Can Conditional Grants Attract Better Students: Evidence from Chinese Normal Universities.

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Abstract

One recent trend in policies on improving teacher quality is to provide conditional grants to trainees in teacher colleges and commit them to working in disadvantaged areas upon graduation. Yet little is known whether such policies can attract better trainees. This paper evaluates a conditional grant program in Chinese teachers' colleges, which commits students to teaching in their home province. Using a triple difference method, we find that teaching majors obtain better students due to the conditional grants. Further exploring the heterogeneous treatment effects across regions, we find that the policy effects not only increase as the costs of living during college decrease, but also are larger in provinces with larger share of disadvantaged students—those who are rural, female, rural female, and have more siblings—are higher. Taken as a whole, these results suggest that the Chinese free teacher education program does successfully attract high quality students into teaching force, and these high quality teacher trainees are very likely to be credit constrained.

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1 Introduction

Teacher quality is a key factor for students' learning outcomes (Hanushek 2009, 2010). Yet policies on improving teacher quality often fail to deliver the expected outcomes when other forces are at play. Low-income areas often lose their potential pool of good teachers to other economically advanced areas; also in areas where the private sector has fast development, the teaching profession sometimes suffers from a "brain drain", i.e., high-quality teachers are driven out of this profession by attractive outside options (Lakdawalla, 2006; Bacolod, 2007). To prevent potential decay of teaching force, the Chinese Ministry of Education announced a huge conditional grant program for the six top national teachers' colleges in 2007, which waives all tuitions and fees of students in teaching majors but requires them to teach in their home province for ten years upon graduation. This paper examines the effect of this free teacher education program and finds that it successfully draw academically more capable students who are very likely to be credit constrained into the teaching force.

As a new direction of public policies, conditional grants aim at diverting talent to particular jobs, contrary to the effect of loans which are found driving students away from low-paid "public interest" jobs, especially education industry (JpE, 2011). It also can resolve the efficiency-equity problem facing by the traditional financial aids. When merit-based aids gradually replacing the need-based aids in the past decades, some worries that, although enhancing the efficiency of educational investment, it also diverts funds away from the disadvantaged groups, given the positive association between academic performance and family background (Goodman, 2008). In contrast, conditional grants allow the credit constrained students to distinguish themselves from their unconstrained counterparts. For example in the US, ABA Diversity Fellowship in Environmental Law provides financial aid to law school students only when they commit to service in certain not-for-profit organizations, while the Texas department of transportation gives scholarship to civil engineering students when they agree to work for the department for two years immediately after graduation. Such career commitments may deter those financially free students who have no interests in the pertinent jobs.

Despite much policy interest, the effect of such programs is theoretically ambiguous and empirically unexplored. On one hand, the financial aids induce more enrollment by cutting the net price. On the other hand, the career commitments deter potential participants by reducing their future returns. The trade-off between enjoying immediate price cut and avoiding future locked-in varies case-by-case and remains unexplored. Recent efforts to identify the price effect on enrollment by exploiting the exogenous policy changes generally find that reducing the net price increases the overall college enrollment rate of the targeted students.(Dynarski, 2000; Kane, 2003; Cornwell et al., 2006; Abraham and Clark, 2006; Monks, 2008; Linsenmeier, Rosen and Rouse, 2006). But evidences on the effect of merit aid programs on college choices are mixed. Analyzing their detailed survey data, Avery and Hoxby (2004) find that the high-aptitude students in their sample make rational decisions in face of the trade-off between net price and perceived quality of college education. Relying on administrative data however, neither Abraham and Clark (2006) find evidence that DCTAG Program led students who would otherwise attend more selective colleges to attend less selective schools eligible for the grant, nor Pallais (2009) find that the TELS program induce more students to stay in in-state colleges.

Utilizing aggregate administrative data from the unique setting of Chinese free teacher education program, our study contribute to the literature examining students' trade-off across time horizons. First, we examine a national policy that applies to all China's provinces while previously studied aid programs are conducted by individual states independently. The superiority of a national policy with across-the-board conditions is that it creates exogenous regional variations in participants' current condition and future returns, and thereby allow our exploration of the heterogeneous program effects as well as the underlying mechanisms. Second, little has been said in the previous literature about how the supply of college slots would affect the final enrollment outcome. An exception is that Kane (2003) use Cal Grant to minimize impact from supply side. Yet he could not rule out the explanation that the effect results from the adjustment of the admission policies in program colleges. In this study, we could directly control for the change in college supply and examine the student demand without assuming a perfectly elastic supply curve, because the enrollment quota is determined in advance by the Ministry of Education. Third, we construct the student quality measure which is comparable across region and over time. This measure can be helpful in future analysis related to the quality of human capital on wider cross section of regions or over longer time horizon with no standardized test.

Our setting also allows the difference-in-differences (DID) approach to identify the effect of grant program on the quality of incoming students. According to the program policy, only normal students—those who matriculated into teaching majors of the six program colleges—admitted since 2007 can enjoy free education. By contrast, students who matriculated into non-teaching majors of these six colleges will face the same college cost as before. Hence, we can estimate the impact of this grant program by comparing the change in the entry scores for teaching majors before and after 2007 to that for non-teaching majors. We also use other elite teachers' colleges as additional control group and employ the difference-in-differences-in-differences (DDD) method to eliminate potential teaching-major specific time trend.

We draw on a data set on the province-major-level enrollment information from 2005 to 2009. It contains information on both the number of students in each major enrolled from each province and their mean and maximal scores in the college entrance exams (CEE). Our main finding is that teaching majors obtain better students after the policy change. We further find that the policy effects not only increase as the costs of living during college decrease, but also are larger in provinces with larger share of disadvantaged students—those who are rural, female, rural female, and have more siblings—are higher. Taken as a whole, these results suggest that the Chinese free teacher education program does successfully attract high quality students into teaching force, and these high quality teacher trainees are very likely to be credit constrained.

The rest of this paper is organized as follows. Section II describes the institutional background and the conditional tuition waive program. Section III introduces our data and empirical strategy. We report and interpret our main results in Section IV and explore the channels for policy effect in Section V. Finally, Section VI concludes.

2 Institutional Background and the Conditional Tuition Waive Program

2.1 The Procedure of College Entrance Examination (EEC) System

To attend college, students in China have to take the College Entrance Examination (CEE) first, and their scores of this annual exam almost determine admission results.[1]

There are three major agents in this test-matriculate process: the college, the student,

[1] Very limited number of students has been directly recommended to a college.

and the provincial admission office. Colleges are the sellers in the market of higher education: they draw up and release an enrollment plan[2] before the exam, which specifies the number of slots to be allocated to each province at major level. As the buyer, a student has two tasks: taking the examination administrated uniformly by the province in which his hukou registered and submitting an application in which colleges and majors are listed in order of preference.[3] After that, colleges would be matched with students by the provincial admission office, which serves as the intermediary in the market. First of all, the office sorts out all colleges into several tiers—the first tier consists of China's elite colleges and thus has the highest thresholds among all the tiers, second tier the regular colleges, and third tier the private colleges with the lowest thresholds.[4] Besides, the advanced tier includes majors with additional enrollment requirement: the students either have some special talent, such as athletic, musical, painting skills, or make commitment to engage in certain jobs upon graduation, such as the conditional grant examined here. Second, the office coordinates the enrollment of each tier—the advanced tier colleges enjoy the priority to admit students at the very beginning, and then the first, second, and third tier follow on.[5] Third, the office ranks the first-choice applicants of each college according to their CEE score and send the files of students from top to bottom to the relevant college. If the number of students applying a college as first-choice is smaller than the specified quota, then the office will further send the files of second-choice applicants in the same way.[6] Therefore, students prudently identify the academically affordable

[2]Literally, this plan is subject to the coordination of the Ministry of Education. But colleges have gained growing autonomy since 2001.

[3]The timing of application varies across provinces and over time. In our examined period, majority of provinces collect application after the release of CEE score, some right after the exam, only Beijing and Shanghai before the exam.

[4]China's higher education system is predominately supported by the government in the sense that the best colleges are public ones and the higher the administrative level of the college the better the college is.

[5]Once a student has been admit by the former tier college, his documents will be put out of the following tiers applicant pool.

[6]In some cases, the second-choice students are considered at the same time with the first tier students but with a cut back on their original score.

colleges and majors and mainly focus on their first choice.

The academic competition in the CEE system takes place within each province-track[7] annually. On the one hand, colleges plan for their annual enrollment plan respectively for each province-track. On the other hand, both examination and application collecting are administered by individual provinces—the content and scoring of tests, the timing of application, and the rule of matching vary across provinces.[8] Hence, the most important academic constraint for a student's college choices is CEE score relative to his peers in the same track within the home province in the same year.

2.2 Teacher Training and the Conditional Tuition Waive Program

Lack of qualified teachers is a common problem plaguing the education system in many developing countries. China is no exception. The economically backward areas such as western regions and rural areas suffer even more as the fast economic development in eastern and middle regions has driven the talents from the west to the east, from the rural to the urban areas, and from the teaching profession to other professions. This problem has been exacerbated during the marketization reforms of the higher-education system. Therefore, the state introduced the free teacher education program in 2007 to guarantee the teaching force in the disadvantaged areas.

The training of teachers usually begins at the college level in China. In particular, the teaching track is only available in certain majors of teachers' colleges. Applicants to these majors can choose to enter the teaching track or remain in regular track. Students

[7] Students usually choose track between science and humanity in the second year of high school and will answer the corresponding exam papers in the CEE.

[8] Although organized by the province, the examinations in all provinces take place simultaneously.

in teaching track are required to receive additional pedagogical training besides taking courses in their majored fields which are usually basic subjects like mathematics, physics, chemistry, biology, Chinese language, English, history and geography.

Students in the teaching track were traditionally exempted from tuitions and enjoyed a subsidy before the marketization reform in higher education. Upon graduation they would be posted through a mandatory allocation process. Both the pricing and the placement policy have changed since 1997 during the marketization reform. The national government allowed teachers' colleges to charge tuitions and various fees[9] like other regular colleges and began to call off the mandatory allocation[10] of graduates. Without the advantage of low cost, teachers' colleges were believed to have lost its attractiveness for eligible applicants with credit constraints. The quality of incoming trainees has declined. Meanwhile, it is also hard for economically backward regions to obtain qualified teacher trainees graduated from teachers' colleges as the allocation is no longer mandatory.

To address this problem, the national government first implemented the conditional grant program in 2007 in six top national-level teachers' colleges under the direct supervision of the Ministry of Education, including Beijing Normal University, Huadong Normal University, Dongbei Normal University, Huazhong Normal University, Shaanxi Normal University and Xinan University.[11] Students who matriculate in the teaching majors in these six colleges will be exempted from tuition fees and accommodation during their four-year study and receive a monthly allowance of about 400 *yuan*.[12] Meanwhile, they

[9] Normal students only enjoy negligible amount of subsidy, no more than 100 RMB per month.

[10] Students can find teaching jobs for themselves since 1997 and the state will assign teaching positions for those who fail to find their jobs.

[11] State Council [2007] No. 30.

[12] Compared to students who matriculate into the non-teacher majors, a student who is eligible for the conditional grant program would save at least 10,000 *yuan* (about 1,500 U.S. dollars in 2009 dollar) per year, which is roughly the average annual income of a rural household with three people.

have to teach in elementary or middle school in their home province for ten years upon graduation. Those who get a position in an urban school will first be assigned to teach in a rural school for two years. Pressured by the national government, some provincial governments such as Hebei, Sichuan, Xinjiang, Guansu, Shandong and so on have also begun to experiment with the same practice in the teachers' colleges under their supervision since 2010.[13] The pioneering role of this program is shown clearer in Figure 1. The green and red bars correspond to the size of normal enrollment from first tier, while the green for the 6 elite program teachers' colleges under the ministry of education and the red for other elite teachers' colleges supervised by subnational governments. Together they only account for a small share of total normal enrollment in tertiary education (blue bar).

The first three cohorts have graduated already till 2013. The default rate is extremely low, as shown in Table 1. Under the close supervision of the ministry of education, the subnational education departments coordinate the matching between their teacher trainees and the elementary and middle schools within their jurisdiction. Besides strong government intervention, the low actual rural employment, which has been written in the agreement, also prevent the students from default. The 6 program colleges also open part-time master program for these graduates since 2012 to facilitate the development of their teaching career.

[13]The provincial policy change happened after 2009, so will not bias our estimate.

3 Data and Empirical Strategy

3.1 Data

To examine the effect of conditional grant on student quality, we compile from various public sources a five-year panel from 2005 to 2009 on the number of students of each entering class and their average CEE score at major level, as well as college- and region-specific characteristics.

Our key major-level variables are constructed from Gao Kao Sheng Xue Tong, a book collection authorized by the Ministry of Education. This collection contains enrollment information of each major at every Chinese college from all the 31[14] provinces, including the maximum score and mean score as well as number of students admitted. We examine the first-tier[15] enrollment of all teachers' colleges from the cohorts[16] of 2005 through 2009, and end up with 29128 individual majors' admission records. During the five-year period, the former two years are before the program and the later three are the post-period. Moreover, 2005 is the earliest year in which the data is available, while 2009 is the latest year before other teachers' colleges launch similar programs. Among the examined teachers' colleges, 6 of them are designated for the free education program, while the other 32 are not. Therefore, our analysis covers the whole population of policy affected majors during a period when no other similar programs exist.

The huge regional disparities documented in Table 2, among both students' origin provinces and colleges' location cities, greatly facilitate our exploration in the heteroge-

[14] We don't have information about Zhejiang and Jiangsu in 2009. We also exclude Tibet and Xinjiang in our analysis, while the results remain qualitatively the same even after including these two provinces.

[15] We only look at the first-tier enrollment because the policy program colleges are all elite colleges and mainly take in students during the first tier enrollment.

[16] A cohort is defined as the group of students who matriculated college by taking the CEE in the indicated year.

neous policy effects. To be specific, we merge the enrollment data to the demographic structure and socio-economical characteristics of province in which students' hukou are registered, including the share of high school student who are rural, female, and rural female, the average number of siblings high school student have, and the average wage in the education sector. In addition, we merge the data to the living standard of cities where a university located, including the level of individual income, total consumption, and food consumption. The provincial high student composition is aggregated from 2005 minicensus, while the regional socio-economic data are from China Statistical Yearbook, China Fiscal Yearbook, and Regional Economic Statistical Yearbook.

3.2 Measurement

Identifying Teaching Major We define a major as teaching if it is listed in the official website of the free normal education program (sfs.ncss.org.cn) regardless of the tier in which it admits students. The only exception is that we exclude the first tier enrollment for the program colleges during the post-policy period, because the program policy stipulates advanced tier enrollment. Conventionally, normal enrollment happens in the advanced tier. But this rule is loosely followed since late 1990s when the governments don't allocate jobs for college graduates any more. This is confirmed by our incomplete survey of college enrollment plans after year 2005—normal enrollment from the first tier is a common practice in both groups of colleges before the program, and also in non-program colleges after the program. Thus, our definition of teaching major ensures a full coverage of all policy affected students. It might also include some non-normal enrollment and bias our estimation, but we could test the sensitivity of our measure by imposing various restrictions upon our definition.

The normal enrollment in the program colleges increases steadily during the examined period and such growth speeds up after the policy, as shown in Figure 2(a). By contrast, the non-program colleges downsize its enrollment—both in normal and non-normal—after 2007 (Figure2(b)), a pattern shared by the non-normal enrollment in program colleges. Clearly, within the program colleges, there seems to have an re-allocation of slots from non-teaching to teaching majors, while in the non-program colleges, the enrollment of teaching and non-teaching majors go hand in hand. It's worth pointing out that the observed divergent paths of normal enrollment in program and non-program colleges also support our change of gauge in defining the teaching majors.

Standardizing CEE Score Our dependent variable is the academic quality of incoming students entering each major, measured by CEE scores. But the raw scores are not directly comparable across province or across year given two facts: (1).both CEE and the admission process are administered within individual provinces, and (2).CEE calculates absolute scores, rather than standardized scores. Therefore, we perform our own standardization according to the score distribution in each province-track-year—the pool of examinees who answer the same exam paper—in the following way:

1. For each province-track-year, we know the number of total applicants[17](P) and the total enrollment from the first tier(F), so we can calculate the share of enrollment from first tier ($\frac{F}{P}$).

2. According to the score distribution of first tier majors, we can find the percentage point of a specific score in the corresponding distribution[18] (S).

3. Assume the upper tail of the whole score distribution in each province-track-year contains only (in fact, mainly) the first tier, we can calculate the percentage point of a specific score in the whole distribution:

[17]These numbers are coded from newspapers.

[18]The first tier score distributions are coded from Gao Kao Sheng Xue Tong.

$$Y = (1 - \frac{F}{P}) + s\% \cdot \frac{F}{P} \tag{1}$$

Figure 3 show the changes in student quality for teaching and non-teaching majors measured by the incoming students' standardized CEE scores. It is clear that, in program colleges, standardized scores(mean and maximal score in figures 3(a) and 3(b)) for teaching and non-teaching majors diverge since 2007, while in non-program colleges, scores of these two type of majors go hand in hand(mean and maximal score in figures 3(c) and 3(d)) during the whole five-year period. Another distinction is that teaching majors admit better students than non-teaching majors in program colleges, while the opposite happens in non-program colleges. The further increased score in program teaching majors suggests that this free teacher education program indeed is affecting the group of students with outstanding academic performance. To make it more precise, table 3 reports the average student quality for teaching majors and non-teaching majors in these examined teachers' colleges, before and after the grant program was introduced in 2007. We compare in Panel A the changes in standardized score within the program colleges—for teaching majors, there is 0.168 percentage points increase in mean and 0.162 in maximum after the introduction of the grant program, while decrease is observed in non-teaching majors with magnitudes of 0.175 percentage points in mean and 0.178 in maximum. The changes in these two major types are differenced in the last row of panel A, which can be interpreted as the casual effect of the grant, under the assumption that in the absence of the policy, the decrease in student quality would not have been systematically different in teacher and non-teaching majors. The implied effect of the grant program is 0.343 percentage points increase in standardized mean score and 0.341 percentage points increase in standardized maximum score and both are significant at 1% level. As a placebo test, Panel B displays the same comparison in non-program colleges. It shows that, without the free education program, there is indeed no significant difference in the score changes before and after year 2007 between teaching and non-teaching majors.

3.3 Identification Strategy

This subsection describes the identification strategy to isolate the policy effect. In our benchmark model, we first apply the difference-in-differences (DID) type model to the sample of all program teachers' colleges. We define teaching majors as the treatment group and non-teaching majors as the control group, because only students in teaching majors are eligible for the conditional grant after the policy change while both teaching and non-teaching majors are offered in these teachers' colleges. By comparing the change in the score of students in teaching majors after the implementation of the grant program to the change for those in non-teaching majors, we are able to tease out the time effect. The regression can be specified as follows:

$$Y_{ijkst} = \alpha_0 + \alpha_1 TM_{ijkst} + \alpha_2 TM_{ijkst} \times post_t + A_{ijkst}\gamma_1 + \theta_i + \mu_{jkst} + \epsilon_{ijkst} \tag{2}$$

where Y_{ijkst} is the standardized (mean or maximal) score of students from province s and track k of major i in college j at time t; TM_{ijkst} is an indicator for teaching majors, it takes the value of 1 if major i in college j taking students from province s and track k in year t is a teaching major and 0 otherwise; $post_t$ is an indicator for the introduction of the grant program, it takes the value of 1 before year 2007 and 0 otherwise; A_{ijkst} is a vector of the number of students admitted to major i from province s and trank k in year t and its squared term. We also control for subdiscipline[19] fixed effects θ_i and track-

[19]The Chinese college subject classification system is built on a 3-level structure: discipline, subdiscipline, and major. For example, the discipline of Economics consists of 4 subdisciplines—economics, public finance, finance and trade, while these 4 are further divided into 17 majors—economic theory, econometrics, public finance, taxation, finance, financial engineering, insurance, investment, international

province-college-year fixed effects $\mu_j kst$. Therefore, α_2 in regression (**??**) will capture the program effect on scores of incoming students.

Note that the assumption underlying the DID approach is that teaching majors and non-teaching majors have a parallel trend in the quality of incoming students. Thus a related threat to validity comes from the possibility that the time trends differ between the two types of majors. For example, the willingness of students to join the teaching profession as opposed to other professions may be increasing or decreasing over time, which is likely affected by changing circumstances in the labor markets. In such cases, our DID model cannot accurately estimate the program effect. To address this concern, we will rely on another source of variation. In particular, we make the other 33 teachers' colleges in the first tiers as the group of non-program colleges. They are the most comparable ones with the 6 program colleges in terms of academic ranking and thereby student quality. Moreover, the non-program colleges are not eligible for alike grant programs during the studied period. Given these two conditions, the difference in score changes between teaching and non-teaching majors in the non-program colleges should be able to capture the potential different time trends between these two types of majors in general. Therefore, these non-program colleges form a valid control group, because they are exposed to the same change in popularity of teaching majors as the 6 program colleges except the grant program.

In particular, we include teachers' colleges which and use them as an additional comparison group. Therefore, subtracting this difference from the above DID estimate will yield a more accurate estimation for the policy effect. This leads to the following difference-

economics and trade, and economics of trade.

in-difference-in-difference (DDD) specification:

$$
\begin{aligned}
Y_{ijkst} &= \beta_0 + \beta_1 TM_{ijkst} + \beta_2 TM_{ijkst} \times post_t + \beta_3 TM_{ijkst} \times PC_j \\
&+ \beta_4 TM_{ijkst} \times PC_j \times post_t + A_{ijkst}\gamma_2 + \theta_i + \mu_{jkst} + \epsilon_{ijkst}
\end{aligned} \tag{3}
$$

where PC_j is an indicator for program colleges, it takes the value of 1 if college j is a program college and 0 otherwise. The coefficient β_4 is thus the DDD estimate for the program effect.

4 The Effects of Conditional Grant on Incoming Student Quality

4.1 Baseline Results: the Difference-in-Differences Estimates

Table 4, based on the estimation of equation (2), indicates significant quality increase of incoming students in teaching majors relative to those in non-teaching majors, within the program colleges, before and after the policy change. As shown in column (1), the positive coefficients of interaction between teaching major and policy timing show that the quality improvement in teaching majors comparing to that in all other majors in the same college is 0.163 percentage point measured by mean score and 0.197 percentage point by maximal score, both with statistical significance. The insignificant coefficients of teaching major suggest no persistent difference in student quality between teaching and non-teaching majors, while the coefficients of admission terms reveal that only maximal scores, rather than mean scores, are sensitive to major size. Besides the reported variables, we always controlled for subdiscipline fixed effects and track-province-college-year fixed effects, which capture not only the unobserved characteristics of each CEE arena—the pool of students answering the same exam paper, but also the unobserved dynamics of the college popularity among different provinces. Also, we cluster standard errors at province level.[20]

Fairer comparison, in column (2) and (3), arises from excluding non-teaching majors under irrelevant disciplines and subdisciplines to teaching majors, respectively, from our control group. In particular, only 7 of the total 12 disciplines include teaching majors, so we exclude the other 5 from the control majors in column (2). Similarly in column (3), we include only the 14 relevant subdisciplines out of the total 92. Such refinement leads to larger estimates of the policy effects—from 0.163 to 0.167 percentage point increase in mean score and from 0.197 to 0.239 in maximal score. That is to say, comparing to non-teaching majors under the same subdisciplines within the same college, teaching majors attract students on average ranked 0.167 percentage points higher after the free teacher education program. This estimate therefore implies that an average teacher trainee from this program, if without which he would still like to become a teacher, is ranked ahead of 16,700 of his CEE competitors due to this conditional grant, given 10 million students take the exam in each year.

To avoid bias from preferential local admission policy[21], we exclude the enrollment from the province in which the college locate and run the same set of regressions in Columns (4) to (6). The results are in line with those in the first three columns. The relatively larger policy effect is consistent with the public perception that national elite colleges always reserve slots in more popular majors for students from the local province.

[20]We also try other clusters, including for the same province-university, province-university-cohort. The results are essentially the same.

[21]

4.2 Controlling for Major Specific Time Trend: the Difference-in-Difference-in-Differences analysis

We estimate equation (3) and report the results in Table 5 to explore the threats from potential different time trends between teaching and non-teaching majors via the introduction of non-program colleges. Paralleling Table 3, the former three columns of Table 4 report the DDD estimates for the national enrollment, using all other non-teaching majors, non-teaching majors under same disciplines, non-teaching majors under same subdisciplines, respectively, as the control majors, while the latter three further excluding the local enrollment. The triple-interaction of teaching major, program college, and policy timing identifies the policy effect in this regression. Our preferred estimate under the most refined specification, presented in column (3), shows that, in program colleges, teaching majors increase their standardized mean scores relative to non-teaching majors under the same subdisciplines by 0.234 percentage point more than they do in the non-program colleges. That is to say, the free teacher education program attracts students on average ranked 0.234 percentage points higher to the teaching majors in program colleges. Comparing to difference-in-differences estimates, the triple-difference estimates are larger, implying a decreasing trend of student quality in teaching major relative to non-teaching major under the same subdiscipline in these elite teachers' colleges. We will stick to this most refined group of control majors—non-teaching majors under the same subdisciplines as the teaching majors and focus on the triple-difference estimates of policy effect in further analysis.

4.3 Robustness Checks

Spillover on Non-Teaching Majors? Our control majors lose their validity if, without the policy change, the grant recipients would have instead chosen non-teaching majors in the program colleges. We test this potential spillover by comparing the non-teaching majors' score change in program colleges with that in comparable non-program colleges. If the program diverts students from non-teaching majors to teaching majors, we should observe a score decrease in program colleges relative to non-program colleges. But results in Table 6 shows no such pattern, thus assures us the validity of our control majors.

Alternative Definitions of Teaching Majors? To test the robustness of our estimation to the delineation of teaching major, we run the above set of regressions with two other definitions: the first one assumes that normal enrollment occurs only in advanced tier both before and after the policy change, just follow the general rule, while the second assumes that non-program colleges follow the pattern of program colleges, that is, they admit normal students in both tiers before the policy change and in advanced tier only after the policy change[22]. Table 7 shows that both of these two definitions lead to qualitatively the same estimates of policy effect, only with even larger magnitude.

Taken as a whole, these results suggest that the program successfully attract academically more capable student into the teaching force. In the following section, we would argue that this policy is more attractive among credit constrained students.

[22]Delineation in program colleges remains unchanged, so the DID estimates are same as those in the original definition.

5 Who Are These Free Educated Teachers?

A natural question to ask is do these policy induced high quality teacher trainees have anything in common? Are they more likely from high-income families as in the case of merit-based aids or from disadvantaged groups as need-based aids? Although individual level information is unavailable, our setting still allows an meaningful comparison at aggregate level—this national wide policy with across-the-board conditions creates exogenous variation in cost-and-benefit for students coming from different provinces and applying to different colleges. We explore these variations from three dimensions: first, we compare the living costs among cities in which the colleges locate and find that policy effects increase as the living costs decrease; second, we look at the demographic composition of students in each province during the examined period and find the policy effect is larger in province with higher share of disadvantaged students; These results suggest that the high quality students attracted by this conditional grant are very likely to be credit constrained.

5.1 Effect of Living Cost: Heterogeneity by College Location

We first explore students' sensitivity to the living cost during college. This matters for the teacher trainees, because they, besides enjoying tuition and accommodation exemption, uniformly receive monthly allowance of about 400 *yuan* for daily consumption. But living costs vary greatly from city to city. We use three measures—individual income, individual total consumption and individual food consumption—to proxy for living cost in the city where a college locate. Figure 4 presents the geographic distribution of the colleges and mark the level of annual food consumption in corresponding cities. In particular, we mark red the high consumption colleges—those annual food consumption level higher than 4800 *yuan*, which is the allowance amount and two out of the 6 program colleges fall into this group.

We thus add one more layer of interactions with the three living cost proxies and report the results in Table 8, which confirms that the program is more attractive in cities with colleges in lower cost cities. These policy induced teacher trainees studying in an average city rank 0.057 percentage points higher than those in a city with extra 1000 *yuan* annual consumption, which is about 11 US dollars per month. And they are particularly sensitive to food consumption—additional 11 US dollar increase in the monthly food consumption leads to a 0.157 percentage point decease in policy effect. Students attracted by this free teacher education program are so responsive to a living standard close to the poverty line (300 *yuan* per month according to 2009 world bank standard) that they are very likely to be credit constrained.

5.2 Effect of Students' Demographic Composition: Heterogeneity by Students' Home Province

We further test if students' reactions to the policy change vary by their hukou, gender, or sibling size. We use the 2005 minicensus to construct provincial averages of these demographic features. In particular, we treat the group of students attending high school in November 2005 and graduating from high school in year 2006, 2007, and 2008 as the CEE examinees from 2005 to 2009, assuming both a stable demographic composition over 5 years and high school students' aspiration to college education[23]. We first calculate, for each province, the share of high school students who are rural, female, and rural

[23] This assumption grounded on two facts in China: first, high school is costly and limited financial support is available. second, the wage gap between junior high and high school students is small. Thus parents have no incentive to send kids to high school if college education is not expected. In fact, the share of high school students who take CEE is ???

female, because these are conventionally disadvantaged groups and supposed to be more sensitive to cost change. Then we calculate the average siblings size in each province for high school student, as well as for rural, female, and rural female students, because previous studies suggest that any presence of sibling effects indicates credit constraints (Jacoby, 1994, Morduch, 2000, and Sawada and Lokshin, 2009). Higher these measures are, more prevalent of credit constraint is in each province. Figure 5 presents the regional variance in rural share and sibling size.

We interact again the policy effect with these demographic proxies and report the results in Table 9. The evidence for the sibling effect is stronger than that for hukou and gender. The significant coefficients of the interactions in column (4)–(7) suggest that policy effect increases significantly as the provincial average of student sibling size grows. Specifically, if an average students have one extra sibling, the teacher trainee in that province would rank ahead in his pool by 0.411 percentage point. Such sibling effect grow consistently as the examined group falls more disadvantaged—the sibling effect, compare to column (4), is larger among rural students(0.454) and female students (0.442) and reaching the peak of 0.512 for the most disadvantaged group—rural females. However, the interactive evidence for student identity—rural, female, and rural female share—are insignificant. So we perform a relatively relaxed comparison by dividing the provinces into three (Low/Middle/High) and two groups (Low/High) respectively by the levels of these three shares, and show the results in Table (10). Now the corresponding pattern emerges—policy effects are indeed mainly driven by the provinces with highest share of rural and rural female high school students. The larger policy effects in provinces with higher share of disadvantaged students imply that it is credit constraints at work.

6 Discussion and Conclusion

We examine the effect of the conditional grants in teachers' colleges on the quality of incoming teacher trainees. We find that the grants generally increase the student quality, given enrollment expansion, in teaching majors. We find that the policy effects not only increase as the costs of living during college decrease, but also are larger in provinces with larger share of disadvantaged students—those who are rural, female, rural female, and have more siblings—are higher. Taken as a whole, these results suggest that the Chinese free teacher education program does successfully attract high quality students into teaching force, and these high quality teacher trainees are very likely to be credit constrained.

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Figure 1. Enrollment in Teacher Education by College Type

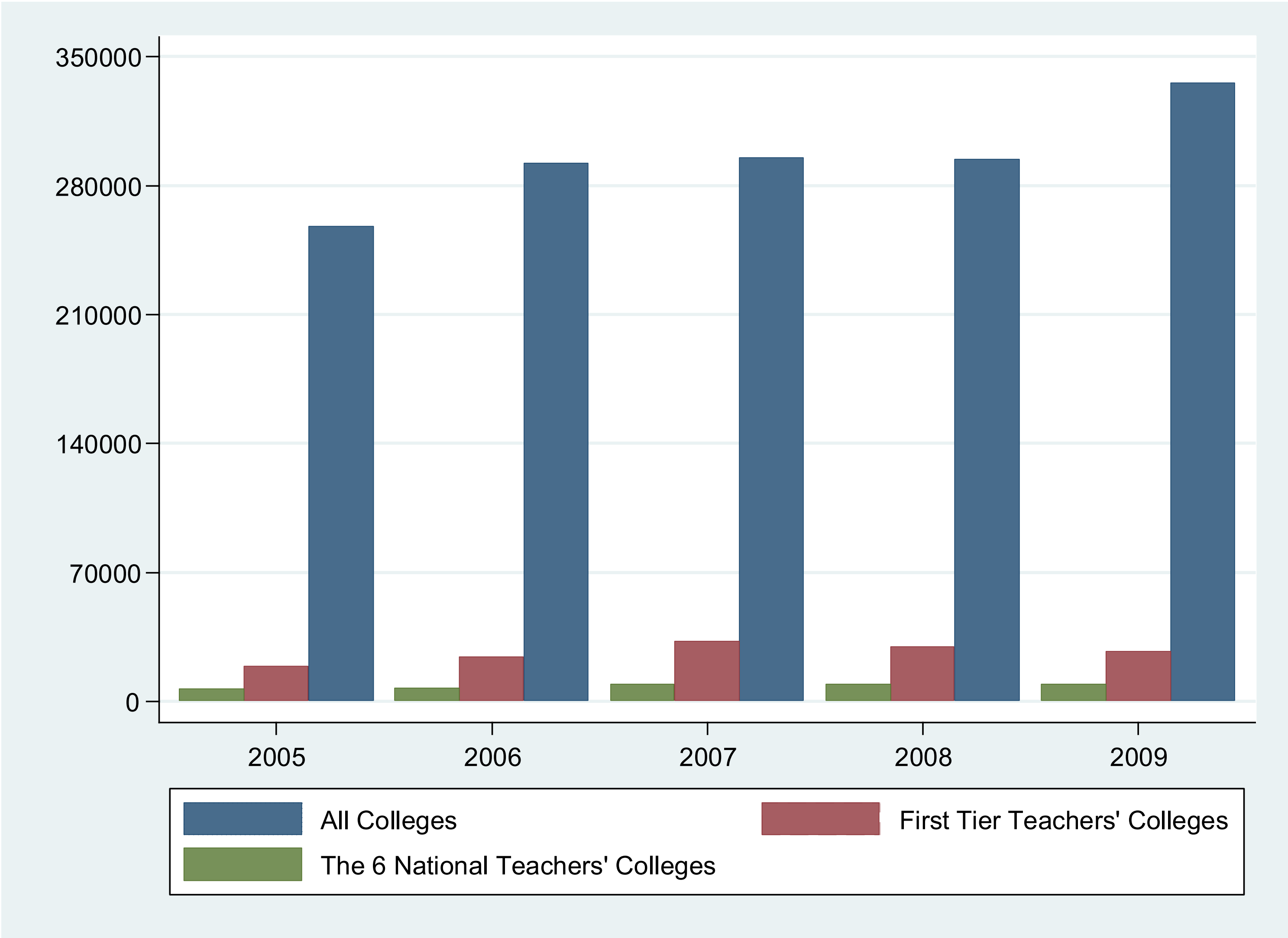

Figure 2. Enrollment Change by Major and College Type

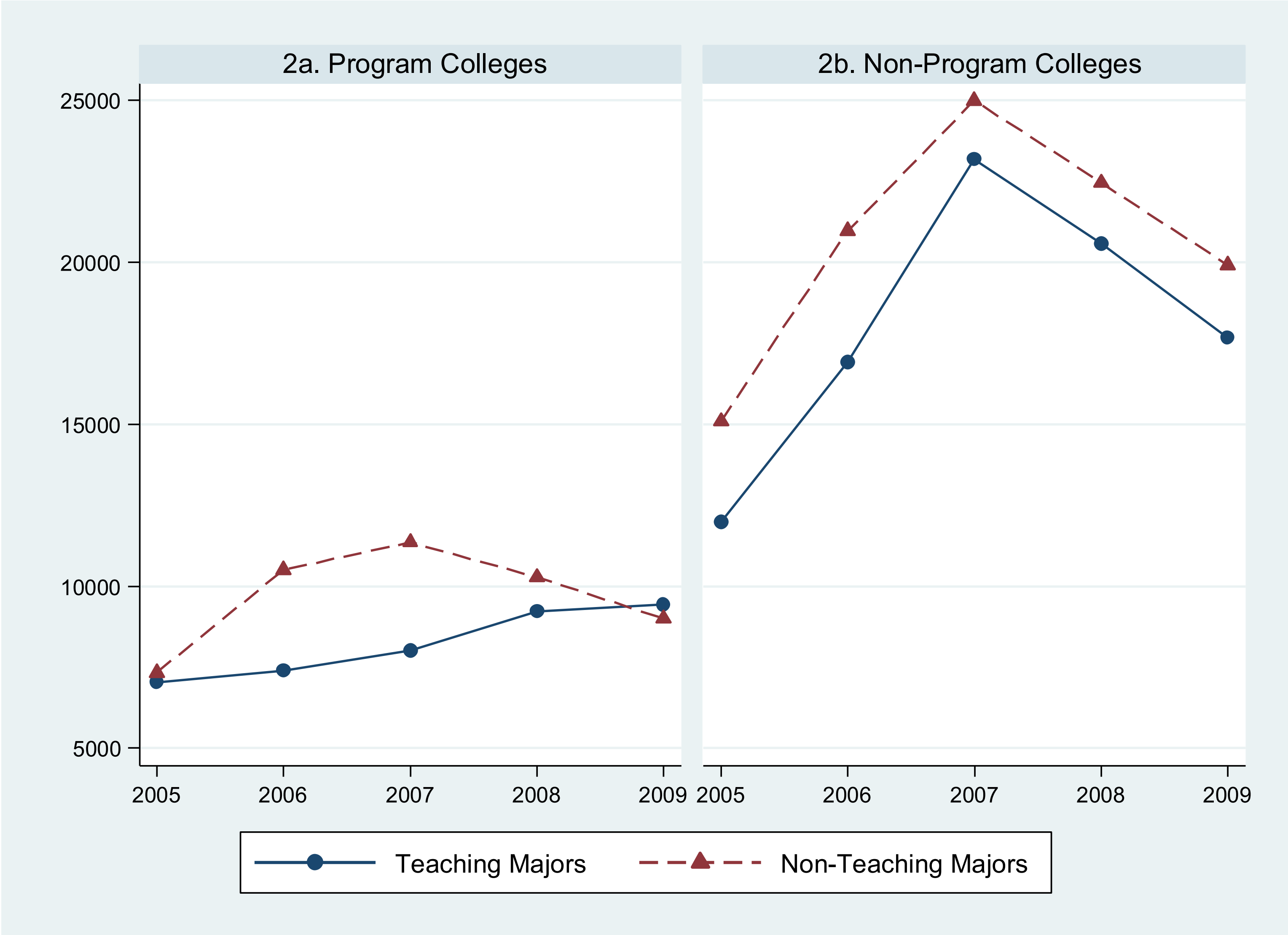

Figure 3. Quality Change by Major and College Type

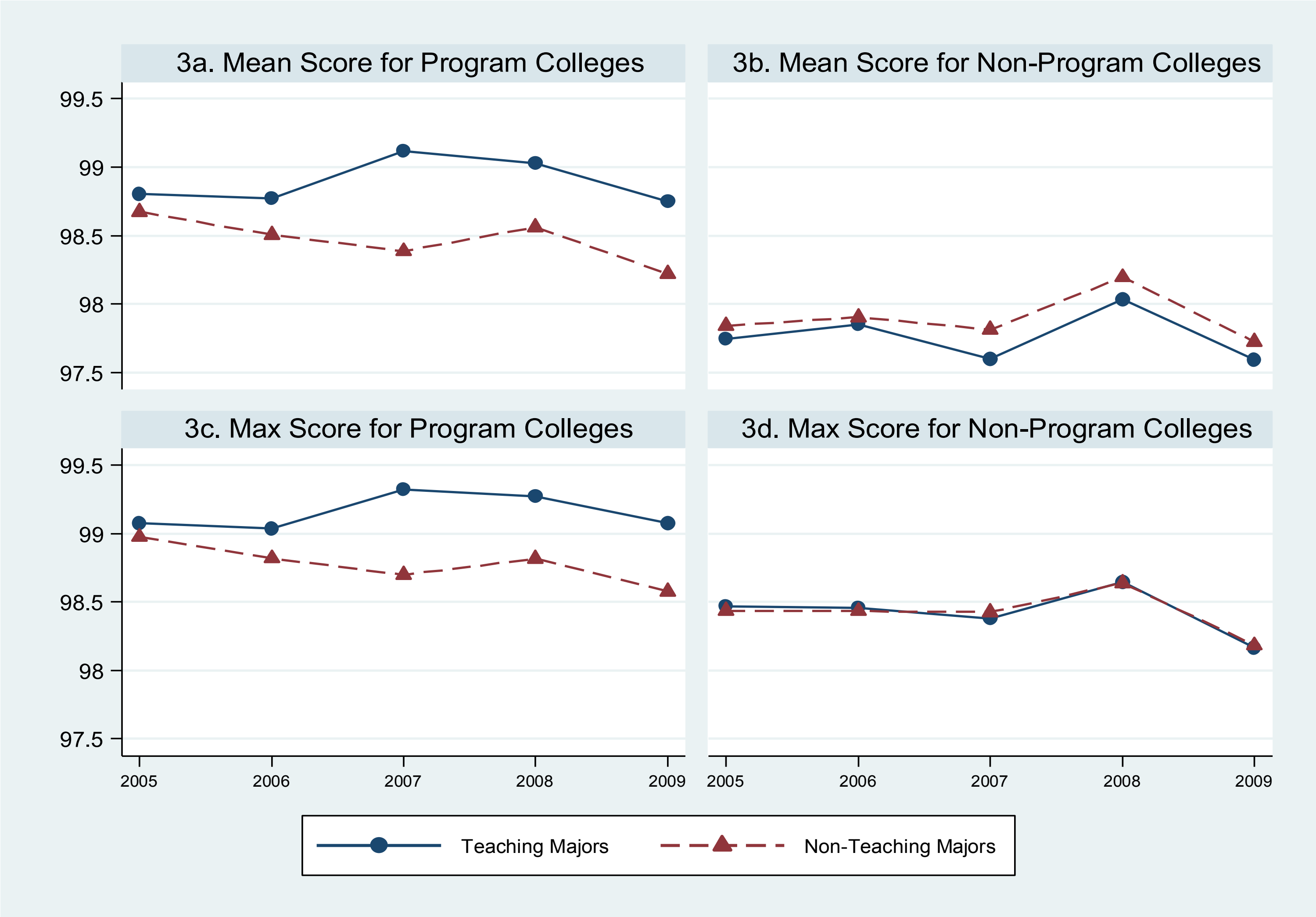

Figure 4. College Location and Living Costs

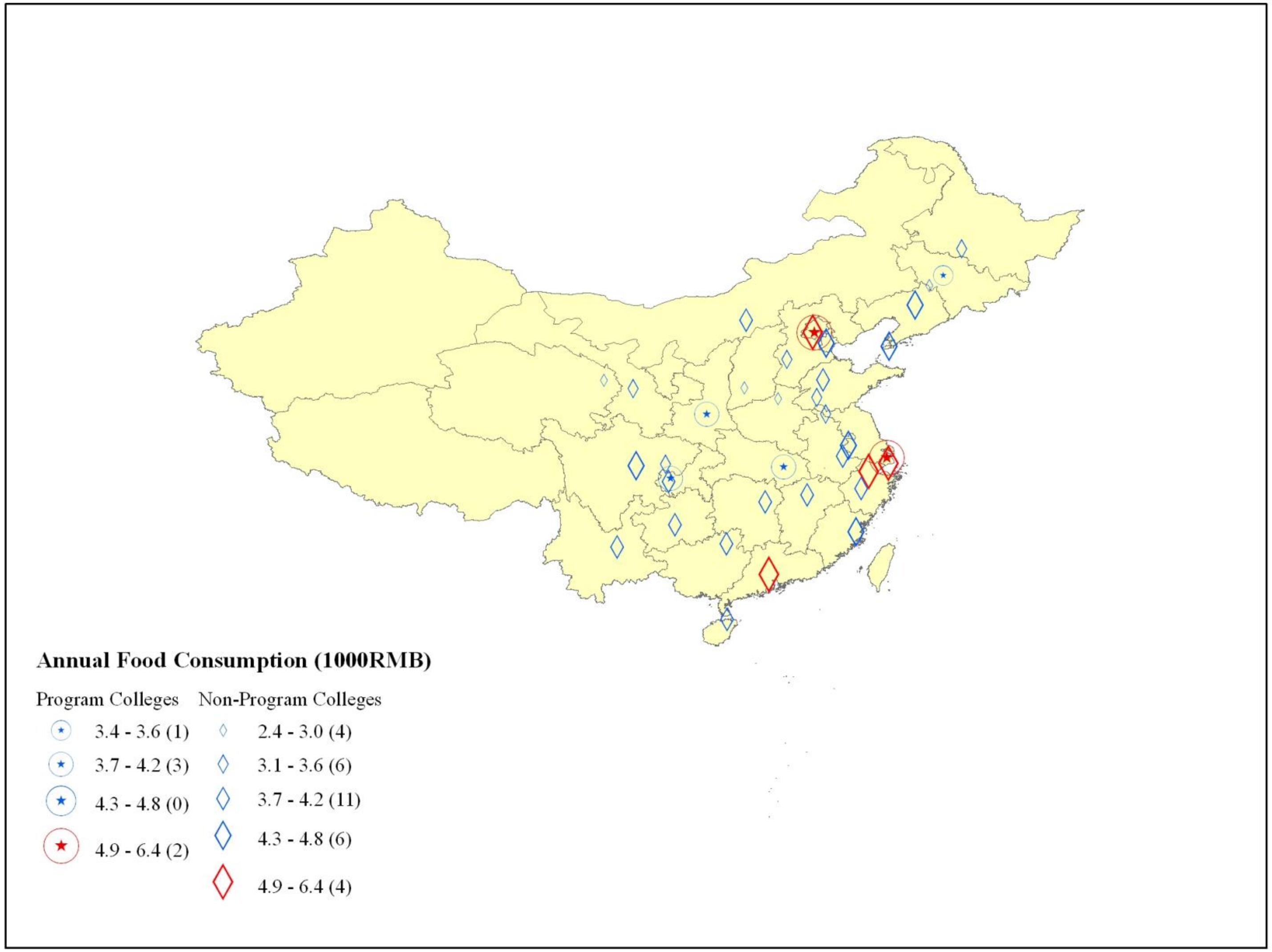

Figure 5. Students Composition

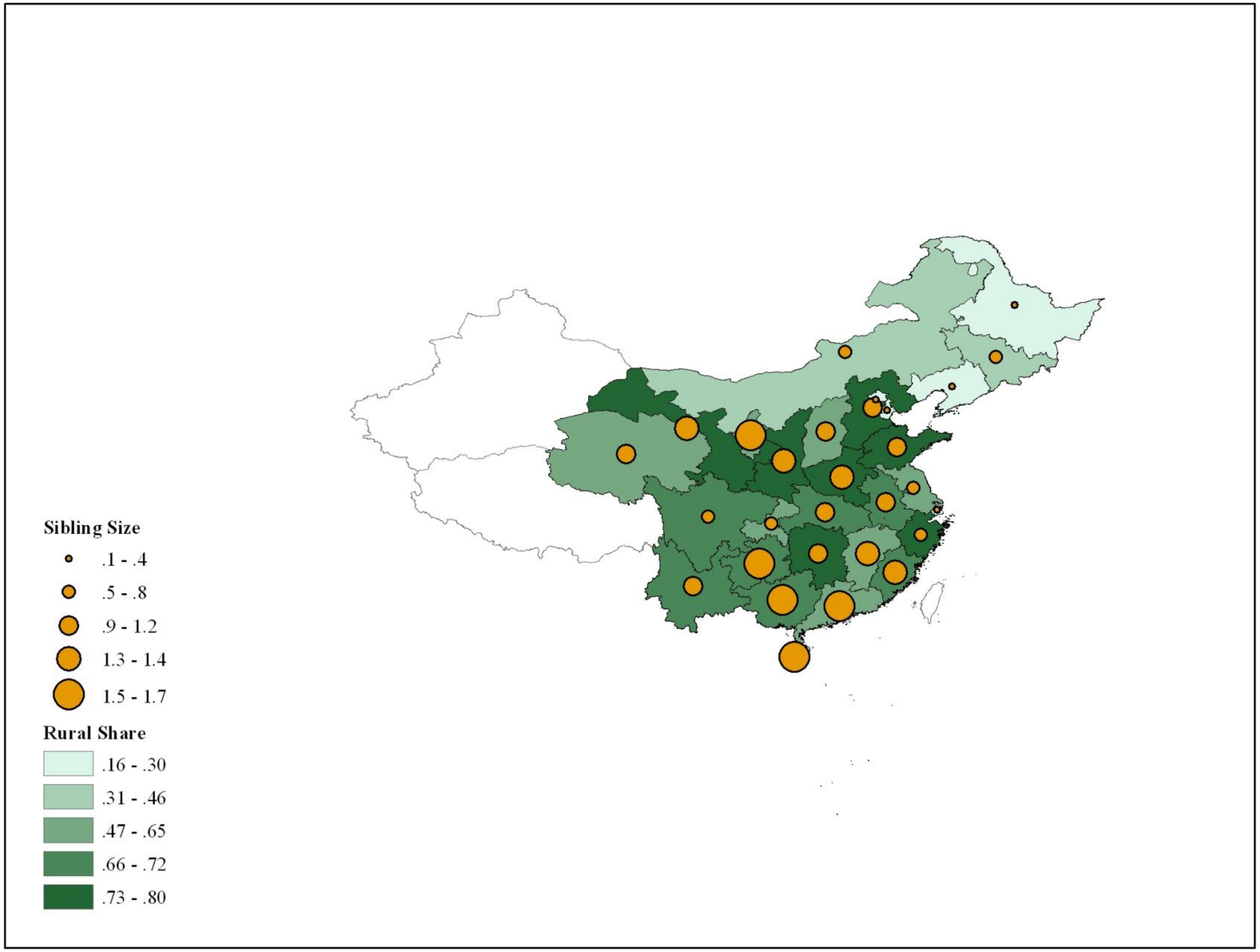

Table 1—Employment of 2007 Cohort

<table>
<tr><th>Province</th><th>Default</th><th>City</th><th>County</th><th>Rural Village</th></tr>
<tr><td>Shaanxi</td><td>3</td><td>445</td><td>741</td><td>117</td></tr>
<tr><td>Jiangsu</td><td>9</td><td>25</td><td>16</td><td>36</td></tr>
<tr><td>Yunan</td><td>0</td><td>235</td><td>174</td><td>18</td></tr>
<tr><td>Anhui</td><td>0</td><td>140+</td><td>32</td><td>8</td></tr>
<tr><td>Jiangxi</td><td>10</td><td>239</td><td>92</td><td>2</td></tr>
<tr><td>Hebei</td><td>4</td><td>52</td><td>56</td><td>2</td></tr>
<tr><td>Zhejiang</td><td>0</td><td>43</td><td colspan="2">55</td></tr>
<tr><td>Shanxi</td><td>3</td><td colspan="2">296</td><td>0</td></tr>
<tr><td>Inner Mongolia</td><td>1</td><td>187</td><td>39</td><td>0</td></tr>
<tr><td>Fujian</td><td>1</td><td>71</td><td>44</td><td>0</td></tr>
<tr><td>Shandong</td><td>0</td><td>57</td><td>166</td><td>0</td></tr>
<tr><td>Guangdong</td><td>3</td><td>72</td><td>3</td><td>0</td></tr>
<tr><td>Hainan</td><td>0</td><td>68</td><td>22</td><td>0</td></tr>
<tr><td>Guizhou</td><td>3</td><td>359</td><td>103</td><td>0</td></tr>
<tr><td>Gansu</td><td>4</td><td>121</td><td>134</td><td>0</td></tr>
<tr><td>Qinghai</td><td>0</td><td>85</td><td>21</td><td>0</td></tr>
<tr><td>Ningxia</td><td>0</td><td>159</td><td>47</td><td>0</td></tr>
</table>

Table 2—Summary Statistics for Regional Characteristics

Variable	Obs.	Mean	Std. Dev.	Min	Max
A. The share of high school students who are					
rural	29128	0.619	0.168	0.164	0.790
female	29128	0.462	0.057	0.214	0.554
rural female	29128	0.286	0.088	0.079	0.451
B. The provincial average sibling size of					
high school students	29128	1.025	0.415	0.085	1.918
rural high school students	29128	1.318	0.475	0.167	2.915
female high school students	29128	1.107	0.433	0.103	2.143
rural female high school students	29128	1.420	0.478	0.192	3.091
C. The city average of individual					
income	29128	16.641	4.100	9.155	23.690
consumption	29128	12.246	2.864	7.193	18.504
food consumption	29128	4.341	0.923	2.376	6.386

Table 3—Means of Student Quality by Cohort, Major and College

	Standardized Mean Score		Standardized Max Score	
	Teaching Major	Non-Teaching Major	Teaching Major	Non-Teaching Major
	(1)	(2)	(3)	(4)
Panel A: Program Teacher Colleges				
pre policy:	98.787	98.571	99.056	98.879
	(0.033)	(0.028)	(0.030)	(0.025)
post policy:	98.956	98.396	99.218	98.701
	(0.020)	(0.021)	(0.017)	(0.018)
Difference	**0.168**	**-0.175**	**0.162**	**-0.178**
	(0.036)	**(0.035)**	**(0.031)**	**(0.031)**
Difference-in-Differences	**0.343**		**0.341**	
	(0.052)		**(0.046)**	
Panel B: Non-Program Teacher Colleges				
pre policy:	97.804	97.877	98.462	98.434
	(0.063)	(0.049)	(0.046)	(0.042)
post policy:	97.751	97.914	98.400	98.411
	(0.042)	(0.031)	(0.032)	(0.026)
Difference	-0.053	0.037	-0.063	-0.023
	(0.075)	(0.056)	(0.060)	(0.047)
Difference-in-Differences	-0.089		-0.041	
	(0.092)		(0.073)	

Table 4—DID Effects on Standardized Score using Difference Subsamples

	Standardized Score					
	All	Similar Disciplines	Similar Majors	Nonlocal	Nonlocal & Similar Discipline	Nonlocal & Similar Major
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Mean Score			
Teacher Major (TM)	0.040	0.032	0.046	0.025	0.018	0.028
	(0.045)	(0.037)	(0.035)	(0.048)	(0.039)	(0.035)
Post*TM	0.163**	0.172***	0.167**	0.190***	0.199***	0.199***
	(0.060)	(0.061)	(0.077)	(0.052)	(0.053)	(0.063)
admission	-0.001	-0.001	-0.001	-0.006*	-0.006*	-0.007*
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
admission^2	0.000	0.000	0.000	0.000*	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	*18,212*	*16,337*	*11,588*	*16,547*	*14,856*	*10,656*
R-squared	*0.889*	*0.890*	*0.890*	*0.896*	*0.897*	*0.900*
			Panel B: Maximal Score			
Teacher Major (TM)	0.018	0.008	0.007	0.008	0.001	0.003
	(0.047)	(0.039)	(0.040)	(0.050)	(0.040)	(0.038)
Post*TM	0.197***	0.217***	0.239***	0.203***	0.219***	0.235***
	(0.048)	(0.053)	(0.070)	(0.047)	(0.049)	(0.067)
admission	0.010***	0.009***	0.008***	0.012**	0.011*	0.010*
	(0.002)	(0.002)	(0.002)	(0.006)	(0.005)	(0.005)
admission^2	-0.000***	-0.000***	-0.000***	-0.000**	-0.000**	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	*18,205*	*16,329*	*11,582*	*16,541*	*14,851*	*10,653*
R-squared	*0.829*	*0.833*	*0.835*	*0.840*	*0.844*	*0.848*

Robust standard errors in parentheses

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

Table 5—DDD Effects on Mean Score using Difference Subsamples

	Standardized Score					
	All	Similar Disciplines	Similar Majors	Nonlocal	Nonlocal & Similar Discipline	Nonlocal & Similar Major
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Mean Score			
Teacher Major (TM)	-0.028	-0.034	0.021	-0.005	-0.011	0.060
	(0.044)	(0.047)	(0.047)	(0.035)	(0.036)	(0.057)
Post*TM	0.003	0.007	-0.047	0.036	0.038	-0.020
	(0.042)	(0.043)	(0.049)	(0.042)	(0.042)	(0.059)
Program College (PC)*TM	0.065	0.066	0.013	0.039	0.041	-0.026
	(0.051)	(0.051)	(0.055)	(0.060)	(0.054)	(0.057)
post*TM*PC	0.171**	0.177**	0.234**	0.155**	0.161**	0.219**
	(0.077)	(0.080)	(0.106)	(0.069)	(0.067)	(0.083)
admission	-0.002**	-0.002*	-0.002*	-0.006*	-0.006*	-0.007**
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
admission^2	0.000*	0.000	0.000	0.000*	0.000*	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	29,108	26,518	18,890	23,750	21,631	15,442
R-squared	0.906	0.909	0.912	0.908	0.910	0.915
			Panel B: Maximal Score			
Teacher Major (TM)	-0.014	-0.010	0.050	-0.005	-0.007	0.092
	(0.027)	(0.028)	(0.037)	(0.038)	(0.040)	(0.059)
Post*TM	0.034	0.029	-0.030	0.042	0.045	-0.039
	(0.039)	(0.041)	(0.051)	(0.050)	(0.051)	(0.057)
Program College (PC)*TM	0.048	0.035	-0.035	0.024	0.021	-0.084
	(0.044)	(0.041)	(0.040)	(0.064)	(0.058)	(0.060)
post*TM*PC	0.171***	0.194***	0.279***	0.158**	0.170**	0.270***
	(0.059)	(0.062)	(0.079)	(0.068)	(0.067)	(0.081)
admission	0.007***	0.007***	0.007***	0.016**	0.015**	0.013**
	(0.002)	(0.002)	(0.002)	(0.007)	(0.007)	(0.006)
admission^2	-0.000***	-0.000***	-0.000***	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	29,101	26,510	18,885	23,743	21,625	15,438
R-squared	0.842	0.846	0.849	0.860	0.864	0.872

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

Table 6—Placebo Test: Policy Effects on Non-Teaching Majors

	Standardized Mean Score		Standardized Max Score	
	All	Nonlocal	All	Nonlocal
VARIABLES	(1)	(2)	(3)	(4)
Post*PC	0.025	-0.072	-0.016	-0.065
	(0.082)	(0.071)	(0.047)	(0.042)
admission	-0.005**	-0.013**	0.006***	0.047***
	(0.002)	(0.006)	(0.002)	(0.013)
admission^2	0.000**	0.000**	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	17,265	13,977	17,260	13,971
R-squared	0.815	0.811	0.762	0.771

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

Table 7—Policy Effects using Alternative Teaching Major Definition

	Policy Effects on Standardized Score					
Teaching Major Definition	All (1)	Similar Disciplines (2)	Similar Majors (3)	Nonlocal (4)	Nonlocal & Similar Discipline (5)	Nonlocal & Similar Major (6)
			Panel A: DID Estimates on Mean Score			
Currently Using	0.163**	0.172***	0.167**	0.190***	0.199***	0.199***
	(0.060)	(0.061)	(0.077)	(0.052)	(0.053)	(0.063)
Advanced Tier Only	0.207**	0.218**	0.177*	0.268***	0.283***	0.259***
	(0.089)	(0.090)	(0.100)	(0.083)	(0.084)	(0.089)
			Panel B: DID Estimates on Maximal Score			
Currently Using	0.197***	0.217***	0.239***	0.203***	0.219***	0.235***
	(0.048)	(0.053)	(0.070)	(0.047)	(0.049)	(0.067)
Advanced Tier Only	0.281***	0.296***	0.287***	0.293***	0.310***	0.288***
	(0.075)	(0.077)	(0.085)	(0.079)	(0.081)	(0.086)
			Panel C: DDD Estimates on Mean Score			
	0.171**	0.177**	0.234**	0.155**	0.161**	0.219**
Currently Using	(0.077)	(0.080)	(0.106)	(0.069)	(0.067)	(0.083)
	0.508**	0.509**	0.586*	0.381***	0.377***	0.417***
Both Tiers	(0.227)	(0.239)	(0.287)	(0.087)	(0.096)	(0.136)
	0.389*	0.398*	0.387	0.279**	0.268**	0.184
Advanced Tier Only	(0.195)	(0.208)	(0.272)	(0.107)	(0.114)	(0.186)
			Panel B: DDD Estimates on Maximal Score			
Currently Using	0.171***	0.194***	0.279***	0.158**	0.170**	0.270***
	(0.059)	(0.062)	(0.079)	(0.068)	(0.067)	(0.081)
Both Tiers	0.389***	0.401***	0.475***	0.388***	0.393***	0.473***
	(0.092)	(0.101)	(0.138)	(0.074)	(0.086)	(0.137)
Advanced Tier Only	0.329***	0.337***	0.322*	0.276**	0.259**	0.197
	(0.102)	(0.112)	(0.159)	(0.108)	(0.116)	(0.189)

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

Table 8—Heterogeneous Policy (DDD) Effects across Different University Locations

	Standardized Mean Score		
VARIABLES	(1)	(2)	(3)
DDD	0.889**	0.885**	0.884**
	(0.362)	(0.414)	(0.407)
Income*DDD	-0.043**		
	(0.017)		
Consumption*DDD		-0.057**	
		(0.0273)	
Food Consumption*DDD			-0.157**
			(0.075)
Observations	18,890	18,890	18,890
R-squared	0.912	0.912	0.912

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

Table 9—Heterogeneous Policy (DDD) Effects across Different Student Origins

	Standardized Mean Score						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post*TM*PC (DDD)	-0.049	1.572	0.085	-0.171	-0.335	-0.239	-0.461*
	(0.377)	(0.956)	(0.391)	(0.256)	(0.262)	(0.265)	(0.255)
Rural Share*DDD	0.454						
	(0.541)						
Female Share*DDD		-2.920					
		(2.115)					
Rural Female Share*DDD			0.520				
			(1.225)				
Sibling No.*DDD				0.411*			
				(0.221)			
Sibling No. of Rural*DDD					0.454**		
					(0.181)		
Sibling No. of Female*DDD						0.442**	
						(0.212)	
Sibling No. of Rural Female*DDD							0.512***
							(0.162)
Observations	18,890	18,890	18,890	18,890	18,890	18,890	18,890
R-squared	0.912	0.912	0.912	0.912	0.913	0.912	0.913

Robust standard errors in parentheses

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

Table 10—Heterogeneous Policy (DDD) Effects across Different Student Origins

	Standardized Mean Score				
	Panel A: Grouping by Provincial Rural Share				
	Low	Middle	High	Low	High
VARIABLES	(1)	(2)	(3)	(4)	(5)
DDD	0.250	0.066	0.276**	0.226	0.225**
	(0.280)	(0.165)	(0.102)	(0.204)	(0.088)
Observations	6,337	5,308	7,245	9,331	9,559
R-squared	0.903	0.917	0.907	0.907	0.913
	Panel B: Grouping by Provincial Female Share				
	Low	Middle	High	Low	High
VARIABLES	(1)	(2)	(3)	(4)	(5)
DDD	0.148	0.264	0.222	0.222	0.238
	(0.132)	(0.280)	(0.130)	(0.134)	(0.171)
Observations	5,745	6,069	7,076	9,319	9,571
R-squared	0.904	0.916	0.908	0.923	0.903
	Panel C: Grouping by Provincial Rural Female Share				
	Low	Middle	High	Low	High
VARIABLES	(1)	(2)	(3)	(4)	(5)
DDD	0.235	0.123	0.268**	0.288	0.182*
	(0.290)	(0.161)	(0.110)	(0.197)	(0.101)
Observations	5,888	6,159	6,843	9,164	9,726
R-squared	0.901	0.925	0.909	0.910	0.910

Robust standard errors in parentheses

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

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