**The Impact of Vocational Teachers on Student Learning in Developing Countries:
Does Enterprise Experience Matter?**

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ABSTRACT

Although a large number of students around the world attend vocational schools, there is little evidence about what factors matter for learning in these schools. Using data on approximately 1,400 vocational students in one eastern province in China, we employ a student fixed effects model to identify whether teacher enterprise experience, direct occupational experience and not just program training, increases students' technical skills. We find this to be the case, especially for students who began the program as high performers. In contrast, "professional certification" which is given to teachers who participate in short-term training programs has no positive impact.

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1. Background

Vocational schooling is responsible for educating a large share of high school students in the world today. In a number of developed countries, such as Austria, the Czech Republic and Germany, approximately one-third of all high school students graduate from vocational schooling (OECD, 2013). The proportion of high school graduates from vocational schooling has also grown substantially over the last decade in a number of other developed countries such as Finland, Ireland and Spain (OECD, 2013). In the United States, over 80 percent of public high school graduates earn at least one credit in vocational education (commonly referred to as "career and technical education"—NCES, 2013). Vocational schooling at the high school level is therefore an important fixture of education systems in developed countries today.

Since the turn of the century, policymakers in developing countries have also begun placing considerable emphasis on the promotion of vocational schooling at the high school level. In Brazil policymakers are expanding enrollments in vocational high schools, with the goal of reaching 8 million by 2014 (National Congress, 2011). In Indonesia the government aims to increase the share of students in vocational (versus general) high schools to 70 percent (from 30 percent) by 2015 (Ministry of National Education, 2006). In China, enrollments in vocational high schools have almost doubled over the last decade, reaching more than 22 million students (NBS 2001; NBS, 2012). Policymakers in each of these countries believe that the expansion of vocational schooling at the high school level is necessary to build a skilled labor force that can contribute to national economic development (OECD, 2010).

Surprisingly, given the scale of vocational schooling at the high school level and government interest in its expansion, to our knowledge there have been few, if any, studies that

examine "what works" to improve student learning in vocational schooling. While scholars make claims about what works in vocational schooling (e.g. Grollmann, 2008)), their claims are not based on results from research that are set up to identify causal relationships. The absence of cause-effect evidence on what works in vocational schooling implies that policymakers in a large number of countries have little empirical basis for how best to educate a large proportion of their future workforce.

The lack of knowledge about what works is even more conspicuous when contrasted to the literature for general schooling for which scholars have published hundreds of causal impact studies to identify ways to increase student learning in both developed and developing countries. For example, the United States government has cataloged hundreds of experimental and quasi-experimental studies on the best practices in general schooling in the "What Works Clearinghouse" (IES, 2013). Moreover, in developing countries, scholars have begun publishing systematic reviews to summarize the literature on best practices in general schooling (Glewwe et al., 2011; McEwan, 2012).

Among the established evidence for what works in general schooling, what has been found that can potentially apply to vocational schooling? One foundational claim in the general schooling literature is that teachers matter (Rockoff, 2004; Rivkin, Hanushek and Kain, 2005). In particular, a number of studies have identified teacher qualifications that have a significant impact on student learning. These qualifications include, but are not limited to, teacher experience (Ferguson and Ladd, 1996; Clotfelter et al., 2010; Rockoff, 2004), teacher educational background (Clotfelter et al., 2010; Goldhaber and Brewer 1997, 2000; Kukla-Acevedo, 2009; Monk, 1994) and teacher certification (Boyd et al, 2006; Clotfelter et al., 2010). Unfortunately, although there is rich evidence about which teacher qualifications impact student learning in general schooling, there are reasons to believe that the teacher qualifications that

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matter in general schooling may be different from those that matter for vocational schooling. One reason for this is that the technical nature of vocational schooling is thought to require a specialized set of teacher qualifications (Bannister, 1955; Singh, 1998; Harris, Simons and Bones, 2000; Zhang, 2009; Kasipar, 2009).

Enterprise experience is one of the main vocational teacher qualifications that policymakers and researchers hypothesize may have substantial impact on vocational student learning (Kasipar, 2009; Zhang, 2009; OECD, 2010). The rationale is that vocational teachers with enterprise experience (occupational experience in industry) are more able to convey up-to-date, real-world vocational knowledge and experiences to their students (Zhang, 2009; OECD, 2010). This reasoning is part of the widespread claim that strong enterprise-school relations are essential for improving student learning (Harris, Simons and Bones, 2000; OECD 2010). Despite the fact that policymakers and researchers prioritize enterprise experience when making important decisions about the hiring and training of vocational teachers, we can find no evidence in the literature about whether enterprise experience actually matters for student learning.

The overall goal of our paper is to understand whether enterprise experience, perhaps the teacher qualification most emphasized in the literature on vocational schooling, improves student learning. In addition to examining the main impacts of enterprise experience on student learning in general, we also examine whether enterprise experience affects higher versus lower achieving students differently.

To fulfill our objectives, we use data that we collected on 1,398 computer major students in 28 vocational high schools in one eastern province in China in 2012. In particular, we examine the impact of two measures of teacher enterprise experience on student achievement. The first is a direct measure in which we ask teachers whether they have worked in an enterprise (we call this "enterprise experience"). The second is an indirect measure created by the government to

identify which teachers have received both a teaching certification and a professional certification (called "dual certification"). We examine the second measure because of its policy relevance; the Chinese government uses the dual certification measure to distribute resources and hold schools accountable, but it is unclear whether the dual certification in fact captures enterprise experience or improves student learning.

We analyze the data using a cross-subject student fixed effects model (see Dee, 2005, 2007; Clotfelter et al., 2010). The student fixed effects model exploits the fact that computer major students in vocational schools in China are required to take both hardware and software subjects, typically taught by different computer teachers, and that computer major students in our analytical sample took standardized tests in both subjects. This research design allows us to examine whether teacher enterprise experience matters by exploiting within-student variation in teacher qualifications and student scores.[1]

Our results indicate that a teacher's enterprise experience (measured directly) does increase student learning. Specifically, when teachers have previously obtained occupational experience in enterprises in the field/major in which they teach, they have a substantial positive impact on student learning. Furthermore, this positive impact tends to be concentrated on higher-achieving (as opposed to lower-achieving) students. By contrast, a teacher's dual certification has no positive impact on student learning either for higher- or lower-achieving students. This may be because such certifications are based on attendance in short-term, generally ad hoc, training programs that do not necessarily confer the skills and expertise better gained through actual enterprise experience.

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[1] Within-student variation' refers to variation for the same student across different contexts. This term is used in a number of studies that employ the same methodology (Dee 2005, 2007; Aslam & Kingdon, 2007; Clotfelter, Ladd, & Vigdor, 2010; Schwerdt & Wupperman, 2011; Metzler & Woessman, 2012; Kingdon & Teal, 2010; Altinok & Kingdon, 2012, Van Klaveren, 2011; Zakharov, Carnoy & Loyalka, 2014). In this case, "within-student variation" refers to (for example, teacher and classroom) characteristics that vary across each student's hardware and software subjects.

The remainder of the paper proceeds as follows. In section 2, we describe our research design, including our sampling strategy, data collection, and analytical approach. In section 3, we present our results. We conclude in section 4.

2. Research Design

2.1 Enterprise Experience and Dual Certification in China

To examine the impact of teacher enterprise experience on vocational student learning, we draw on China as a case study. Understanding whether teacher enterprise experience improves student learning has particular policy relevance in China today (MoE, 2013). Historically, a large number of vocational school teachers came from the academic schooling system and lacked technical knowledge (Guo and Lamb, 2010). Moreover, because of the rapid growth of the Chinese economy which have greatly expanded the opportunities to earn higher wages in enterprises, workers with enterprise experience rarely chose to become teachers (Guo and Lamb, 2010). However, believing that enterprise experience is important for vocational student learning, policymakers emphasize that schools should attempt to hire teachers who already have enterprise experience or provide existing teachers who do not have such experience with opportunities to acquire it (MoE, 2013). Significantly, the government measures enterprise experience through the dual certification scheme. A teacher holds a dual certification if he or she has *both* a teaching certificate and some sort of professional certificate which shows that the teacher has enterprise-related knowledge in a specific, technical domain. The way that professional certificates are conferred usually involves enrolling in a short-term training course and passing a written examination. Notably, enterprise employment experience is not always a requirement to receive a professional certificate, and dual certification may therefore not be the same as having true enterprise experience (MoE, 2013).

Estimating the impact of dual certification is of interest because policymakers allocate resources and evaluate schools based on the dual certification benchmark (State Council, 2002). Specifically, policymakers evaluate the quality of vocational schools in part by referencing the proportion of dual certification teachers in a given school. Because of this unique Chinese political context, we estimate the impact of two indicators (one direct measure and one indirect government measure) for enterprise experience on student learning.

2.2 Sampling

The data for our study come from a survey of schools in one eastern province of China. The survey sample was chosen in several steps. First, we selected Zhejiang Province, a coastal province that ranks fifth in terms of GDP per capita (after Tianjin, Shanghai, Beijing, and Jiangsu—NBS, 2012). Second, we identified the four most populous prefectures in Zhejiang. Approximately half of the province's vocational high schools are located in these four prefectures. Third, we created a sampling frame of all vocational high schools from the four prefectures using administrative records. From this sampling frame, we first excluded 152 schools, out of a total of 285 schools, which did not offer a computer major, the most popular major in Zhejiang province. Of the remaining schools, we excluded 78 "small" schools from our sampling frame, that is, those schools with fewer than 50 first-year students enrolled in the computer major. We excluded small schools because policymakers informed us that these schools were at high risk of being closed or merged during the school year. Although the number of excluded schools was higher than we expected, the excluded schools comprised less than 10 percent of the share of computer major students in the four prefectures of Zhejiang. We then surveyed the remaining 55 schools as part of our sample.

In each of the 55 sample schools, we randomly sampled two first-year computer major classes (or just one class if the school had only one computer major class) and administered a baseline survey to all students in these classes in May 2012, the end of the school year. We also administered a 30-minute standardized examination in basic computer knowledge. The exam was based on items from a student-focused qualifying examination that students can take to receive a credential for computing proficiency from China's Ministry of Human Resources. We also collected information from the schools on the types of computer skills that students would be learning during their second year of studies.

Using data from the baseline survey, we applied three additional exclusion criteria to determine our final sample of schools. First, because our estimation strategy of student fixed effects (see subsection 2.4) requires teachers from two different subjects to teach the same students (within a particular school), we included only schools that offered both hardware and software subjects, thus, excluding those schools that offered only software subjects or only hardware subjects. Applying this criterion meant excluding an additional 16 schools. Second, because our estimation strategy requires variation in teachers across subjects, we also excluded six schools in which the same instructor taught both hardware and software computer subjects. Third, we excluded five schools that offered different curricula for the computer major such that our standardized tests were not relevant for those schools; these schools failed to teach concepts tested in our measure for student learning (see subsection 2.3). After applying these additional sampling criteria, only 28 of 55 vocational high schools remained in our sample. To test whether this smaller sample of schools is in any way special relative to other vocational schools, we compare their characteristics with the characteristics of the sample of 55 schools using administrative data on school size, number of majors offered, expenditures, income, and teachers

(see Appendix Table A1). We find that there are no significant differences between the two samples in terms of school size, number of majors, expenditures, and teacher characteristics.

The following year (May 2013), we conducted an endline data collection with the same set of students in the 28 sample schools. At this time, we also identified and surveyed all of the computer teachers of the sample students. Altogether, we surveyed and administered standardized examinations to 1,398 students and surveyed 150 computer teachers.

2.3 Data

At both baseline (May 2012) and endline (May 2013), we administered student-level surveys through which we collected information on basic student characteristics. In addition, we asked students to report the computer courses they completed and the number of hours per week they spent in each computer course (in both hardware and software subjects).

Computer major students in vocational schools in China are required to take both hardware and software subjects. Hardware courses generally focus on foundational concepts in computing, computer maintenance and repair. Software courses focus on word processing, data entry, website design, and the use of specific software packages. Students are assigned into a "class" (or fixed group of students) and take the same hardware and software courses as the other students in their class. In other words, there are typically no electives that are under the control of students. All members of their "class" take the same required courses.

In line with our experiences in surveying vocational schools in other parts of China, our data on students' course schedules reveal (a) that there is no within-school tracking of students (in a given major) into classes or different types of courses; (b) students in a given class take exactly the same schedule of courses. In other words, as expected, all students in the same class,

in fact, do follow the same schedules and courses. This means, of course, that there is no systematic or non-random selection of students into courses (classes) in our sample.

As part of both baseline and endline data collections, we obtained measures on student achievement in hardware and software subjects through administering subject-specific standardized tests. We followed a four-step procedure to collect reliable and valid measures of student achievement in both subjects. First, we collected a large pool of hardware and software subject exam items (questions) from official sources. The exam items were taken from past versions of national computer examinations (specifically, the National Computer Rank Examination and the National Applied Information Technology Certificate exam). The hardware examination contained questions on foundational concepts in computing, computer repair, computing components and information technology. The software examination contained questions on data entry, Microsoft Office, Visual Basic, Access, Flash, Photoshop, CorelDraw and website design. Second, we piloted a pool of 100 hardware and software exam items with more than 300 students. A psychometrician used data from the pilot to create standardized hardware and software exams. Third, we administered and closely proctored the standardized hardware and software exams during the baseline and endline surveys. The baseline examinations contained 14 items about hardware and 25 items about software; the endline examinations contained 40 and 38 items, respectively. Fourth, the hardware and software exam scores were each normalized into z-scores by subtracting the mean and dividing by the standard deviation (SD) of the exam score distribution.

As part of the endline survey, we also surveyed the hardware and software teachers. To obtain a measure of teacher enterprise experience, we collected data on two enterprise experience variables: (a) whether the teacher had actual enterprise experience and (b) whether the teacher

had dual certification.[2] In regards to actual enterprise experience, we asked teachers to indicate whether they had prior employment in an enterprise relevant to the courses they were teaching (e.g., computer hardware or computer software courses). In regards to dual certification, we directly asked teachers if they had a teaching certification and a professional certification. Teachers who reported having acquired certification in both domains are regarded by policymakers and administrators as having dual certification.

We also collected information on a number of basic teacher characteristics which serve as control variables in our analyses. Specifically, we collected information on age (in years), gender (whether female or not), level of education (bachelor's degree or not), and whether the teacher majored in computing in college. Additionally, we asked teachers about their teaching experience (in years), whether the school officially hired them or if they were part-time/adjunct, and how many hours per week they taught in each subject, whether hardware or software.

To construct additional control variables, we further collected information on a teacher's rank, awards, and certifications. In China, all vocational school teachers are given a rank ranging from 4 (lecturer) to 1 (distinguished teacher). Being a top-ranked teacher has implications for salaries and opportunities to receive further training. We also asked whether the teacher had received any teaching awards at the county, municipal or provincial/national level. Finally, we asked teachers if they had ever taken and passed the National Computer Rank Examination or the National Applied Information Technology Certificate, the two most widely used examination-based certification schemes for computing professionals in China today, as well as whether they passed other computer-focused certification schemes offered by established private providers (e.g. Novell, Microsoft, Oracle, Adobe, etc.). We coded a teacher as having

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[2] In our sample, ninety percent of teachers holding a dual certificate do not have enterprise experience. Fifteen percent of teachers in our sample have neither enterprise experience nor a dual certificate, while eight percent of the sample has both enterprise experience and a dual certificate.

computer certification if he or she passed the first level of any of the above exams, meaning that the teacher achieved at least one exam-based certification.

Because the second-year students in our survey complete multiple hardware and software courses, they may each be taught by multiple hardware and software teachers. As our analytical strategy relies on within-student variation across hardware and software subjects (see subsection 2.4), our estimation model does not account for variation within-teachers and within-subjects. Thus, because each student may be taught by multiple hardware or software teachers, we estimated weighted averages for each student to account for the combined characteristics of all of his or her teachers in each subject based on the amount of time that that student spent in class with each teacher. This is similar to the approach employed by Bettinger and Long (2005; 2010). For example, a student may have two hardware teachers. The first teacher is male and works with the student seven hours a week, and the second is female and works with the student three hours a week. In our approach, the value of the averaged dummy variable (female=1) of the "average hardware teacher" of this student is 0.3. This weighted average of the gender of the two teachers is thus equivalent to the proportion of time a student spends with a female hardware teacher. Thus, our treatment arms are perhaps better defined as equivalent to 1) the proportion of time a student spends with a teacher with a dual certificate, and 2) the proportion of time a student spends with a teacher with enterprise experience. Through this approach, students are matched to a single set of teacher characteristics for each subject, weighted by the amount of time a student spends with teachers in each subject area. In other words, in our model, each student will ultimately be associated with an "average" hardware teacher and "average" software teacher (two "average" teachers in total). We use the variation in the set of averaged teacher characteristics for each student to examine its impact on student achievement.

Finally, it is worth noting that while there is no clear theoretical reason to use weighted averages, we conjecture that the amount of time students spend with teachers matters. A teacher instructing a student for ten hours a week would likely have a larger influence on achievement than one teaching that student for two hours a week. However, as a robustness check, we also ran our analyses using an unweighted average of teacher characteristics. Our results are substantively identical.

2.4 Analytic Strategy

One of the main challenges in estimating the causal impact of teacher qualifications (in our case, teacher enterprise experience) on student achievement is the selection bias that can arise due to the non-random sorting of students and teachers into classrooms. This bias can occur in one of two different ways. First, higher-achieving students can be placed with teachers with higher qualifications, resulting in an upward bias when estimating the effect of teacher qualifications on student achievement. Alternatively, lower-achieving students can be matched with teachers with higher qualifications, perhaps as the result of an intentional policy to compensate for the weakness of lower-achieving students. This method of sorting results in a downward bias when estimating the effect of teacher qualifications on student learning.

In an attempt to address the problem of selection bias, many studies employ student fixed-effects models. One type of student fixed-effects model uses longitudinal data (over time) to remove the potentially confounding effects of unobservable, time-invariant student characteristics, those characteristics that could be simultaneously correlated with teacher qualifications and student outcomes (Clotfelter, Ladd and Vigdor 2007; Kane, Rockoff and Staiger, 2008). Another type of student fixed-effects model uses cross-subject panel data to remove the potentially confounding effects of unobservable, subject-invariant characteristics,

those characteristics that could be simultaneously correlated with teacher characteristics and student outcomes (Dee, 2005, 2007; Clotfelter, Ladd, & Vigdor, 2010; Kingdon & Teal, 2010; Van Klaveren, 2011).

The cross-subject student fixed-effects approach is a method that examines how the variation in teacher characteristics between subjects affects the achievement of each student. In this analysis, we are looking at how achievement varies for the same student across subjects in which teacher characteristics vary. In short, the student functions as his or her own counterfactual. By comparing within-student variation, we remove the problem of the non-random sorting of students and teachers into classrooms by essentially controlling for everything about the student that does not vary between subjects, both observed and unobserved. Student characteristics such as motivation or ability are unlikely to vary considerably between the hardware and software subjects, particularly given their similarity in content and instructional style.

We use a cross-subject student fixed-effects model to estimate the impact of teacher enterprise experience on student achievement. Specifically, we use within-student variation across computer hardware and software subjects to identify the causal impacts. To illustrate how the cross-subject student fixed-effects model removes the potentially confounding effects of unobservable, subject-invariant characteristics, we first examine the relationship between student achievement and teacher enterprise experience using a standard linear regression model:

$$A_{is} = \alpha + \beta\, T_{is} + \delta\, C_{is} + \lambda_i + \varepsilon_{is} \qquad (1)$$

where A_{is} is the achievement of student i in subject s (as represented by the ith student's score on either hardware or software test). Treatment variables are represented by T_{is}, which includes two specific measures of enterprise experience of the teachers of student i in subject s: actual (reported) teacher enterprise experience and dual certification. C_{is} is a vector of additional

student and teacher and classroom characteristics that vary across students i and subject s that serve as control variables.[3] Specifically, we control for students' baseline test scores in each subject, as well as a number of observed, pre-treatment, cross-subject teacher and classroom characteristics, including teacher's age, gender, teaching rank, highest award received, number of years of teaching experience, number of hours teaching the subject area, whether the teacher holds an official teaching position, have computer certification or majored in a computer-related subject area, as well as the average achievement of the student's peers in the classroom and number of hours per week each student spends in each course.[4] We also include a hardware dummy variable to examine whether the student performs differently between the two subjects. While observable student characteristics such as age and gender can easily be controlled for in a standard linear regression model, unobservable characteristics such as student ability and motivation cannot. To account for both observable and unobservable confounding student characteristics, we include the term λ_i, a set of dummy variables for each student that effectively controls for all student characteristics that do not vary across subjects.[5] ε_{is} represents an error term that varies across students and across subjects. The other terms (α, β, and δ) in equation (1) are coefficients (or vectors of coefficients) to be estimated. The coefficients reflect the relationship between the variables on the right-hand side and student achievement on the left-hand side. We are most interested in β which identifies the relationship between teacher enterprise experience and student learning.

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[3] As mentioned, a "class" in China is a group of students (of a particular grade) who take the same subjects/courses together. We thus do not control for "class" characteristics (such as class size), since students of the same class take all of their (e.g. hardware and software) courses as a class.

[4] As a robustness check, we undertook analyses that both control and not control for peer effects (as measured by the average baseline test scores of each student's class peers) separately. Both sets of analyses yielded results that were substantively identical. Results are available upon request.

[5] Note that the student characteristics also include family, school, and broader contextual characteristics (associated with the student) that do not differ across subjects.

Because the student fixed-effects (λ_i) are equivalent across both subjects, differencing

equation (1) for the two subjects (computer hardware and software, or s=1 and s=2) yields an

equivalent equation (2) as follows:

$$-) = \beta\ Ti1 - Ti2 + \delta\ (Ci1 - Ci2) + (\varepsilon i1 - \varepsilon i2)\ \ (2)$$

Unobserved student, teacher, and classroom characteristics that vary across subjects are captured

in the differenced error term ($\varepsilon i1 - \varepsilon i2$).

To obtain unbiased estimates of β, this model relies on the assumption that the error term

$\varepsilon i1 - \varepsilon i2$ in equation (2) is uncorrelated with either the treatment across the two subjects $Ti1 - Ti2$

or with the outcome across the two subjects $-$). In other words, this model can only be

interpreted causally to the extent that all unobservable characteristics that are confounding (i.e.

factors related to both treatment variables and outcomes) are *invariant* across subjects or

captured in the observed control covariates.

A violation of this assumption could occur if students were sorted differentially (or non-

randomly) into the hardware and software subjects—for instance, if higher-ability students were

sorted into hardware subjects and lower-ability students into software subjects. As explained in

Section 2.3, because of the nature of the curricula and course schedules in vocational schools in

Zhejiang (where students in the same major are not tracked and where students in the same class

take the same courses), sorting of this nature does not occur. Students are assigned into a "class"

(or fixed group of students) and together take the same hardware and software courses. Not only

is there no systematic tracking in the vocational schools in the sample, but all students are

required to take generally the same hardware and software courses.

Another violation of this assumption may occur if there were differential educational

inputs across subjects, such as if schools systematically assigned more highly skilled teachers to

hardware courses over software courses. To check whether this had occurred, we examined the mean characteristics of hardware and software teachers across a number of covariates (see Table 1). With the exception of the gender variable, there are no statistically significant differences across the characteristics examined between hardware and software teachers, indicating that there is no systematic sorting of teachers by subject. Although the nature of differences between the teachers of the software and hardware subjects is small (one variable out of 17), we control for all of these observable teacher characteristics since it is possible that one or more of the variables may be systematically correlated with both enterprise experience and student achievement.

The cross-subject student fixed-effects model rests on an additional assumption that the model is specified with appropriate functional form. Specifically, the way in which teacher characteristics affect student achievement must be the same across hardware and software subjects (Dee, 2005). A violation of this assumption occurs when the treatment variables do not function in the same way across subjects, because the functional form of the model does not allow this relationship to vary.[6] An extreme case of this is one in which teacher enterprise experience is beneficial only for the learning of hardware skills, but somehow detrimental for the learning of software skills. Because the hardware and software subjects are similar in nature and content, it is unlikely that the treatment variables affect achievement differently across the two subjects.[7]

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[6] The differenced equation, equation (2), rewritten to show the specific subject coefficients, $-\ )=\beta_1\ \ \ 1-\beta_2\beta_1\ \ \ 2+\delta_1\ (\ \ \ 1-\delta_2\delta_1\ \ \ 2)+(\ \ \ 1-\ \ \ 2)$, demonstrates that the effects of teacher characteristics must be the same across subjects, i.e., that $\beta_1=\beta_2$ and $\delta_1=\delta_2$.

[7] As a check on this assumption, we reran our main specification presented in Table 2, interacting the hardware dummy with both types of treatment. The interaction terms are non-significant (even at the 10% level) suggesting that as conjectured, the teacher treatments do not appear to affect achievement differentially across the hardware and software subjects.

Finally, the Stable Unit Treatment Value Assumption (SUTVA) maintains that potential outcomes for one student do not depend on the treatment status of another student. The SUTVA assumption is violated to the extent that there are spillover effects, that is, that having a particular type of teacher in one subject affects performance in the other; for instance, having a hardware teacher with enterprise experience may positively impact a student's learning not just in the hardware subjects, but also in the software subjects. While this may indeed occur, it is worth noting that these spillovers would bias estimates downward. Thus, the results of this study can be interpreted as "net" of any such spillovers.

3. Results

Our results show that few teachers report having actual enterprise experience; in contrast, a large proportion of teachers receive dual certification. As shown in Table 1, we find that 88 percent of hardware teachers and 83 percent of software teachers had dual certifications (row 1). However, only 10 percent of hardware and 9 percent of software teachers reported having actual enterprise experience (that is, having prior employment in an enterprise relevant to the subject they are teaching—row 2). This discrepancy suggests that, as suspected, dual certification does not reflect actual enterprise experience. At the same time, 85 percent of those with enterprise experience hold dual certification.

According to our findings, actual enterprise experience has a positive and significant impact on student achievement (Table 2, Columns 1 and 2). After controlling for teacher and classroom characteristics—vector C_{is} in equation (1)—in our cross-subject fixed-effects model, relevant enterprise experience is associated with a 0.50 standard deviation higher subject test score for students (significant at the .01 level). These results suggest that having a teacher with actual occupational experience related to the subject taught can indeed have a substantive

positive impact on student achievement. In other words, teachers with computer-related work experience help computer major students learn more than teachers without such experience.

In contrast, dual certification does not have a positive effect on student scores. When controlling for teacher- and class-level characteristics, the effect of having a teacher with dual certification is negative, a 0.65 standard deviation lower subject test score (significant at the .05 level). These results suggest that professional certifications, such as those captured by the dual certification scheme created by schools and local governments that are meant to endow teachers with skills associated with enterprise experience, do not increase student learning. The negative effect may be a result of teachers substituting time away from teaching and towards obtaining the professional certification. The negative effect may also be due to less motivated or capable teachers self-selecting into obtaining a certification rather than spending time acquiring meaningful enterprise experience.

We examined the heterogeneity in treatment effects on different students by interacting the treatment variables with binary variables representing whether students were "low-achieving" and "high-achieving" students at the start of the vocational program. High-achieving students are defined as those who scored in the top third of the student distribution on an entry-level general computer test administered in October 2012, whereas low-achieving students are defined as those who scored in the bottom third of the distribution on this general computer test administered at the start of students' vocational schooling.[8]

According to this heterogeneity analysis, high-achieving students benefit more from having a teacher with enterprise experience than mid- and low-achieving students (Table 3).

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[8] Additionally (that is, beyond examining heterogeneous effects for those students in the top and bottom terciles), we vary the cut-off values for defining high- and low-achieving students, examining the effects: a) for students in the top and bottom quartiles; and b) for students above and below the median. We find that our results when examining the heterogeneity in effects for these different parts of the class (top/bottom quartile; above and below the median) are essentially the same as for the students in the top and bottom terciles.

Under teachers with actual enterprise experience, high-achieving students score 0.43 standard deviations higher than middle-achieving students (statistically significant at the 0.01 level). Furthermore, their counterparts in the bottom third of the distribution show no statistically significant increase in scores. These results suggest that the positive impact of enterprise experience is concentrated among higher-achieving students. This heterogeneous impact may be because high-achieving students are better able than middle- and low-achieving students to gain from the enterprise experience of their teachers, or teachers with enterprise experience focus more on students whom they perceive to have a higher probability of future success in their field. This differential attention by teachers is not uncommon in education systems (e.g. Neal & Schanzenbach, 2010).

4. Discussion and Conclusion

Vocational schooling is a major part of the education systems of developed and developing countries alike. Despite its importance, however, there is little causal evidence on "what works" in vocational schooling. In particular, little is known about which characteristics of vocational teachers matter for student learning. In this study, our objective was to analyze whether a teacher's actual enterprise experience—a vocational teacher characteristic stressed by researchers and policymakers—in fact increases student vocational skills.

Our first set of findings indicates that actual enterprise experience matters more than certification programs. Vocational teachers who have experience working in industry, in the field in which they teach, have a positive and significant impact on student vocational skills. Our analysis of heterogeneous effects, however, indicates that the benefits may be concentrated among those students who began the year as higher-achieving students. From a policy

perspective, hiring teachers with enterprise experience may increase student learning, but does not guarantee the same benefit for students who enter the program as low-achievers.

There are a number of reasons why teacher enterprise experience may be particularly important for vocational student learning. For one, vocational teachers with actual enterprise experience may have a better grasp of the subject matter. Within the literature of academic student achievement, studies have shown that teacher content knowledge is important for student learning (Clotfelter, Ladd & Vigdor, 2010; Metzler & Woessman, 2012). Furthermore, teachers with prior enterprise experience may also be better able to convey how to apply up-to-date, real-world knowledge and technical skills to solving problems in the workplace (Kasipar, 2009; Zhang, 2009; OECD, 2010). To this end, a teacher's ability to relate classroom content to real-world vocational settings may better motivate students to learn.

While we have controlled for teacher background characteristics, including a number of standard measures of teacher quality in China, we cannot be sure that the impact we observe on student achievement is due to teacher enterprise experience itself, rather than some other unmeasurable quality that differentiates teachers with enterprise experience from other teachers. Indeed our regression analyses explain little of the variance in change in student achievement. It is possible that the kind of people who make better vocational teachers are those who are also more likely to pursue jobs in industry, have a higher aptitude for hands-on work, and thus seek and acquire enterprise experience. Alternatively, those who show greater motivation for teaching vocational students may be those who are also more likely to pursue jobs in industry. It may be these qualities, rather than enterprise experience, that result in the positive impact on student vocational skills.

Despite the ambiguity, we argue that enterprise experience is nevertheless capturing something unique and important for vocational learning that commonly used measures of

teaching quality do not reflect. To this end, having enterprise experience appears to be a viable basis on which to hire and promote vocational teachers. We believe that more research is needed in the future to disentangle the mechanisms through which enterprise experience improves student achievement.

Surprisingly, our second set of findings indicates that the government's measure of enterprise experience (dual certification) by itself does nothing to increase student-specific vocational skills. From a policy perspective, this finding is useful for at least two reasons. First, requiring that all teachers earn dual certifications is costly and ineffective. By promoting dual certification as a requirement for teachers, policymakers and schools incur direct costs (e.g. for training) and indirect costs (e.g. teacher's time) without improving student achievement. Second, policymakers and schools may be inadvertently using dual certification as a (poor, ineffective and cheap) substitute for hiring teachers with real enterprise experience. The high demand for skilled labor in China's rapidly growing economy has likely made it difficult for schools to hire teachers (at least in a technical field such as computers) at current salary levels. As a result, schools may have ensured their teachers have dual certification without necessarily hiring teachers who have actual enterprise experience. Such an interpretation is similar to other work showing the "diploma mill" nature of the Chinese vocational education system (Robinson 1986): schools meet formal requirements but ultimately do not link these formalities to real improvements in the quality of teaching.

Policymakers may have to reassess the standards for vocational teacher hiring and certification practices. They may, for example, wish to revise dual certification measures to ensure that teachers have some enterprise employment experience. Or, they may hire teachers based on characteristics other than certification requirements that can improve student learning. Identifying such characteristics will require more rigorous research into the causal impacts of

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different vocational teacher characteristics on students' vocational skills.

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Table 1: Comparison of Hardware and Software Teachers

Teacher Characteristics	(1) Hardware teachers			(2) Software teachers			(3)=(1)-(2) Difference
	mean	SD	N	mean	SD	N	
Dual certification (y/n)	0.88	0.33	50	0.83	0.38	124	0.05
Enterprise experience (y/n)	0.10	0.30	50	0.09	0.29	124	0.01
Computer certification (y/n)	0.76	0.43	49	0.74	0.44	122	0.02
Computer major (y/n)	0.79	0.41	47	0.67	0.47	119	0.11
Age	33.70	4.59	50	33.04	5.80	124	0.66
Female	0.36	0.48	50	0.54	0.50	124	-0.18**
College degree (y/n)	0.54	0.50	50	0.63	0.49	123	-0.09
Hours spent teaching class	4.10	1.56	50	4.44	1.87	124	-0.34
Rank (lowest y/n)	0.04	0.20	50	0.03	0.18	122	0.01
Rank (second lowest y/n)	0.34	0.48	50	0.33	0.47	122	0.01
Rank (second highest y/n)	0.36	0.48	50	0.39	0.49	122	-0.03
Rank (highest y/n)	0.08	0.27	50	0.09	0.29	122	-0.01
County award (y/n)	0.16	0.37	50	0.14	0.35	120	0.02
Municipal award (y/n)	0.30	0.46	50	0.35	0.48	120	-0.05
Provincial or national award (y/n)	0.20	0.40	50	0.22	0.41	120	-0.02
Official teaching status (y/n)	0.73	0.45	49	0.81	0.39	124	-0.08
Years of teaching experience	10.28	5.72	50	9.63	6.04	124	0.65

** $p<0.01$, * $p<0.05$, † $p<0.1$

Table 2: The Impacts of Dual Certification and Enterprise Experience on Student Achievement

	(1)	(2)
Dual certification (y/n)	-0.44**	-0.65*
	(0.14)	(0.27)
Enterprise experience (y/n)	0.31†	0.50**
	(0.18)	(0.18)
Hardware subject (y/n)	0.01	0.03
	(0.05)	(0.05)
Baseline subject-specific score	0.07**	0.06*
	(0.02)	(0.02)
Average achievement of peers		-0.11
		(0.16)
Computer certification (y/n)		0.17
		(0.24)
Computer major (y/n)		0.41*
		(0.16)
Age		0.04
		(0.02)
Female		0.17
		(0.12)
College degree (y/n)		0.09
		(0.15)
Hours per week in class		0.00
		(0.05)
Rank (lowest y/n)		0.26
		(0.26)
Rank (second lowest y/n)		-0.21
		(0.16)
Rank (second highest y/n)		0.01
		(0.20)
Rank (highest y/n)		-0.43†
		(0.22)
County award (y/n)		0.20
		(0.19)
Municipal award (y/n)		-0.04
		(0.24)
Provincial or national award (y/n)		-0.19
		(0.11)
Official teaching status (y/n)		0.31†
		(0.16)
Constant	0.37**	-1.39*
	(0.12)	(0.67)
R-squared	0.018	0.053
Number of observations	2,796	2,796
Number of students	1,398	1,398

** $p<0.01$, * $p<0.05$, † $p<0.1$

Note: Cluster-robust standard errors in parentheses.

Table 3: Impact of Dual Certification and Enterprise Experience on the Achievement of Low-Achieving and High-Achieving Students

	(1)	(2)
Dual certification (y/n)	-0.19*	-0.38
	(0.21)	(0.32)
Enterprise experience (y/n)	0.05	0.25
	(0.22)	(0.23)
Dual certification * low achiever	-0.23	-0.30
	(0.24)	(0.28)
Enterprise experience * low achiever	0.04	0.13
	(0.31)	(0.37)
Dual certification * high achieving	-0.39	-0.34
	(0.25)	(0.22)
Enterprise experience * high achieving	0.54*	0.43**
	(0.27)	(0.19)
Hardware (y/n)	0.00	0.03
	(0.05)	(0.05)
Controls	No	Yes
Observations	2,796	2,796
R-squared	0.017	0.055
Number of students	1,398	1,398

** $p<0.01$, * $p<0.05$, † $p<0.1$

Note: Cluster-robust SEs in parentheses. Controls are the same as Table 2. Low achieving is defined as scoring in the bottom third of the distribution on the baseline standardized computer test. According to post-estimation statistical tests (examining whether there are any differences between the coefficients of low-, middle- and high-achieving students with teachers with enterprise experience), high-achieving students appear to benefit more from teachers with enterprise experience than low- and middle-achieving students.

Table A1: Characteristics of Sample Schools

	(1) full sample	(2) in sample	(3) difference	(4) p-value
Nationally designated school (1=yes)	0.18 (0.39)	0.19 (0.39)	0.01	0.96
Provincially designated school (1=yes)	0.37 (0.48)	0.49 (0.50)	0.13	0.35
Number of enrolled students (all majors)	2200.98 (1275.91)	2553.52 (1475.20)	352.54	0.30
Number of majors offered	8.98 (5.30)	10.74 (6.98)	1.77	0.24
Annual income (in millions of RMB)	36.15 (27.96)	32.29 (24.43)	-3.87	0.51
Annual expenditures (in millions of RMB)	35.18 (24.10)	29.75 (21.52)	-5.43	0.29
Number of teachers in school	134.12 (72.76)	165.23 (105.84)	31.12	0.21
Number of teachers with dual certificates	51.01 (34.63)	65.49 (55.64)	14.48	0.26
Observations	55	28		