College Affirmative Action and Students' Long-Term Outcomes: A Matter of the Dose*

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Abstract

Extensive discussion centers around the question of whether affirmative action (AA) in higher education "works," despite AA being in practice a continuous policy instrument. We study how the dose of AA affects its intended beneficiaries by exploiting a nationwide AA program in China's centralized college admissions system, where ethnic minority students receive explicit bonus points in the college entrance exam. Cohort-level fluctuations in exam score distributions generate plausibly exogenous variation in the effective strength of AA. Using data that link administrative exam records to comprehensive transaction data, we track students' economic outcomes 10 to 23 years after taking the entrance exam. The effects of AA are highly nonlinear. Low doses increase long-run consumption by about 19%, while high doses reduce it by around 28%. Higher doses expand access to elite colleges but worsen academic fit, lower relative performance, and reduce satisfaction with college life. The results highlight the importance of calibrating AA policies.

JEL Classification: H75, I24, J24

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1 Introduction

Affirmative action (AA) in higher education is one of the most consequential and contested public policies worldwide (Arcidiacono and Lovenheim, 2016). Despite decades of debate, policies are typically evaluated as if AA were a binary choice — either implemented or not — and researchers have been keen to answer the question of whether AA "works". In practice, however, AA is a continuous policy instrument: governments/colleges choose how strongly to tilt admissions criteria in favor of disadvantaged groups. Treating AA as an on/off switch obscures a central policy question: how much AA is too much, and how much is too little?[1]

In this paper, we take a step forward by studying a major nationwide AA program in China, the ethnic minority bonus-point policy in the College Entrance Examination (CEE). Our setting has three features that make this progress feasible. First, in contrast to settings where AA operates through opaque or institution-specific mechanisms that make the magnitude of AA difficult to quantify (Bagde et al., 2016; Hoxby, 2025), AA in our setting is transparent and easy to measure. Minority students receive explicit bonus points added directly to their CEE scores; one's total score, in turn, determines one's priority in a centralized admissions procedure.

Second, although nominal bonus points are often fixed within a county-ethnicity group, their effective value varies continuously across cohorts due to fluctuations in exam difficulty and hence in CEE score distributions, resulting in plausibly exogenous variation in the dose of AA within narrowly defined groups. This variation allows us to move beyond a dichotomous evaluation of AA.

Third, our data provide comprehensive measures of students' admission, in-college, and long-run outcomes. Our main data, pre-merged by our data provider at the individual level, consists of two major data sets. The first is the administrative CEE records (demographics, test scores, and admission results) for every test taker in 1999-2003 cohorts, allowing us to

[1]Throughout the paper, we focus on the effect of AA on its intended beneficiaries and put aside the issue of AA shifting scarce resources away from non-targeted groups; see, for example, Barahona et al. (2023); Black et al. (2023) on how AA affects targeted and non-targeted students.

measure students' immediate outcomes, i.e., college admissions. The second is the comprehensive transaction records from one of China's dominant payment networks, allowing us to track individuals' long-term economic outcomes measured by their consumption 10 to 23 years after they took the CEE. Our supplementary data, from the China College Student Survey (CCSS), provides rich information on students' in-college performance and subjective well-being.

With these institutional and data advantages, we start our empirical analysis by measuring the dose of AA. Our main measure is the ratio of nominal bonus points to the standard deviation (sd) of the CEE score distribution within a province-cohort-track cell. Given the cross-cohort variation in the CEE test difficulty and score distribution, the same nominal bonus point can translate into different effective advantages across cohorts. Utilizing this variation, our estimation, similar in spirit to the re-centering approach by Borusyak and Hull (2023), relies on the assumption that year-to-year variation in AA doses for a given minority in a given county is as good as random, holding fixed all time-invariant characteristics of counties, ethnic groups, and exam tracks. In addition, we include county-cohort-track fixed effects to account for unobserved local shocks that may affect students' CEE outcomes (e.g., cohort-specific changes in education policies within a given county-track). To validate our identifying assumption, we show that, after controlling for the set of fixed effects we include, CEE rankings are not associated with within-cell variation in AA doses.

Utilizing the variation in AA doses, we examine AA's impacts on a rich set of student outcomes. First, we find that higher doses of AA substantially expand access to elite colleges but also lead to poorer academic fit. A 0.1 increase in AA doses raises the probability of admissions to college by 3.1 percentage points (ppts) and to Tier-1 or elite colleges by 1.0 ppts, the average rates being 61% and 12%, respectively. However, the same increase in AA doses also puts students in colleges where they are relatively under-prepared, lowering their relative CEE-score ranking among peers by about 2.0 ppts (13.6% of the sample s.d.), and increasing their probability of choosing a bottom-three-earning major by 1.4 ppts (11.8% of

the sample mean).

Second, following these students up to two decades after they took the CEE, our central finding is that the effect of AA on long-run economic well-being is highly nonlinear. Relative to their counterparts receiving no bonus point, minority students exposed to low doses of AA (the bottom quintile of the dose distribution) experience substantial gains: long-run consumption rises by approximately 19%. In contrast, students exposed to high doses suffer large and persistent losses, with consumption falling by 14% (28%) among those in the fourth (fifth) quintile of the dose distribution. Intermediate doses generate no detectable effects. These patterns are mirrored in the income data for a subsample where such information is available. In addition, we find no evidence that the nonlinear long-run consumption effects are driven by differences in living costs across residential locations or by substitution between consumption and savings/investment.

Breaking students into subgroups, we find that students with higher ability (ranked in the top quartile of the CEE score distribution) are more resistant to higher doses of AA: their long-run consumption is reduced only when receiving the highest quintile of AA doses. We also find that, compared to their counterparts, male students, students with rural hukou, and students from lower-quality high schools benefit less from low doses of AA and suffer more from high doses of AA.

Finally, to bridge the immediate enrollment effect with the long-run consumption effect, we exploit the CCSS data and find that higher AA doses are associated with lower in-college GPA ranking relative to peers, and lower satisfaction with interpersonal relationships and overall college life. On average, a 0.1 increase in the AA dose lowers the self-reported satisfaction with GPA by 11% of the sample mean and overall satisfaction with college life by 16% of the sample mean. However, these patterns are highly nonlinear. The decline in both academic standing and subjective well-being is concentrated among students in the highest AA dose group, who are, for example, 5.1-ppt more likely to report lower satisfaction with college life. In contrast, students exposed to lower doses show little evidence of such

difficulties. These findings suggest that while high AA doses place students in prestigious colleges, these students may struggle to adapt both academically and socially. These short-run academic and social life challenges can translate into persistent differences in human capital accumulation and long-run economic outcomes.

While our analysis focuses on China, the lesson learned is general. Many AA systems — whether through bonus points, admission thresholds, top $x\%$ programs, or holistic evaluations — implicitly vary in strength across institutions, cohorts, and applicants. Our results suggest that averaging over heterogeneous policy intensities can mask both sizable gains from moderate AA and substantial losses from overly aggressive implementation. The dose-response analysis we conduct provides a lens for interpreting mixed evidence from other settings and for designing AA policies to improve the outcomes for their intended beneficiaries. More broadly, it highlights the importance of calibrating redistributive policies when benefits and costs respond nonlinearly to policy intensity.

Our paper contributes to the long-standing debate about the effects of AA on its intended beneficiaries. On the affirmative side, a growing body of work shows that AA expands access to higher-quality colleges, increases college attendance and completion, and improves early- and mid-career labor market outcomes and socioeconomic mobility (e.g. Bagde et al., 2016; Estevan et al., 2019; Bleemer, 2022; Black et al., 2023; Bleemer, 2023; Akhtari et al., 2024; Bleemer, 2024; Machado et al., 2025). On the negative side, critics are concerned about "mismatches," in that AA may lower academic performance, persistence, and degree completion when students are placed in environments for which they are underprepared. This argument is supported by a series of empirical studies (e.g. Arcidiacono et al., 2011, 2016; Arcidiacono and Lovenheim, 2016; Barrow et al., 2020; Dillon and Smith, 2020). It is hard to settle this debate because there is truth to both sides of the argument: a college's overall quality and the student-college match quality are both important for a student's outcome (e.g. Arcidiacono and Lovenheim, 2016). By exploiting the transparent and continuous variation in the effective doses of AA, our paper reconciles these seemingly conflicting views

and shows that the ultimate effect of AA depends on its dose.

In addition, our rich data provides a comprehensive view on how AA might affect students' outcomes in the short- and long-run. Moreover, using the in-college experience survey (CCSS), we bridge students' immediate enrollment outcomes and their long-run outcomes with new evidence on how the dose of AA affects students' in-college performance and subjective well-being with respect to peer relationships and overall college life.[2] Our findings from CCSS echo those from previous studies on students' sense of belonging and social integration in college, which highlight that disadvantaged or underrepresented students may face challenges in peer relationships and campus life (Brady et al., 2020; Aucejo et al., 2023).

The remainder of the paper proceeds as follows. Section 2 describes the background. Section 3 presents a simple model to illustrate the trade-offs generated by AA. Section 4 introduces the data and defines our AA-dose measure. Section 5 presents the empirical strategy. Section 6 and 7 present the main results and evidence on mechanisms. Section 8 concludes.

2 Background Information

2.1 Chinese Colleges and Admissions

College Tiers Chinese higher education consists of two categories of colleges: colleges granting Bachelor's degrees, and those granting Associate degrees (vocational colleges). Within the first category, colleges are stratified into tiers. During our study period, programs in the most selective institutions, Tier-1 colleges (closely overlapping with the 115 "Project 211" colleges),[3] admitted roughly the top 12% of examinees. Within each tier, col-

[2] A growing literature uses survey-based data to study students' expectations, valuations, and non-pecuniary aspects of higher education (e.g., Zafar (2011, 2013); Wiswall and Zafar (2015); Patnaik et al. (2021)).

[3] "Project 211" is a strategic initiative launched by the Chinese government in 1995 to enhance the global competitiveness of selected colleges. The term "211" refers to the goal of developing approximately 100 elite colleges for the 21st century.

leges also differ by peer quality (measured, for example, by admitted students' CEE ranking) and program quality, both of which matter for human-capital accumulation.

College Entrance Exam China's annual national college entrance examination (CEE) is the decisive gatekeeper for higher education. Each year, approximately 10 million students take the exam, typically in one of a few tracks (principally Science or Social Science). The Science track generally included physics, chemistry, and biology, while the Social Science track covered history, politics, and geography. Within the CEE system, most provinces in our sample used the uniform national exam papers, while some provinces designed their own exam papers. Nevertheless, CEE scores are comparable within a province-year-track cell.

Unlike admission systems that weigh grades, extracurriculars, and holistic reviews, a student's CEE score, relative to her province-year-track peers, plays a nearly exclusive role in determining college placement, leaving little room for discretion in admissions, as we describe next.

College Admissions College admissions are conducted in a centralized system at the provincial level. In each province, students apply within their chosen track by submitting a rank-ordered list of college programs (college-major combinations); admissions are program-specific. In a typical year-province, a student's choice set includes about 2,839 programs nationwide.[4] We aggregate the 96 majors into 10 broader categories — Agriculture, Economics, Education, Engineering, Health, History, Law, Literature, Management, and Science — consistent with the one-digit major classification defined by the Ministry of Education of China.

Admissions to college programs are determined by applicants' rankings based on their total CEE scores, inclusive of bonus points, and by program-specific capacity constraints, through centralized matching mechanisms that vary across provinces and over time. During

[4]The corresponding figures are approximately 4,693 programs for Science-track students and 1,625 programs for Social-Science-track students.

our sample period, two broad classes of mechanisms were in place. Under the sequential mechanism, a variant of the Boston or immediate acceptance mechanism, programs first admit applicants who rank them as their top choice and consider lower-ranked applicants only if seats remain. By contrast, the Chinese "parallel" mechanism allows applicants to list multiple programs within a choice band and is designed to reduce manipulability and strategic risk. Detailed descriptions of these mechanisms are provided in Wu and Zhong (2014) and Chen and Kesten (2017).

These assignment rules do not generally induce truthful preference revelation, and applicants may behave strategically when constructing their rank-ordered lists. Because our data record realized admission outcomes but not applicants' submitted preference lists, we cannot analyze application behaviors and how these behaviors are affected by AA policies. Instead, we focus on the reduced-form effects of affirmative action on college enrollment, major assignment, and subsequent outcomes, abstracting from the strategic considerations underlying students' application choices.

2.2 Minority Bonus Points

Alongside these institutional features, the central and provincial governments operate several preferential mechanisms; the most widespread is ethnic-minority CEE bonus programs.[5] Since the early 1980s, government-determined eligible ethnic minority candidates have frequently received nominal extra points, commonly in the range of 5-30 points, added to their CEE scores; the (post-bonus) total score is the sole criterion differentiating students in college admissions. In our sample, the average CEE (pre-bonus) score is 426.2 (s.d. is 96.1) overall, 539.2 among students admitted to Tier-1 elite colleges, and 411.1 among those admitted to non-elite colleges. In this context, a bonus of 5 to 30 points is quite meaningful.

The bonus program is administered at the county-ethnicity level and typically applies uniformly to all qualifying candidates in a county, where the qualification criteria and the

[5]Other major programs include bonus points for athletic achievement and for winning National Academic (e.g., Math and Physics) Competition.

bonus points are set by the provincial government. Figure A.1 shows that, consistent with the intended goal of equalizing opportunities, bonus points are positively correlated with local illiteracy rates and ethnic minority shares, and negatively correlated with GDP per capita.

The nominal bonus points awarded to an ethnic minority group in a county are typically fixed. However, due to variation in specific exam questions, the overall CEE exam difficulty varies across years, and so does the distribution of CEE scores. As such, a fixed nominal CEE score maps into different admission advantages across province-cohorts: a given nominal bonus yields a larger (smaller) advantage in a relatively difficult-test or low-scoring (easy-test or high-scoring) province-cohort. These subtle, continuously varying effective bonus values are the main source of variation we exploit in our analysis.

In addition, we also utilize a salient institutional change that occurred in Jiangsu province. In 2001, the provincial government introduced a sharp increase in minority bonus points. Prior to 2001, ethnic minority students in Jiangsu were not eligible for any bonus. Beginning in 2001, the province implemented a uniform five-point bonus for all students officially registered as ethnic minorities. This reform marked a clear shift from zero to positive treatment for affected groups and created a discrete break in bonuses across cohorts.

In the following, we first illustrate the effect of AA through the lens of a simple model. Then, we empirically examine AA dose effects by exploiting the aforementioned institutional features: (i) a single score that largely determines admission, (ii) an expansive choice set of college-major programs, and (iii) explicit minority bonuses.

3 A Simple Model

This section presents a bare-bones model of a student's college choice and achievement. Relative to the empirical setting we study, the model is rather simplified, with the goal of illustrating the essential idea of how AA might affect these outcomes. Extension of this

model to a richer setting is relatively easy, but at the cost of heavier notation.[6]

3.1 Primitives

There is a continuum of potential college enrollees of measure 1, each endowed with a group identity $g_i \in (0,1)$ with 1 being minority, ability a_i, and preferences for different colleges. There are J colleges, each endowed with a quality q_j and a capacity n_j, with $\sum_j n_j < 1$, i.e., the number of students exceeds the total capacity. An outside option is available to all students.

Ability and Test Scores Students' ability is unknown to both students and colleges, who observe a test score s_i — an unbiased measure of a_i. The precision of s_i as a measure of a_i can be group-specific. If minorities face larger uncertainties about their ability, s_i would have a larger dispersion around a_i for $g_i = 1$.

Human Capital Production For a student i enrolled in college j, her human capital attainment is a function of her own ability a_i and the college's quality q_j, subject to a random shock $\epsilon_{ij,}$ such that

$$h_{ij} = H(q_j, a_i, \epsilon_{ij}) = \gamma_1 q_j + \gamma_2 a_i + D_h\left(q_j - a_i\right) + \epsilon_{ij}, \tag{1}$$

where $D_h\left(q_j - a_i\right)$ is a function of the distance between q_j and a_i, capturing the effect of match quality in producing human capital. An "overmatch" occurs when $q_j - a_i >> 0$ and an "undermatch" occurs when $q_j - a_i << 0$;[7] most relevant to the "mismatch" argument against AA is the potential negative effect arising from "overmatch."

[6]For example, students' ability is modeled as a scalar, which can be easily extended to explicitly account for multi-dimensional abilities and students' college-major choices.

[7]Dillon and Smith (2017) find that both cases are prevalent among U.S. students in general.

In-College Utility: The net consumption value of a college depends on college quality, student-college match, student group identity, and one's taste η_{ij}, given by

$$u_{ij} = U_{g_i}(q_j, a_i, \eta_{ij}) = \lambda_{g_i} q_j + D_u\left(q_j - a_i, g_i\right) + \eta_{ij}. \tag{2}$$

The coefficient λ_g captures the group-specific net consumption value for college quality (e.g., preference for quality net of price); the function $D_u\left(q_j - a_i, g_i\right)$ captures the effect of match quality on one's utility, which may vary with g.

3.2 Students' College Choices

In the centralized system, admissions are subject to college-specific cutoffs on test scores $\left\{s_j^*\right\}_j$: student i is eligible for college j if $s_i \geq s_j^*$. We present the model assuming students have rational expectations of $\{s_j^*\}_j$ and abstract from potential application mistakes arising from mis-forecast of cutoffs. As such, this simple model focuses on informational friction with respect to one's ability and match quality.

A student chooses the option yielding the highest expected payoff among the colleges she is eligible for and the outside option, i.e.,

$$\max\{\max_{j|s_i \geqslant s_j^*} \left\{\tilde{E}_{g_i}[(U_{g_i}(q_j, a_i, \eta_{ij}) + \beta H(q_j, a_i, \epsilon_{ij}))|s_i]\right\}, \tilde{E}_{g_i} V_0\left(g_i, a_i | s_i\right)\}. \tag{3}$$

In making her decision, given that ability a_i is unknown to the student, she needs to form expectations about it using information available — her test score s_i. This expectation may differ from the objective expectation; we use $\tilde{E}$ to denote the subjective expectation operator and allow it to differ by group identity.

Even if students have correct beliefs about the distribution of their ability, but do not know their ability level when making college choices, their choices can be ex-post regrettable. If students' subjective beliefs about their own ability deviate from the objective distribution, it increases the probability of ex-post regrettable choices; specifically, an overly optimistic

(pessimistic) student is more likely to choose an overmatched (undermatched) college.[8]

3.3 Model Implications

This model captures the arguments on both the positive and negative sides of the AA debate. On the affirmative side, AA expands a student's option set from $\{j|s_i \geq s_j^*\}$ to $\{j|s_i + b \geq s_j^*\}$. The expanded set includes more higher-quality colleges, which can improve a student's achievement, through the effect of q_j on h_{ij} in Equation (1), as well as her non-pecuniary well-being, through the effect of q_j on u_{ij} in Equation (2). On the negative side, information friction with respect to one's ability a_i can lead a student to mis-predict how well she is matched to various colleges; this can hurt her achievement, through $D_h(\cdot)$ in Equation (1)), as well as her non-pecuniary well-being, through $D_u(\cdot)$ in Equation (2).

For a given dose of AA, whether AA would improve or hurt the economic well-being of its intended beneficiaries depends on several factors. First, the relative importance of college quality and match quality for one's achievement (Equation (1)). Second, the degree of uncertainties over one's ability and/or the deviation of one's subjective belief from the truth, which govern the likelihood of ex-post regrettable decisions. Third, the relative importance of non-pecuniary consumption value of a high-quality college (λ_g in Equation (2)), which can be large in the Chinese setting.[9]

Holding these primitives fixed, the effect of AA on its intended beneficiaries varies with its dose: a larger dose b expands one's choice set to include higher-quality colleges, but it also increases the probability that a student is over-matched. We examine how the dose of AA affects one's educational and long-term economic outcomes, using our main data, and one's (in-college) non-pecuniary well-being, using our supplementary survey data.

[8]Some studies (e.g. Stinebrickner and Stinebrickner, 2012; Bobba and Frisancho, 2022; Aucejo and Wong, 2025; Aucejo et al., 2025) find that disadvantaged students (e.g., low-income, low-performing, or first-generation college students) have more biased (overly optimistic) beliefs about their ability; while some other studies (e.g. Hoxby and Avery, 2012; Hoxby and Turner, 2015) find that information frictions about net tuition and the application process cause undermatches among high-achieving low-income U.S. students.

[9]Even in the absence of information friction, a large λ_g can lead a student to choose a high-quality college with lower economic payoffs (Oreopoulos and Salvanes, 2011; Gong et al., 2019; Aucejo et al., 2023).

4 Data

We get access to students' administrative records from the College Entrance Examination (CEE) pre-merged with consumption data from the UnionPay (our data provider). For matched individuals, we observe their CEE scores, demographic characteristics, college admission outcomes, and detailed expenditure data spanning 10 to 23 years after taking the CEE or 6 to 19 years after college for those who enrolled in and graduated from college.

4.1 College Entrance Examination Data

The core dataset covers the universe of students who took CEE between 1999 and 2003. For each test taker, we observe their demographics (gender, ethnicity, urban/rural hukou), exam year and birth county, academic track, raw CEE score, bonus points, and a set of admission outcomes, including the college-major that admitted the student and whether the college was the student's top choice on her preference list, which is particularly important under the sequential mechanism.

The CEE data have two limitations. First, we do not observe students' application lists, beyond whether a student was admitted to her top choice. This prevents us from studying AA's impact on students' application behaviors; however, it does not affect our ability to study the (reduced-form) effect of AA on students' admission and long-term economic outcomes.

Second, while the CEE administrative data report the bonus points awarded to each student, they do not disclose the reason for the bonus. We overcome this data limitation and isolate bonuses stemming from ethnic minority status by undertaking extensive archival work to collect official bonus point policies across provinces and cohorts. We contacted all provincial education departments and utilized library archives, ultimately compiling 68 official documents. Figure A.2 displays a sample of an official document on the bonus point policy. We further supplemented policy information with contemporaneous media records,

including news coverage and periodical archives. In return, we obtained clean information on ethnic minority bonuses from 19 provinces in China and focus our attention on CEE test takers from these provinces, who account for 47.8% of all CEE test takers in an average year.

As detailed in Appendix B, test takers from the following provinces are excluded either because official bonus policies were unavailable (Qinghai, Ningxia, Shanxi, and Jilin), or because bonus points cannot be reliably inferred due to structural or definitional inconsistencies in policy documents, including Xinjiang (bonus depend on parents' ethnicity, which is not observed in the CEE data), Chongqing and Sichuan (bonus varies by university type), Shandong (pre-2002 bonuses applied to all first-time CEE takers), Inner Mongolia (policy description is ambiguous), and Guangxi (minority bonuses are confounded with underdevelopment-area bonuses).

4.2 Consumption and Income Data

The second main database for our analysis is the universe of credit and debit card (or "bank card") transactions in China that are settled through the UnionPay network; the database also includes cardholders' demographics (gender, age, and birthplace).

The UnionPay network is the only inter-bank payment network in China and is state-owned. It is the largest network in the world in terms of both the number and the value of transactions, ahead of Visa and Mastercard. From 2013 to 2022, a total of 9.5 billion bank cards were issued. The database covers over 300 merchant categories and records annual transaction values growing from $5.2 trillion in 2013 to over $19 trillion in 2022 (People's Bank of China, 2014, 2024).[10] UnionPay bank card transactions represented about 80% of overall retail consumption in 2018 (Lai et al., 2022). To our knowledge, this dataset offers the most comprehensive account and fine-scale of consumption activity in China in temporal and spatial dimensions. It is worth noting that the use of mobile payments (e.g., WeChat Pay and Alipay) rose sharply since 2018. As a robustness check, we restrict our sample to

[10]The major merchant categories are retail; wholesale; direct sales; real estate and finance; residential and commercial service; hotel, restaurant, and entertainment; and education, health, and government service.

2013–2018, a period in which mobile payments were less popular.

From this data, we observe the transaction location (city), date, merchant category, and amount for all card transactions of all individuals in our CEE sample, except for students from Guangdong province and Tibet.[11] Figure A.3 shows a strong positive relationship between CEE percentile rank and long-term average annual consumption, consistent with the expectation that higher academic achievement predicts better long-term economic outcomes. The slope steepens notably in the upper tail of the distribution, particularly beyond the 85$^{\text{th}}$ percentile, mirroring the structure of our sample in which roughly 12% of students were admitted to elite colleges.

UnionPay also provides a subsample of income records for employees at firms that use UMS to process payroll.[12] This dataset includes individuals' annual income and industry of employment. Among these individuals, the correlation between average annual consumption and income over our sample period exceeds 0.6, suggesting that consumption is a reasonable proxy for longer-run economic outcomes.

We compare individuals with observed income data to the full sample and find systematic compositional differences (see Table A.3): those in the income subsample are more likely to hold urban hukou, have higher CEE rankings, and be younger on average. To account for these differences, we reweight the representative samples to match the income subsample's joint distribution of rural status, age, CEE rank, and sex. This adjustment ensures that comparisons based on consumption better reflect the demographic and academic profile of individuals for whom income is directly observed.

[11] National IDs are missing from Guangdong and Tibet CEE data, preventing linkage to the UnionPay consumption records.

[12] Note that this subsample accounts for only 1.6% of the full sample. This figure is reasonable mainly because, while UnionPay is a major network for consumption in China, it is not a typical channel for income distribution. Most employers pay income through direct bank transfers rather than through UnionPay. Therefore, this income subsample is used for a complementary analysis rather than as a baseline specification.

4.3 China College Student Survey

We complement our main data with the Chinese College Student Survey (CCSS), a nationally representative dataset of graduating college students from 2010 to 2015 (Jia and Li, 2021). The survey was conducted across 90 institutions selected to reflect China's diverse higher education landscape, from elite colleges to vocational colleges. It covers roughly 40,000 students and contains rich information on CEE scores, demographic background, college and major, and in-college performance and experience.

We focus on a subset of variables that capture students' in-college performance (e.g., GPA percentile rank, course failure) and subjective well-being (e.g., satisfaction with peer relationships and overall experience). These variables allow us to shed light on how AA shapes educational attainment as well as students' in-college well-being.

4.4 Summary Statistics

Table I presents summary statistics for the main analysis sample. **Panel A** reports demographic characteristics. The sample includes over 9.1 million CEE takers, of whom 40% are female, 4% are ethnic minorities, and about half come from rural areas. Around 55% of students follow the science track in high school, 27% follow humanities track, and 19% follow the comprehensive track.

Panel B documents students' CEE performance. The average raw CEE score is 426.2, with a sd of 96.1. We construct a within-province-cohort-track percentile ranking to standardize student performance; the mean percentile rank is 49.8. Among all test takers, the average minority bonus points is 0.47, with only 4% of CEE candidates receiving a positive bonus. Among those who receive any minority bonus, the mean bonus points are 13.1.

Panel C summarizes college admission outcomes. About 61% of students are admitted to college, 12% admitted to Tier-1 colleges, and 41% admitted to their first-choice program. In addition, we also examine two admission-related outcomes: one's ability relative to her peers within the same college-major-cohort cells.

We construct two complementary measures of peer quality. Although we study students from a subset of provinces in China, their college peers include students from other provinces; therefore, we construct peer quality using the universe of all CEE takers in the relevant cohorts. Our first measure of peer quality uses each student's CEE rank within her province-track-cohort; our second measure use students' (pre-bonus) raw CEE scores among provinces that administered the same (national) exam paper in the same track and year. The two measures are complementary: the first measure is available for all students but the within-province percentile rank may not be comparable across provinces, the second measure improves cross-province comparability of academic quality but excludes peers from the 13 province-cohorts using different exam papers, consisting of 25% of all college enrollees in these cohorts.[13]

For college majors, we construct the variables "Top-three majors" and "Bottom-three majors," indicating whether a student was enrolled in one of the three majors with the highest or lowest average income after graduation, respectively. Average income data by major are drawn from the 2023 Chinese College Graduate Employment Report published by MyCOS–the leading higher education consulting firm in China and one of the world's largest of its kind. The top three majors include Economics, Management, and Engineering, while the bottom three majors are Health, Education, and History. A parallel classification based on our own UnionPay consumption data yields a highly similar ranking of fields, providing independent validation of this grouping. Among students admitted to college, 29% (12%) enroll in top-three (bottom-three) majors.

Panel D reports consumption and income 10 to 23 years after taking the CEE. On average, annual consumption is around 10,963 RMB, with notable variation across consumption categories, where we group detailed consumption items into four categories: non-durables, durables, financial investment, and leisure. The average annual income, among the subsam-

[13]We verify that sample attrition induced by this restriction is not systematically related to peers' academic ability. Specifically, the regression of the attrition dummy on percentile rank yields a near-zero coefficient (-0.0005).

ple of 144,172 individuals with income data available, is around 76,986 RMB.

5 Empirical Strategy

5.1 AA Doses

To identify the dose effect of AA, we exploit year-to-year variation in the "effective value" of bonus points within county-ethnicity-track cells. Although the nominal bonus points awarded to an ethnic minority group in a county are typically fixed over time, the admission advantage they confer depends on the province-cohort-specific distribution of CEE scores, leading to variation in AA doses.

As one measure that captures this variation, we define the AA dose a student received as the ratio of her bonus points to the sd of CEE scores within her province-cohort-track. Specifically, the AA dose D_{jest} for ethnicity e in county j (province p), track s, and cohort t is given by

$$D_{jest} = \frac{\text{BonusPoint}_{jet}}{SD_{pst}}, \tag{4}$$

where BonusPoint_{jet} is the nominal bonus awarded to the corresponding county-ethnicity-cohort cell; and SD_{pst} is the sd of CEE scores in province p, track s, and cohort t. Given the AA policy, all students within a (j, e, t) cell receive the same dose. With the typical bonus being 10 points and the typical CEE score sd being 100, a typical AA dose is 0.1. Yet, due to temporal fluctuations in exam-score distributions, there is significant variation in AA doses within narrowly-defined groups across cohorts, as shown in Figure I.

As an alternative measure of AA doses, we use the ratio of bonus points to the difference between the Tier-1 admission cutoff score and the mean CEE score in a given province-track-cohort cell.

$$D^{alt}_{jest} = \frac{\text{BonusPoint}_{jet}}{\text{Cutoff}_{pst} - \text{Avg. score}_{pst}}, \tag{5}$$

which captures how far bonus points move a student toward the elite admission threshold.

5.2 Empirical Specification

Having constructed our AA-dose measures, we estimate the effect of AA on educational and long-term economic outcomes by regressing individual outcomes on AA doses while controlling for a rich set of fixed effects and covariates.

Linear Specification Letting Y_{ijest} denote an outcome for individual i, with ethnicity e, in county j, track s, and cohort t, we estimate the following model:

$$Y_{ijest} = \beta D_{jest} + \gamma Rank_{ijest} + X'_{ijest}\delta + \lambda_{jes} + \theta_{jst} + \epsilon_{ijest}. \tag{6}$$

The parameter of main interest is β, assoicated with the AA dose D_{jest} defined in Section 5.1; $Rank_{ijest}$ is i's rank within her province-year-track; X_{ijest} is a vector of i's baseline characteristics, including gender, age when taking the CEE, rural hukou indicator, and high school quality, as measured by the average CEE performance of the school's first cohort observed in our sample. Similar in spirit to Borusyak and Hull (2023), we include county-ethnicity-track fixed effects (λ_{jes}) to absorb any time-invariant differences across these groups. To account for unobserved local shocks that could influence students' CEE outcomes, such as year-specific variations in education policies within a county-track, we also incorporate county-cohort-track fixed effects.

Once we control for individual characteristics and this rich set of fixed effects, the remaining year-to-year fluctuations in AA doses are assumed to be as good as random. To validate the exogeneity of the AA dose measure in our specification, we implement a key balance test. Specifically, conditional on the county-ethnicity-track and county-cohort-track fixed effects, we regress AA doses on students' raw CEE scores. Table A.1 shows that AA doses are uncorrelated with CEE scores, supporting the assumption that within-cell variation is orthogonal to students' academic ability.

Non-Linear Effects To further explore potential nonlinearities in the effects of AA doses, we extend our baseline specification by replacing the continuous measure with quintile dummies. Specifically, we divide the distribution of AA doses into five equally sized bins and estimate separate effects for each quintile.

$$\begin{aligned} Y_{ijest} = \beta_1 D_{jest}^{1^{st}Q} + \beta_2 D_{jest}^{2^{nd}Q} + \beta_3 D_{jest}^{3^{rd}Q} + \beta_4 D_{jest}^{4^{th}Q} + \beta_5 D_{jest}^{5^{th}Q} + \gamma Rank_{ijest} \\ + X'_{ijest}\delta + \lambda_{jes} + \theta_{jst} + \epsilon_{ijest} \end{aligned} \tag{7}$$

where $D_{jest}^{1^{st}Q}$,...,$D_{jest}^{5^{th}Q}$ are indicators for the lowest to the highest quintiles of AA doses. The reference group consists of students who do not receive any minority bonus points. This specification allows us to assess how students are affected by different doses of AA, rather than assuming a constant marginal effect. As an alternative nonlinear specification, we also estimate a spline regression model, allowing the slope to vary across different parts of the AA-dose distribution, which provides a complementary way to visualize and quantify the dose-response relationship.

Across our specifications, we cluster standard errors at the county-cohort-track level. In addition, to allow for potential temporal and spatial autocorrelations, we use a number of other methods for inferences, including clustering at the county-ethnicity-track, province-cohort-track, or province-ethnicity-track level. Our main results are robust (Appendix A.9).

6 Effect of AA on Student Outcomes

6.1 College Admission Outcomes

Access to College and College Quality We begin by assessing the effects of AA doses on college admission outcomes. Panel A of Table II shows that a 0.1 increase in AA doses (the average dose is 0.16 among those who receive bonuses) raises the likelihood of being admitted to any college by 3.10 ppts, to a Tier-1 college by 0.97 ppts, and to a student's top

choice by 2.83 ppts. Consistently, students exposed to higher AA doses attend colleges with better quality.

Panel B shows these effects across the five AA-dose quintiles. Relative their counterpart with zero bonus point, students receiving high bonus doses (the top quintile of the AA-dose distribution) experience the largest improvements: college admission increases by 9.5 ppts, elite admission by 2.5 ppts, and first-choice admission by 7.6 ppts.

Ranking Relative to Peers Next, we examine students' academic preparedness relative to their college peers. We construct two complementary measures: (1) relative ranking, defined as a student's pre-bonus CEE percentile rank minus the leave-one-out average CEE rank of peers in the same college-major-cohort cell, and (2) relative score, defined as the difference in raw CEE scores between the student and the peer average (restricted to those who took the same format of the exam). Panel A of Table III shows that higher AA doses are associated with worse within-college positioning. A 0.1 increase in AA doses lowers one's ranking relative to peers by about 2.0 percentile points and relative score by 3.2 points, approximately 13.6% and 7.3% of their respective sample standard deviations.

These effects exhibit substantial heterogeneity across the distribution of AA doses. As Panel B indicates, students receiving the highest quintile of AA doses are placed in colleges where they rank far behind their peers: their relative rank is lower by 5.5 ppts and relative score by over 7.0 points. In contrast, those receiving the bottom quintile of AA doses are relatively comparable to their peers. These patterns suggest that higher AA doses can cause large overmatches for AA-targeted groups.

Enrolled Majors Finally, we explore how AA doses shape students' major choices. Figure II plots how AA doses affect a student's likelihood of enrolling in different majors against the average monthly income of those majors, sourced from the 2023 Chinese College Graduate Employment Report (MyCOS). The downward-sloping pattern shows that higher AA doses steer students away from high-earning majors like Economics, Management, and Engineering,

and toward lower-consumption/earning fields such as Education and History. An inverse relationship persists in Figure A.4, which replicates this analysis using the average annual consumption observed in our sample as a proxy for the long-term economic potential of each major. This pattern is consistent with findings from previous studies (e.g., Arcidiacono et al. (2011); Arcidiacono and Lovenheim (2016)), which show that students exposed to AA may sort into less demanding majors if they are overmatched to higher-quality institutions.

Panel A of Table IV shows that a 0.1 increase in AA doses reduces the probability of enrolling in a top-three major, defined by the average consumption level of graduates in that major, by 0.4% (but insignificant) and increases the likelihood of entering one of the bottom-three majors by 1.4%. The nonlinear specification in Panel B shows that students in the top quintile of AA doses are 5.6-ppt more likely to enroll in bottom-three major.

6.2 Long-Run Economic Outcomes

Main Results As shown in Table V, a 0.1 increase in AA doses reduces average annual consumption by approximately 7.8% (column 1).[14] This pattern is observed across all major consumption subcategories (columns 2-4). This suggests that, on average, AA-induced academic mismatches outweigh gains in college quality, resulting in long-term economic losses.

However, the average effect masks important nonlinear dose effects. As shown in Panel B, relative to their counterpart with zero bonus points, students receiving the lowest quintile of AA doses experience a 19% *gain* in long-term consumption, while those receiving the top two quintiles of AA doses experience a 14-28% reduction. These findings highlight that the ultimate effect of AA largely depends on its doses: moderate AA doses benefit its intended beneficiaries while excessive AA doses can hurt them.

As an alternative, Figure A.6 and Table A.5 use piecewise linear splines to capture the relationship between AA doses and consumption. The results show that consumption declines are statistically significant and steep only after the dose surpass a threshold around

[14] This figure is calculated as $(e^{-0.814\times0.1} - 1) \times 100\% = -7.8\%$.

0.1 to 0.2, consistent with the quintile-based estimates.

It should be noted that zeros are observed for some individuals in the UnionPay consumption data, we use a modified logarithm as suggested in Chen and Roth (2024).[15] Our main results are robust using alternative methods, such as Poisson pseudo maximum likelihood.

Heterogeneous Treatment Effects We now examine the effects of AA doses on different groups of students. First, we group students by their CEE score ranking within their province-cohort-track: the bottom quartile, the middle 50%, and the top quartile. Figure III shows that for the first two groups of students, the dose responses mimic those in the entire sample; for students in the high-CEE group, AA is largely beneficial, except at excessive doses (in the top quintile of the dose distribution), in which case, their long-run consumption is reduced. This finding is perhaps not surprising. Students with high ability (proxied by the CEE ranking) are less likely to be over-matched or over-matched to a lesser extent when placed in a higher-quality college; nevertheless, even for these students, an excessive dose of AA can still be harmful.

Next, we explore heterogeneous effects by demographics: gender, rural/urban hukou status, and high-school quality (measured by the school-average CEE ranking). Column (1) of Table VI shows that, relative to females, males benefit less from low doses of AA and lose more from high doses of AA. Column (2) shows similar patterns by hukou status: relative to their urban students, rural students benefit less from low doses of AA and lose more from high doses of AA. Column (3) shows that students from better high schools lose less from high AA doses. While providing a definitive explanation for these findings is beyond the scope of this paper, they are all intuitive. As implied by the model in Section 3, when students are misinformed about their own ability and hence match quality, an expanded feasible choice set under AA can lead to overmatches, the harm of which can exceed the benefit from college

[15]The modified logarithm in Chen and Roth (2024) is $m(y) = ln(y)$ if $y > 0$ and $m(y) = -K$ if $y = 0$. We use $K = 0.1$. The interpretation is that the effect of moving y from 0 to 1 is valued the same as a 10 log-point effect on the intensive margin (e.g., the same as the effect from $ln(a)$ to $ln(b)$ where $ln(b) - ln(a) = 0.1$). Our results are robust using alternative K values (see details in Section 6.4).

quality at large AA doses. Studies in behavioral economics and psychology have shown that males are more likely to be overconfident than females (Lundeberg et al., 1994; Barber and Odean, 2001; Niederle and Vesterlund, 2007; Moore and Healy, 2008), which can explain Column (1) of Table VI. It is also well documented that disadvantaged groups, including rural populations and students from lower-quality high schools, are less well-informed (Liu et al., 2011; Giles et al., 2021), which can explain Columns (2)-(3) of Table VI.

6.3 Alternative Explanations

Two alternative explanations may challenge our interpretation. First, one may argue that high AA doses put students in higher-quality colleges, where they become financially more sophisticated, save/invest more and thus consume less. To test this savings/investment-based mechanism, Table VII analyzes financial investment outcomes (e.g., spending on insurance, stocks, and bonds). We find a pattern that mirrors our overall consumption results: investment declines with AA doses, suggesting that differences in saving/investment decisions are unlikely to explain our findings on consumption.

A second alternative story is that bonus recipients may be more likely to return to their hometowns, where living costs are lower. In this scenario, their reduced consumption would reflect lower local prices rather than lower economic well-being. Table A.2 refutes this interpretation: higher AA doses actually increase the likelihood that students settle in Tier-1 and Tier-2 (higher-cost) cities, while reducing their probability of returning to their (low-cost) birth counties, though both effects fail to reach conventional levels of statistical significance. Thus, the decline in consumption likely reflects lower economic attainment rather than cost-of-living differences.

Finally, as a more direct piece of evidence, Table A.4 analyzes the income profiles for the subsample of individuals with income data. Because this subsample differs from the full population along observable characteristics, we reweight the estimation sample so that its joint distribution of rural status, age, CEE rank, and sex matches that of the income

subsample. Due to the small sample size, we divide AA doses into terciles and replace county fixed effects with province fixed effects for the sake of power. The nonlinear pattern in income mirrors the consumption pattern: high doses predict income losses.

6.4 Robustness Checks

Alternative Dose Measures Table A.6 verifies that our results are robust across alternative measures of doses: bonus points standardized by the sd of CEE scores (our baseline) and bonus points relative to the admission gap to elite colleges.

Zero Consumption To ensure that our results are not sensitive to how we handle zero consumption values, Table A.7 applies the Chen and Roth (2024) transformation and tests multiple calibration values ($K = 0, 0.3, 1, 3$). The estimated effects are stable across all specifications, consistently showing more pronounced negative impacts at higher levels of AA doses.

One concern is that people who rarely use UnionPay cards may be underrepresented in our consumption sample. To address this potential sample selection bias, Table A.10 presents Heckman two-step correction estimates, using the number of banks and ATMs per 10,000 residents in students' birth cities as exclusion restrictions. The second-stage results reveal that our main conclusions remain robust after correcting for potential selection in card usage.

Dynamics We assess whether the negative impacts of AA doses persist or fade over time. Instead of using average consumption over the entire period, we apply the specification in Equation (6) to total consumption for each separate year between 2013 and 2022. Figure A.5 plots these point estimates and their corresponding 95% confidence intervals, tracing AA's consumption effects by years since taking the CEE, ranging from 10 to 23 years. We find no evidence of fading out. This suggests that the mismatch effects are not merely short-lived shocks but represent lasting impacts on human capital and career trajectory.

7 Effect on College Experience

Finally, we examine how AA doses shape students' experiences during college, using rich survey evidence from the China College Student Survey (CCSS). While much of the AA literature focuses on access to college and academic performance, students' in-college experiences are central to understanding how AA affects one's (short-term) utility, and via its effect on peer interactions and campus life, shapes one's social network and potentially long-term outcomes.

Because the CCSS sample only labels individuals as Han, one of the top six most populous ethnic minorities, or "other ethnic groups", the treated group is too small to support our baseline specification with a rich set of fixed effects. We therefore adopt an exact matching approach. Specifically, we match students with zero bonus points to those with positive bonus points within narrowly defined demographic cells. We restrict the final analytical sample to cells that contain at least one individual who received positive bonus points. Each cell is defined by a unique combination of birth city, CEE cohort, academic track, gender, hukou status, and retake status. Additionally, due to the limited sample size, we divide AA doses into terciles rather than quintiles when examining nonlinear effects to improve statistical power.

To construct the measure of AA doses, we normalize bonus points by dividing them by the sd of CEE scores calculated within the CCSS sample. We then estimate the following specification to provide suggestive evidence on how AA doses influence academic performance and subjective well-being:

$$Y_{irest} = \beta D_{rest} + \gamma Score_{irest} + \eta_{m(i)} + \epsilon_{irest} \tag{8}$$

where Y_{irest} denotes an outcome for individual i. D_{rest} represents the AA doses, and $Score_{irest}$ is the raw CEE score. The term $\eta_{m(i)}$ represents cell fixed effects, where each cell m is uniquely defined by a combination of birth city (r), cohort (t), academic track (s), gender,

hukou status, and retake status. This structure ensures that β is identified from variation between treated and control students within highly comparable groups. Standard errors are robust to heteroskedasticity.

The first two columns of Table IX present the estimated effects of AA doses on academic outcomes. In the linear specifications (Panel A), higher AA doses are associated with significantly worse academic standing within college. Column (1) shows that a 0.1 increase in AA doses raises the probability of ranking below the median within one's cohort by 2.8 percentage points. Although the positive estimate for course failure is imprecisely estimated (column 2), the overall pattern indicates that students receiving stronger AA doses tend to struggle academically relative to their peers. These results are consistent with the mismatch hypothesis: while higher AA doses facilitate entry into more selective institutions, it may place students in environments where academic demands exceed their preparation, leading to weaker relative performance. The non-linear analysis in Panel B further shows that the negative effects are predominantly driven by students in the highest dose category.

Columns (3)–(6) of Table IX turn to students' subjective well-being and campus life. As shown by Panel A, higher AA doses are associated with lower satisfaction with one's own GPA (column 3), social activities (column 4, although insignificant), interpersonal relationships (column 5), and overall college life (column 6). The magnitudes are economically meaningful. For example, a 0.1 increase in AA doses reduces overall satisfaction by roughly 16.8% of the mean of the outcome. Taken together, these patterns suggest that academic mismatch extends beyond grades to affect broader aspects of students' college experiences, including their sense of belonging and well-being on campus. A similar non-linear pattern emerges for campus satisfaction in Panel B. The detrimental effects on well-being are primarily concentrated among students in the highest dose category. Specifically, compared to students with zero AA dose, those in the highest tercile of AA doses report a 6.9 percentage point lower satisfaction with their GPA, a 4.7 percentage point lower satisfaction with interpersonal relations, and a 5.1 percentage point lower satisfaction with their overall col-

lege experience. In contrast, students in lower terciles do not exhibit statistically significant reductions in satisfaction.

Importantly, these findings help bridge our short-run and long-run results. Lower academic standing and reduced satisfaction with college life can plausibly affect human capital accumulation, peer networks, and non-cognitive skills, all of which matter for later economic outcomes. The CCSS evidence, therefore, sheds light on a key mechanism through which higher doses of AA may generate persistent effects for intended beneficiaries: higher AA doses enable these students to enroll in high-quality colleges, where they may, however, struggle both academically and socially.

8 Conclusion

This paper argues that evaluating affirmative action (AA) as a binary policy obscures a central dimension of policy design. In practice, AA operates as a continuous instrument, and its consequences depend critically on how strongly it is implemented. Using plausibly exogenous variation in the effective strength of bonus points in China's centralized college admissions system, we show that the effects of AA on its intended beneficiaries depends on its dose.

In the short run, higher AA doses expands access to selective colleges but worsens academic fit, lowering students' relative performance, altering major choice, and reducing satisfaction with peer relationships and college life. In the long run, moderate doses of affirmative action generate substantial and persistent gains, while high doses produce large and lasting losses.

Our findings help reconcile long-standing debates in the AA literature. Evidence of positive effects and concerns about mismatch are not mutually exclusive; both can arise, depending on the dose of AA. By averaging over heterogeneous policy doses, binary evaluations may mask both the benefits of moderate AA and the costs of excessive implementation.

Although our analysis focuses on China, the policy logic is broadly applicable. Many affirmative action systems—whether based on bonus points, admission thresholds, or holistic evaluations—implicitly vary in strength across institutions, cohorts, and applicants. Our results suggest that careful calibration of these policies is crucial for achieving their intended goals. More broadly, the paper underscores a general lesson for redistributive policy design: when benefits and costs respond nonlinearly to policy intensity, effectiveness depends not only on whether a policy is adopted, but on how it is calibrated.

Several avenues remain open for future research. First, richer longitudinal data could shed light on how academic and social mismatch evolves over time and whether early in-college frictions persist or attenuate in the long run. Second, future work could extend the analysis to other dimensions of welfare, such as wealth accumulation, occupational trajectories, or non-market outcomes, to further assess the broader consequences of AA doses.

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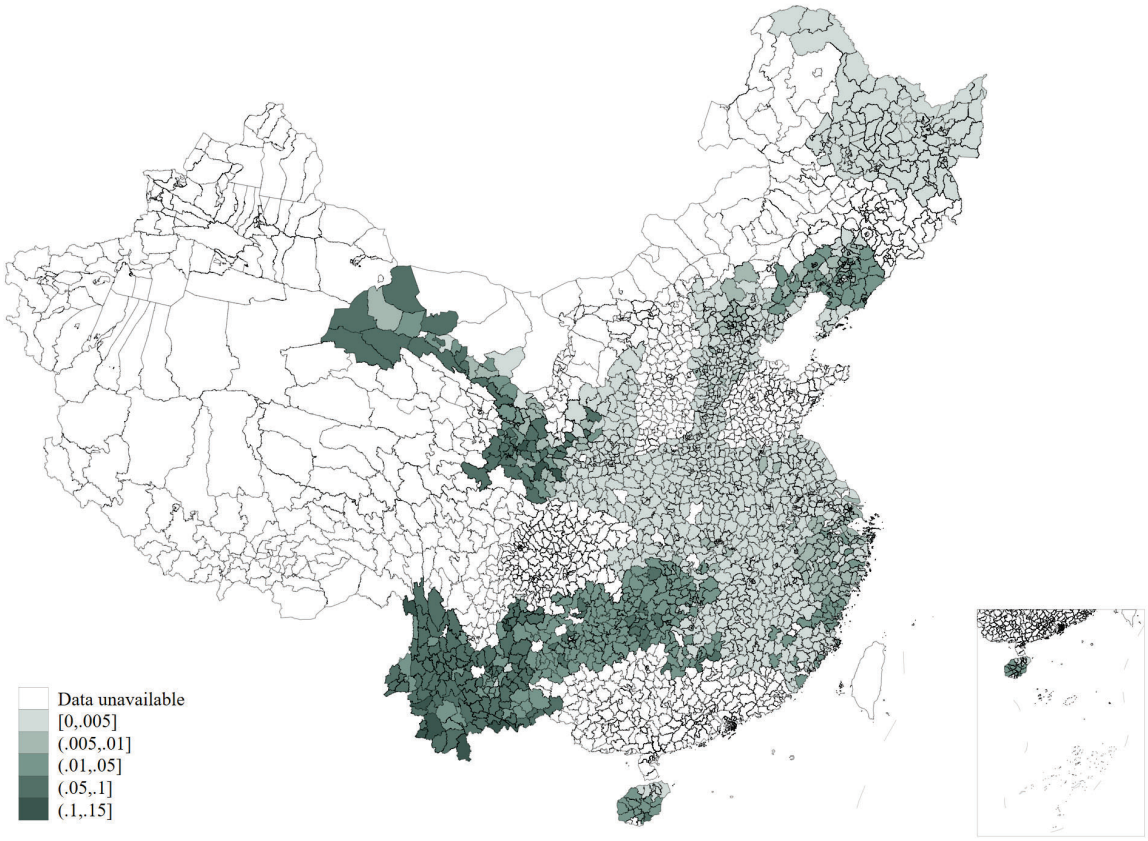


Figure I
Spatial Distribution of the Standard Deviation of AA Doses

Notes: This figure shows the spatial distribution of the sd of AA doses at the birth-county level for the 1999–2003 cohorts. Darker green shading indicates greater within-county variation in AA doses across cohorts. White areas denote regions without usable data, either because entire provinces are excluded from the sample or because a small number of counties within sampled provinces lack observations due to zero bonus recipients during 1999–2003 or non-standard birth-county identifiers that cannot be reliably mapped.

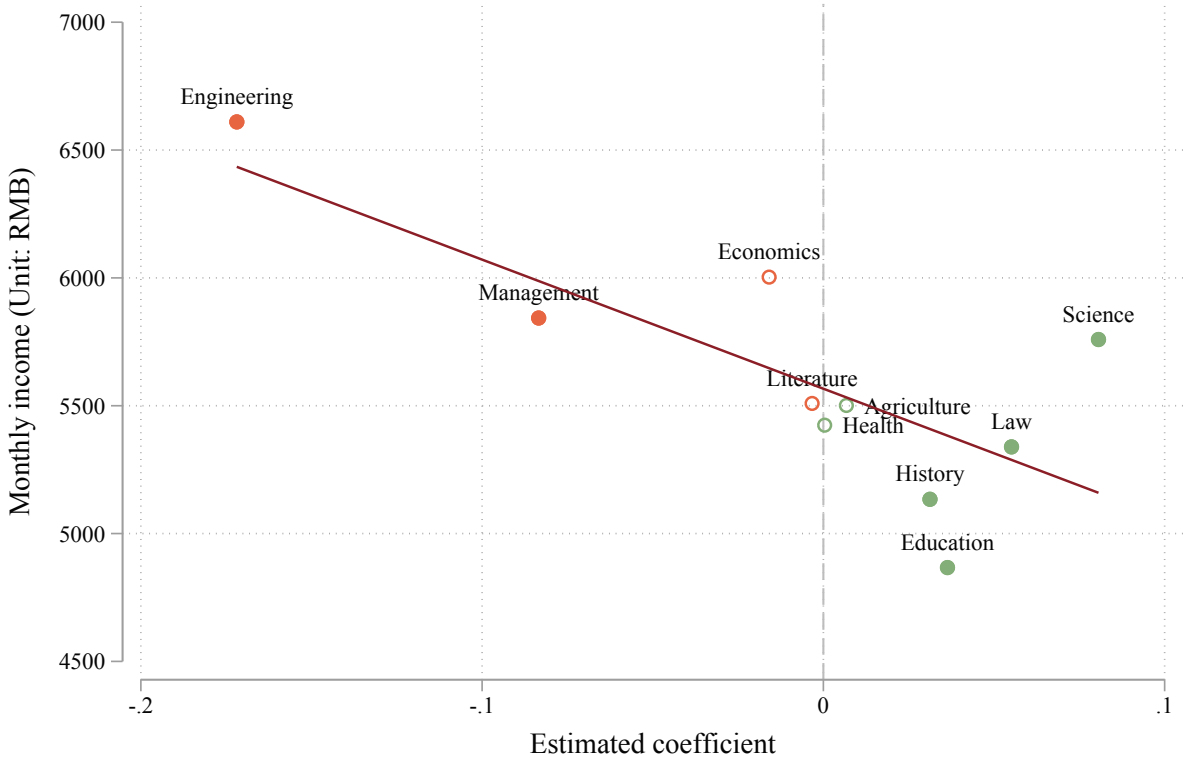


Figure II
Impact of AA Doses on Major Choices

Notes: This figure relates the estimated effect of AA doses on major choice to the average consumption levels associated with those majors. The x-axis reports point estimates of the effect of AA doses on the probability of choosing each major using Equation (6), while the y-axis represents the average income across majors, with data sourced from the 2023 Chinese College Graduate Employment Report published by MyCOS. Solid circles denote estimates that are statistically significant at the 10% level, and hollow circles indicate non-significant estimates. The solid line plots the fitted linear relationship between the major-specific coefficients and average consumption.

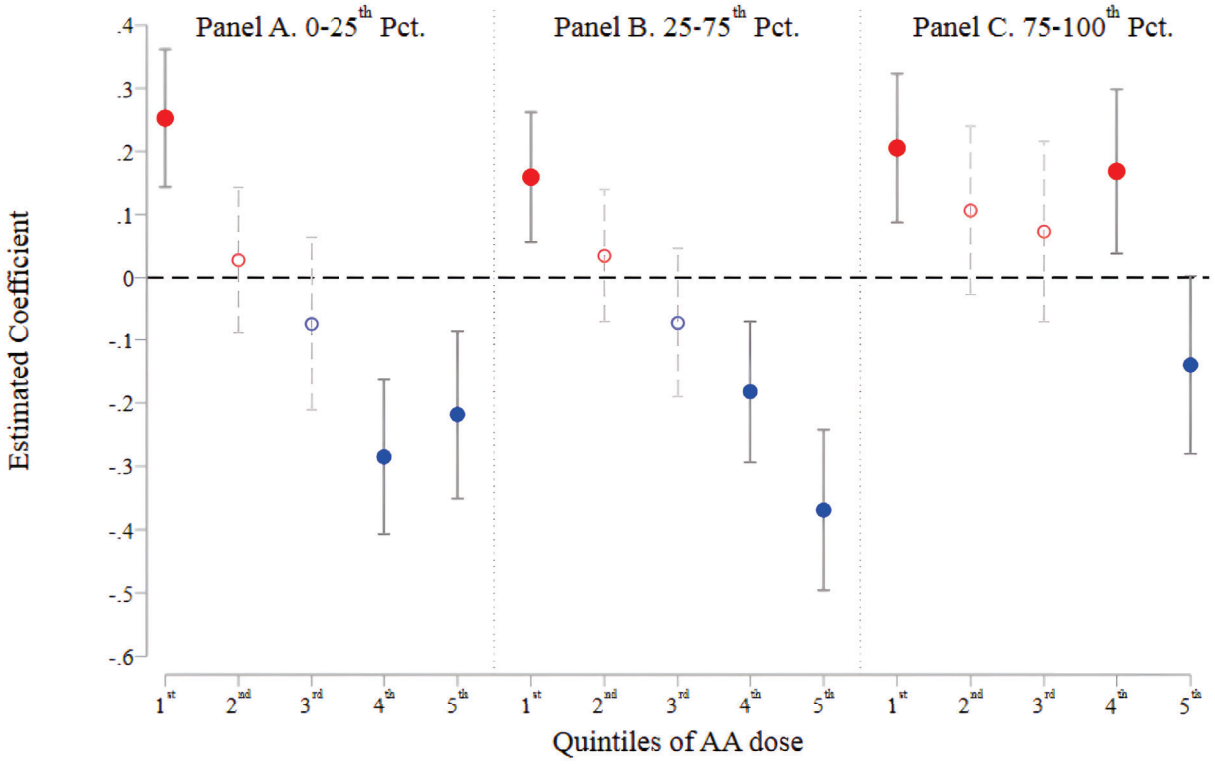


Figure III
Non-linear AA-Dose Effect Across CEE Score Rank Groups

Notes: This figure shows the heterogeneous non-linear effects of AA doses on average annual consumption in later-life across within-province-cohort-track CEE percentile rank groups. Estimates are based on Equation (7), augmented with interactions between five AA-dose quintiles and three CEE score rank-group indicators (0-25$^{\text{th}}$, 25-75$^{\text{th}}$, and 75-100$^{\text{th}}$ percentiles). Dots denote point estimates, and horizontal bars indicate 95% confidence intervals.

Table I: Summary Statistics

Variable	Observations	Mean	Std. Dev.
Panel A: Demographic characteristics			
Female	9,015,498	0.40	0.49
Age when taking CEE	9,015,498	19.0	1.11
Rural	9,015,498	0.54	0.50
Minority	9,015,498	0.04	0.20
Science track	9,015,498	0.55	0.50
Humanity track	9,015,498	0.27	0.44
Comprehensive track	9,015,498	0.19	0.40
Panel B: CEE performance			
CEE score	9,015,498	426.19	96.07
Rankings	9,015,498	49.76	28.81
Bonus points	9,015,498	0.47	2.70
Bonus points> 0	9,015,498	0.04	0.19
Bonus points (Conditional on Bonus>0)	322,878	13.11	6.18
AA doses (Conditional on Bonus>0)	322,878	0.16	0.08
Panel C: Admission outcomes			
Admitted	9,015,498	0.61	0.49
Admitted by elite colleges	9,015,498	0.12	0.32
Admitted by top choice	9,015,498	0.41	0.49
College quality	5,598,226	62.00	24.10
Relative ranking	5,555,834	-0.12	14.92
Relative score	4,124,382	1.9	44.5
Top-three majors	5,555,834	0.29	0.45
Bottom-three majors	5,555,834	0.12	0.32
Panel D: Consumption & Income (RMB)			
Average annual consumption	9,015,498	10,962.9	34,224.2
Durables	9,015,498	4,329.7	18,415.0
Non-durables	9,015,498	571.8	1,612.7
Leisure	9,015,498	27.5	127.4
Financial Investment	9,015,498	1,740.2	8,160.6
Insurance	9,015,498	76.5	354.8
Bond & stocks	9,015,498	1,369.4	6,816.5
Average annual income	144,172	76,985.9	194,921.3

Notes: In this table, each observation corresponds to an individual test taker. Panel A presents demographic characteristics. *Rural* indicates students from rural areas, *Minority* denotes students from minority ethnicity, *Science track*, *Humanity track*, and *Comprehensive track* represent the academic track chosen in high school. Panel B reports CEE performance measures, including raw CEE scores, percentile rankings within province-cohort-track cells, nominal bonus points, and AA doses conditional on receiving positive bonus points. Panel C summarizes college admission outcomes. *Admission*, *Admitted by elite colleges*, and *Admitted by top choice* indicates that students are admitted by any colleges, elite colleges, and their top choice on the preference list, respectively. *College quality* is leave-one-out mean of province-cohort-track admission ranks of enrolled students in each college, normalized to a 0-100 scale, with 100 being the highest. *Relative ranking* captures a student's percentile rank relative to peers in the same college and major (with 100 being the highest rank), while *Relative score* measures the difference between a student's CEE score and the average score of peers enrolled in the same college and major who took the exam in the same format. *Top-three majors* and *Bottom-three majors* are indicators for whether the student enrolled in one of the three majors with the highest and lowest average long-run consumption within their college. Variables from *College quality* to *Major quality* are only available for students who are admitted by any colleges. Panel D reports long-run economic outcomes based on UnionPay transaction records, including average annual consumption and its components, as well as average annual income for the subsample with available payroll information.

Table II: Impact of AA Doses on Admission Outcomes

	(1) Admission	(2) Admitted by elite colleges	(3) Admitted by top choice	(4) College quality
Panel A: Linear effect				
AA doses	0.310***	0.097***	0.283***	22.104***
	(0.025)	(0.020)	(0.024)	(1.240)
Panel B: Non-linear effect				
1st quintile	0.065***	0.008*	0.036***	2.528***
	(0.006)	(0.004)	(0.005)	(0.289)
2nd quintile	0.031***	-0.001	0.045***	1.394***
	(0.006)	(0.006)	(0.006)	(0.285)
3rd quintile	0.043***	0.015***	0.052***	2.699***
	(0.007)	(0.004)	(0.006)	(0.328)
4th quintile	0.063***	0.026***	0.056***	4.939***
	(0.006)	(0.005)	(0.006)	(0.359)
5th quintile	0.095***	0.025***	0.076***	6.128***
	(0.007)	(0.005)	(0.006)	(0.328)
Controls	YES	YES	YES	YES
County-ethnicity-track FE	YES	YES	YES	YES
County-cohort-track FE	YES	YES	YES	YES
Obs.	9,105,498	9,105,498	9,105,498	5,551,765

Notes: This table presents the linear and nonlinear effect of AA doses on college admission. The reference group consists of students with zero AA dose. The dependent variables in columns (1)–(4) are indicators for college admission, elite college admission, first-choice admission, and college quality, respectively. All specifications include a set of controls (CEE ranking, female, age when taking CEE, rural hukou, high school quality) and county-ethnicity-track and county-cohort-track fixed effects. Standard errors are clustered at the county-ethnicity-track level and reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table III: Impact of AA Doses on Relative Ranking to Peers

	(1) Relative ranking	(2) Relative score
Panel A: Linear effect		
AA doses	-20.344***	-32.357***
	(0.874)	(4.022)
Panel B: Non-linear effect		
1st quintile	-1.283***	-2.673**
	(0.199)	(1.048)
2nd quintile	-1.769***	-4.053***
	(0.200)	(0.972)
3rd quintile	-2.479***	-5.876***
	(0.221)	(0.790)
4th quintile	-4.169***	-8.610***
	(0.247)	(1.133)
5th quintile	-5.468***	-7.049***
	(0.243)	(1.055)
Controls	YES	YES
County-ethnicity-track FE	YES	YES
County-cohort-track FE	YES	YES
Obs.	5,554,036	4,122,707

Notes: This table shows the linear and nonlinear effect of AA doses on competition environment in college. The reference group consists of students with zero AA dose. *Relative ranking* is the difference between the individual's percentile rank and the average percentile rank of peers, while *Relative score* is the difference between the individual's CEE score and the average score of peers taking the same exam format. In both cases, the individual is excluded from the peer average. All specifications include a set of controls (CEE ranking, female, age when taking CEE, rural hukou, high school quality) and county-ethnicity-track and county-cohort-track fixed effects. Standard errors are clustered at the county-ethnicity-track level and reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table IV: Impact of AA Doses on Major Choices

	(1) Top-three majors	(2) Bottom-three majors
Panel A: Linear effect		
AA doses	-0.044	0.142***
	(0.032)	(0.030)
Panel B: Non-linear effect		
1st quintile	-0.008	0.001
	(0.007)	(0.005)
2nd quintile	0.004	-0.002
	(0.006)	(0.005)
3rd quintile	0.005	0.006
	(0.007)	(0.006)
4th quintile	-0.011	0.023***
	(0.009)	(0.008)
5th quintile	-0.011	0.056***
	(0.009)	(0.009)
Controls	YES	YES
County-ethnicity-track FE	YES	YES
County-cohort-track FE	YES	YES
Obs.	5,554,036	5,554,036

Notes: This table displays the linear and nonlinear effect of AA doses on major selection. The reference group consists of students with zero AA dose. *Top-three majors* and *Bottom-three majors* are indicators identifying whether a student enrolled in one of the three majors with the highest or lowest average long-run consumption levels, respectively. All specifications include a set of controls (CEE ranking, female, age when taking CEE, rural hukou, high school quality) and county-ethnicity-track and county-cohort-track fixed effects. Standard errors are clustered at the county-ethnicity-track level and reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table V: Impact of AA Doses on Long-term Consumption

	(1) Consumption	(2) Durables	(3) Non-durables	(4) Leisure
Panel A: Linear effect				
AA doses	-0.814***	-0.117	-0.535***	-0.159*
	(0.221)	(0.177)	(0.175)	(0.084)
Panel B: Non-linear effect				
1st quintile	0.196***	0.096**	0.129***	0.020
	(0.049)	(0.038)	(0.034)	(0.019)
2nd quintile	0.048	0.077*	0.053	0.006
	(0.048)	(0.044)	(0.042)	(0.018)
3rd quintile	-0.037	0.035	0.031	0.011
	(0.060)	(0.0461)	(0.044)	(0.018)
4th quintile	-0.144***	0.001	-0.078*	0.003
	(0.056)	(0.048)	(0.046)	(0.024)
5th quintile	-0.283***	-0.076	-0.200***	-0.069***
	(0.063)	(0.048)	(0.049)	(0.024)
Controls	YES	YES	YES	YES
County-ethnicity-track FE	YES	YES	YES	YES
County-cohort-track FE	YES	YES	YES	YES
Obs.	9,015,498	9,015,498	9,015,498	9,015,498

Notes: This table reports estimates of the effect of AA doses on later-life average annual consumption and its components. The reference group consists of students with zero AA dose. The dependent variables in columns (1)–(4) are average annual total consumption and expenditures on durable goods, non-durable goods, and leisure, respectively. To address zero observations, we apply a log transformation with a calibrated extensive margin value, following the approach of Chen and Roth (2024). In our baseline specification, we set $K = 0.1$. Table A.7 presents robustness tests using alternative calibration values. All specifications include a set of controls (CEE ranking, female, age when taking CEE, rural hukou, high school quality) and county-ethnicity-track and county-cohort-track fixed effects. Standard errors are clustered at the county-ethnicity-track level and reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table VI: Heterogeneity Impact of AA Doses by Student Characteristics

	(1)	(2)	(3)
	Dependent variable: Average consumption		
Variable (X):	Male	Rural	HS Quality
Panel A: Linear effect			
AA doses × X	-1.559***	-1.233***	0.033***
	(0.124)	(0.129)	(0.005)
AA doses	0.137	0.079	-2.232***
	(0.234)	(0.239)	(0.292)
Panel B: Non-linear effect			
1st quintile × X	-0.175***	-0.038	0.001
	(0.040)	(0.058)	(0.001)
2nd quintile × X	-0.294***	-0.019	0.003*
	(0.039)	(0.052)	(0.002)
3rd quintile × X	-0.146***	-0.225***	0.006***
	(0.043)	(0.049)	(0.002)
4th quintile × X	-0.394***	-0.294***	0.011***
	(0.040)	(0.046)	(0.002)
5th quintile × X	-0.341***	-0.287***	0.006***
	(0.044)	(0.043)	(0.002)
1st quintile	0.288***	0.201***	0.165**
	(0.053)	(0.052)	(0.080)
2nd quintile	0.231***	0.067	-0.110
	(0.055)	(0.063)	(0.101)
3rd quintile	0.054	0.124*	-0.299***
	(0.065)	(0.072)	(0.099)
4th quintile	0.096	0.080	-0.630***
	(0.060)	(0.066)	(0.091)
5th quintile	-0.075	-0.058	-0.529***
	(0.069)	(0.069)	(0.092)
Controls	YES	YES	YES
County-ethnicity-track FE	YES	YES	YES
County-cohort-track FE	YES	YES	YES
Obs.	9,015,498	9,015,498	9,015,498

Notes: This table reports estimates of heterogeneous effects of AA doses on average annual consumption. The reference group consists of students with zero AA dose. Columns (1)–(3) examine heterogeneity by gender (*Male*), household registration status (*Rural*), and high school quality (*High school average CEE ranking*), respectively. High school quality is measured by the average CEE ranking of students from that high school in the first year it appears in the sample. All specifications include a set of controls (CEE ranking, female, age when taking CEE, rural hukou, high school quality) and county-ethnicity-track and county-cohort-track fixed effects. Standard errors are clustered at the county-ethnicity-track level and reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table VII: Impact of AA Doses on Financial Investment

	(1) Financial investment	(2) Insurance	(3) Bonds & stocks
Panel A: Linear effect			
AA doses	-0.470***	-0.054	-0.478***
	(0.153)	(0.082)	(0.142)
Panel B: Non-linear effect			
1st quintile	0.061	0.077***	0.009
	(0.039)	(0.021)	(0.034)
2nd quintile	-0.013	-0.017	-0.014
	(0.032)	(0.019)	(0.030)
3rd quintile	-0.069*	-0.017	-0.066*
	(0.040)	(0.021)	(0.035)
4th quintile	-0.118***	-0.037*	-0.102***
	(0.042)	(0.022)	(0.038)
5th quintile	-0.150***	-0.013	-0.155***
	(0.043)	(0.022)	(0.040)
Controls	YES	YES	YES
County-ethnicity-track FE	YES	YES	YES
County-cohort-track FE	YES	YES	YES
Obs.	9,015,498	9,015,498	9,015,498

Notes: This table reports estimates of the effect of AA doses on later-life expenditure on financial investment. The reference group consists of students with zero AA dose. The dependent variables in columns (1)–(3) are average annual expenditure on all financial investment, insurance, and bonds & stocks, respectively. To address zero observations, we apply a log transformation with a calibrated extensive margin value, following the approach of Chen and Roth (2024). All specifications include a set of controls (CEE ranking, female, age when taking CEE, rural hukou, high school quality) and county-ethnicity-track and county-cohort-track fixed effects. Standard errors are clustered at the county-ethnicity-track level and reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table VIII: Impact of Bonus Intensity on Consumption Variety and Diversity

	(1) Number of Categories	(2) Diversity Index
Panel A: Linear effect		
AA doses	-0.945**	-0.154***
	(0.378)	(0.036)
Panel B: Non-linear effect		
1^{st} quintile	0.218***	0.023***
	(0.082)	(0.007)
2^{nd} quintile	0.137	-0.002
	(0.103)	(0.009)
3^{rd} quintile	0.063	-0.004
	(0.090)	(0.009)
4^{th} quintile	-0.135	-0.027***
	(0.107)	(0.010)
5^{th} quintile	-0.351***	-0.048***
	(0.140)	(0.014)
Controls	YES	YES
County-ethnicity-track FE	YES	YES
County-cohort-track FE	YES	YES
Obs.	9,015,498	9,015,498

Notes: This table examines the impact of bonus intensity on the diversity and structure of individual consumption. The dependent variables are constructed based on the industry classification codes in the UnionPay transaction data (2013-2022). In Column (1), the dependent variable is the number of unique consumption categories, measuring the variety of an individual's expenditure. In Column (2), the dependent variable is the Shannon Diversity Index, calculated as $H = -\sum_{i=1}^{N} p_i \ln(p_i)$, where p_i denotes the expenditure share of category i. All specifications include a full set of individual-level controls (CEE ranking, female, age when taking CEE, rural hukou, high school quality), as well as county-ethnicity-track and county-cohort-track fixed effects. Standard errors are clustered at the county-ethnicity-track level and reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table IX: Impact of AA Doses on Academic Performance and Subjective well-being in College (CCSS)

	(1) Below median rank	(2) Fail in courses	(3) Sat. with: GPA	(4) Sat. with: Social	(5) Sat. with: Relations	(6) Overall Sat.
Panel A: Linear effect						
AA doses	0.275**	0.225	-0.251*	-0.066	-0.150	-0.185*
	(0.139)	(0.145)	(0.139)	(0.117)	(0.101)	(0.110)
Panel B: Non-linear effect						
1st tercile	0.025	0.003	0.010	0.028	0.014	0.016
	(0.032)	(0.034)	(0.034)	(0.028)	(0.022)	(0.025)
2nd tercile	-0.012	-0.046	0.001	-0.018	-0.003	-0.011
	(0.035)	(0.042)	(0.036)	(0.033)	(0.026)	(0.028)
3rd tercile	0.074*	0.074*	-0.069*	-0.023	-0.047*	-0.051*
	(0.038)	(0.039)	(0.038)	(0.032)	(0.028)	(0.029)
Cell FE	YES	YES	YES	YES	YES	YES
Obs.	3,817	3,776	3,817	3,817	3,817	3,817

Notes: This table reports estimates of effects of AA doses on academic performance and subjective well-being in college using the China College Student Survey data. The variable-of-interest is the AA doses at the ethnicity-birth-city-cohort level. The dependent variables in columns (1)–(2) measure academic outcomes: *Below median rank* is a dummy variable equal to 1 if the student's cumulative GPA rank is below the median within their class. *Fail in courses* indicates whether the student failed at least one course during college. Columns (3)–(6) present dummy variables for satisfaction with GPA, social activities, interpersonal relationships, and overall campus life, respectively, constructed from original 5-point scale (1 = "highly dissatisfied"; 5 = "highly satisfied"). Each dummy variable equals 1 if the original score is equal to or greater than 3, and 0 otherwise. To ensure comparability, we restrict the sample to cells that contain at least one individual with positive bonus points. Each cell comprises individuals who share the identical birth city, CEE cohort, academic track, gender, hukou status, and retake status. All specifications control for individual CEE scores and cell fixed effects. * p<0.1, ** p<0.05, *** p<0.01.