zero for the vocational skill (computers).

We also note that even when \( \lambda \) changes from 0 to -0.1, the point estimate of the impact on math skills remains negative, substantial in magnitude (below -0.3), and statistically significant at the 1% level. The point estimate on computer skills remains small in magnitude (0.135) and only becomes statistically significant at the 10% level. Thus, even when \( \lambda \) slightly deviates in the
opposite direction of what we would expect (whether according to theory or empirical evidence),
the impact estimates do not change substantively.
### Appendix Table S1: Test of Attrition

| VARIABLES       | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  | (7)  | (8)  | (9)  | (10) |
|-----------------|------|------|------|------|------|------|------|------|------|------|
| Low income      | 0.05 | 0.05*| 0.14**| 0.02 | 0.01 | 0.03 | -0.04***| 0.01 | -0.61***| -0.11*|
| Male            | (0.03)| (0.02)| (0.04)| (0.01)| (0.01)| (0.04)| (0.01)| (0.02)| (0.07)| (0.05)|
| Age             | 0.31**| 0.56***| 15.99***| 0.89***| 0.16***| 0.68***| 0.89***| 0.36***| 1.66***| -0.16 |
| Urban           | (0.09)| (0.07)| (0.08)| (0.01)| (0.02)| (0.05)| (0.01)| (0.08)| (0.16)| (0.09)|
| Student Migrated| 0.02 | 0.01 | 0.01 | 0.04 | 0.01 | 0.03 | -0.04***| 0.01 | -0.61***| -0.11*|
| Siblings        | 0.03 | 0.03 | 0.03 | 0.04 | 0.03 | 0.03 | -0.04***| 0.01 | -0.61***| -0.11*|
| Parents Home    | 0.01 | 0.01 | 0.01 | 0.02 | 0.01 | 0.01 | -0.04***| 0.01 | -0.61***| -0.11*|
| Parents Did Not Finish Junior High | 0.68***| 0.89***| 0.36***| 1.66***| -0.16 |
| IRT-scaled Math Baseline Scores | (0.07)| (0.07)| (0.08)| (0.01)| (0.02)| (0.05)| (0.01)| (0.08)| (0.16)| (0.09)|
| IRT-scaled Computer Baseline Scores | -0.11*| -0.11*| -0.11*| -0.11*| -0.11*| -0.11*| -0.11*| -0.11*| -0.11*| -0.11*|
| Attrited        | 7,640| 7,610| 7,644| 7,610| 7,644| 7,644| 7,408| 7,451| 7,644| 7,644 |
| Constant        | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Notes: (1) Attrited refers to dropped out, absent, or on long-term sick leave; (2) Among the 13% of students that were counted attrited on the day of the endline survey, 8% had dropped out, 4% were absent (that day), and 1% were on long-term sick leave.
## Appendix Table S2: First-Stage Instrumental Variable Regression Results

|                                | IV with linear term | IV with quadratic term | IV with interaction centered HSEE score | go VET (y/n) | go VET (y/n) | go VET (y/n) | Observations | R-squared | F-test for Weak Identification (p-value) |
|--------------------------------|---------------------|------------------------|----------------------------------------|--------------|--------------|--------------|--------------|----------|----------------------------------------|
| Below HSEE cutoff (yes/no)    | 0.60***             | 0.55***                | 0.58***                                | 0.60         | 0.55         | 0.58         | 3600         | 0.62     | 0.0000                                 |
|                                | (0.06)              | (0.07)                 | (0.07)                                 | (0.06)       | (0.07)       | (0.07)       |              |          | 0.0000                                 |
| Below HSEE cutoff * Centered HSEE score |                    |                        |                                        |              |              |              |              |          |                                        |
|                                | 0.00***             | 0.00***                | 0.00***                                | 0.00         | 0.00         | 0.00         |              |          | 0.0000                                 |
|                                | (0.00)              | (0.00)                 | (0.00)                                 | (0.00)       | (0.00)       | (0.00)       |              |          | 0.0000                                 |
| Male (yes/no)                  | 0.01                | 0.01                   | 0.01                                   | -0.8         | -0.8         | -0.8         |              |          |                                        |
|                                | (0.02)              | (0.02)                 | (0.02)                                 | (0.02)       | (0.02)       | (0.02)       |              |          |                                        |
| Age                            | 0.03**              | 0.03**                 | 0.03**                                 | 1.59         | 1.59         | 1.59         |              |          |                                        |
|                                | (0.01)              | (0.01)                 | (0.01)                                 | (0.01)       | (0.01)       | (0.01)       |              |          |                                        |
| Urban (yes/no)                 | 0.04**              | 0.04**                 | 0.04**                                 | -1.0         | -1.0         | -1.0         |              |          |                                        |
|                                | (0.02)              | (0.02)                 | (0.02)                                 | (0.02)       | (0.02)       | (0.02)       |              |          |                                        |
| Student migrated (yes/no)      | -0.00               | -0.00                  | -0.00                                  | 0.2          | 0.2          | 0.2          |              |          |                                        |
|                                | (0.01)              | (0.01)                 | (0.01)                                 | (0.01)       | (0.01)       | (0.01)       |              |          |                                        |
| Siblings (yes/no)              | 0.01                | 0.01                   | 0.01                                   | 0.0          | 0.0          | 0.0          |              |          |                                        |
|                                | (0.02)              | (0.02)                 | (0.02)                                 | (0.02)       | (0.02)       | (0.02)       |              |          |                                        |
| Parents home (yes/no)          | 0.01                | 0.01                   | 0.01                                   | 0.8          | 0.8          | 0.8          |              |          |                                        |
|                                | (0.02)              | (0.02)                 | (0.02)                                 | (0.02)       | (0.02)       | (0.02)       |              |          |                                        |
| Parents no junior high school (yes/no) | 0.03**             | 0.03**                 | 0.03**                                 | 0.8          | 0.8          | 0.8          |              |          |                                        |
|                                | (0.01)              | (0.01)                 | (0.01)                                 | (0.01)       | (0.01)       | (0.01)       |              |          |                                        |
| Low-income (yes/no)            | 0.02                | 0.02                   | 0.02                                   | 1.87         | 1.87         | 1.87         |              |          |                                        |
|                                | (0.02)              | (0.02)                 | (0.02)                                 | (0.02)       | (0.02)       | (0.02)       |              |          |                                        |
| Math baseline                  | -0.03***            | -0.03***               | -0.03***                               | 0.3          | 0.3          | 0.3          |              |          |                                        |
|                                | (0.01)              | (0.01)                 | (0.01)                                 | (0.01)       | (0.01)       | (0.01)       |              |          |                                        |
| Computer baseline              | 0.06***             | 0.06***                | 0.06***                                | 0.6          | 0.6          | 0.6          |              |          |                                        |
|                                | (0.02)              | (0.02)                 | (0.02)                                 | (0.02)       | (0.02)       | (0.02)       |              |          |                                        |
| Centered HSEE score            | -0.00***            | -0.00***               | -0.00***                               | 0.0          | 0.0          | 0.0          |              |          |                                        |
|                                | (0.00)              | (0.00)                 | (0.00)                                 | (0.00)       | (0.00)       | (0.00)       |              |          |                                        |
| Centered HSEE score squared    | -0.00***            |                        |                                        |              |              |              |              |          |                                        |
|                                | (0.00)              |                        |                                        |              |              |              |              |          |                                        |
| Observations                   | 3600                | 3600                   | 3600                                   | 3600         | 3600         | 3600         |              |          |                                        |
| R-squared                      | 0.62                | 0.62                   | 0.62                                   | 0.62         | 0.62         | 0.62         |              |          |                                        |
| F-test for Weak Identification (p-value) | 0.0000             | 0.0000                 | 0.0000                                 | 0.00         | 0.00         | 0.00         |              |          |                                        |

Cluster-robust SEs in parentheses

*** p<0.01, ** p<0.05, * p<0.1
### Appendix Table S3: 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 Table S4: 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:

| Variable                       | 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 |
### Appendix Table S5. Robustness Check of IV Estimator across Different Model Specifications

|                | (1)     | (2)     | (3)     | (4)     | (5)     | (6)     | (7)     | (8)     | (9)     |
|----------------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
|                | dropout | endline computer achievement | endline math achievement |         |         |         |         |         |         |
| attended VET (y/n) | 0.011   | 0.024   | 0.018   | 0.116   | 0.131   | 0.122   | 0.299***| -0.230**| -0.271**|
|                 | (0.029) | (0.036) | (0.031) | (0.082) | (0.076) | (0.075) | (0.113) | (0.117) | (0.116) |
| attended VET (y/n) * centered HSEE score | -0.000  | -0.000  | -0.000  | 0.002***| 0.002***| 0.002** | 0.003***| 0.004***| 0.004***|
|                 | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) | (0.000) | (0.001) |
| centered HSEE score | -0.000**| -0.000  | -0.000  | 0.002***| 0.002***| 0.002** | 0.003***| 0.004***| 0.004***|
|                 | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| centered HSEE score – squared | 0.000   | 0.000   | 0.000   | 0.000   | 0.000   | 0.000   | 0.000   | 0.000   | 0.000   |
|                 | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| CONTROLS        | YES     | YES     | YES     | YES     | YES     | YES     | YES     | YES     | YES     |
| N               | 3,600   | 3,600   | 3,600   | 3,309   | 3,309   | 3,309   | 3,303   | 3,303   | 3,303   |
| R-squared       | 0.021   | 0.021   | 0.022   | 0.159   | 0.158   | 0.159   | 0.240   | 0.244   | 0.240   |

Cluster-robust SEs in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Controls include Male (1=yes), Age (in years), Urban (1=yes), Student migrated (1=yes), Siblings (1=yes), Parents home (1=yes), Parents no junior high school (1=yes), Low-income (1=yes), IRT-scaled Math baseline scores, and IRT-scaled Computer baseline scores.
Appendix Table S6. Characteristics of Students who Entered the Labor Market vs. Vocational High School

|                                      | Entered Labor Market (Group A) | Entered Vocational High School (Group B) |
|--------------------------------------|--------------------------------|------------------------------------------|
| Proportion of females                | 0.58                           | 0.64                                     |
| Age (years)                          | 13.73                          | 13.46                                    |
| Family wealth index (based on family assets) | 2540.55                        | 2986.63                                  |
| Mother's education level (years)     | 4.67                           | 5.84                                     |
| Father's education level (years)     | 6.59                           | 7.21                                     |
| Math score gains (grade 7 to grade 9), diff in z-scores | -0.16                          | -0.01                                    |
| Math score gains (grade 9 to HSEE), diff in z-scores | -0.22                          | -0.08                                    |
| N                                    | 125                            | 102                                      |

Source: Longitudinal survey of students in Shaanxi and Hebei provinces from the start of junior high school into high school (or the labor market).
### Appendix Table S7. Comparing School and Teacher Characteristics between Vocational and Academic High Schools

|                        | (1) Percentage of teachers with a college degree | (2) Percentage of teachers with professional experience | (3) Computers per student | (4) Total school year (in sq meters) per student | (5) Has a school laboratory (1=yes) | (6) Has a school library (1=yes) | (7) Has a multimedia room (1=yes) | (8) Expenditures per student (in RMB) |
|------------------------|-----------------------------------------------|-------------------------------------------------------|---------------------------|-----------------------------------------------|--------------------------------|--------------------------------|--------------------------------|-----------------------------------|
| **Vocational high school** (1=yes) | 0.02                                          | 0.02                                                  | 0.10**                    | -15.80                                        | -0.02                          | -0.01                          | 0.01                                    | -942.10                          |
| Constant               | 0.98***                                       | 0.21**                                                | 0.14***                   | 61.74***                                      | 1.00***                        | 1.00                           | 0.95***                                 | 3,350.06***                      |
| **Observations**       | 8,798                                         | 8,006                                                 | 8,362                     | 8,327                                         | 8,802                          | 8,874                          | 9,739                                   | 7,105                             |
| **R-squared**          | 0.00                                          | 0.00                                                  | 0.03                      | 0.02                                          | 0.01                           | 0.00                           | 0.00                                    | 0.02                              |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The results are substantively the same when data are collapsed at the school-level and school-level means are compared.