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Who Wants to Be a Teacher in America?

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Abstract

Long-standing compositional disparities and more recent concerns about the health of the teaching profession highlight the need to increase our understanding of the pipeline into K–12 teaching. Leveraging data from 11.5 million college applicants from 2014–2025, we provide the most detailed description to date of who is interested in teaching in the United States. We document substantially lower interest among men, students of color, and high-achieving students. Comparing teaching to similar career paths, such as nursing or social work, we find that racial/ethnic disparities are far greater for teaching, but gender and academic achievement gaps are comparable or less severe. We also find evidence that students interested in teaching submit fewer applications, are less likely to apply to selective colleges, and tend to apply to colleges close to their home. Controlling for application behavior greatly attenuates the relationship between teaching interest and academic achievement, suggesting that ambition or a desire for prestige is a more salient predictor of who becomes a teacher than achievement. We find corroborating evidence from applicants' teacher-recommenders, who rate students interested in teaching as having lower intellectual promise and self-confidence, but greater concern for others. Finally, career interest in teaching and other lower-wage helping careers has declined by roughly 20% over the past decade, while nursing interest has exploded.

Who Wants to Be a Teacher in America?

Introduction

Strengthening the teacher pipeline is a long-standing education policy goal in the United States (Hansen, 2024; Partelow et al., 2017). Going back decades, research shows that the teaching profession struggles to attract academically high-achieving students and that there are substantial representation gaps between the teacher and K–12 student populations (Bartanen & Kwok, 2023; Boser, 2014; Hanushek & Pace, 1995). Recent evidence provides little reason for optimism, as both career interest in teaching and the perceived prestige of the profession declined in the years leading up to the COVID-19 pandemic (Bartanen & Kwok, 2023; Croft et al., 2018; Kraft & Lyon, 2024). In the midst of steep learning losses concentrated among the lowest-performing students (Soland, 2021; Wyckoff, 2025), ensuring a robust supply of high-quality teachers has perhaps never been more important. That is, minimizing these trends would be a promising lever to increase the quality of the teacher workforce and, ultimately, the quality of instruction received by students.

Effective policy interventions require understanding the dynamics of the teacher pipeline. The teacher pipeline consists of inputs and outputs of where individuals naturally enter the profession. This generally incorporates who is interested and eventually enters teaching, alongside their motivations to do so. But it also includes the negative selection of why individuals who may be interested do not choose teaching, why not, and what profession they choose instead. While research on teacher supply and who becomes a teacher dates back decades (Guarino et al., 2006) a key gap in our understanding concerns initial interest in the profession and how interest translates (or not) to actually becoming a teacher. A handful of papers examine early (i.e., when students are in high school) interest in teaching and subsequent progress towards becoming a teacher (Bartanen & Kwok, 2023; Cooc & Kim, 2023; Hanushek & Pace, 1995). Collectively, they show that interest in teaching tends to be lower among male students, students of color, and students with higher academic achievement in high school.

Despite an accumulating evidence base on academic and demographic disparities in teaching interest, we know far less about what drives them. Our understanding is limited in several important ways. First, prior studies of teaching interest examine a fairly limited set of student characteristics, which yields an incomplete picture of the prospective teacher, particularly given evidence that certain character traits (e.g., altruism) are more prevalent among teachers (Bartanen et al., 2024; Rockoff et al., 2011). Second, existing work almost exclusively compares teachers and non-teachers (or those interested in teaching to those not interested), limiting our understanding of how interest disparities in teaching compare to similar careers. Comparing between teaching and similar careers is important because it speaks to whether interest disparities are unique to the profession or reflect broader labor market trends that affect a common set of occupations. Finally, prior work has not examined the characteristics of post-secondary institutions where individuals interested in teaching apply. While there has been consistent evidence of higher achieving individuals being dissuaded to become teachers (Hanushek & Pace, 1995; Mancenido, 2021), we have yet to see how that plays out across the vast diversity of higher education institutions. Understanding whether there are distinct institutional-based characteristics that individuals interested in teaching tend to go (or not go) could illuminate mechanisms to promote teacher recruitment.

This paper begins to fill these gaps. We use data from the Common Application—an undergraduate college admissions application through which applicants can apply to more than 1,000 member colleges and universities—to analyze interest in teaching among college-bound students. Collectively, we observe 64 million applications submitted by 11.5 million unique applicants between 2014 and 2025. The application process requires applicants to indicate their career interest, which we use to identify those interested in a K–12 teaching career. We also observe a large set of applicant characteristics, including demographics and family background, academic achievement, and ratings across various dimensions (e.g., self-confidence, concern for others) submitted by their teacher-recommenders. Finally, we can observe both where applicants attend high school and the anonymized set of Common App member institutions to which they submit applications. Together, these data allow us to paint, in our view, the most detailed picture to date of the early teacher pipeline in the United States.

There are three main parts to our analysis. First, we predict initial interest in teaching as a function of applicants' characteristics. Consistent with prior work, we find substantially greater teaching interest among women and white applicants. We also find lower interest among higher-achieving applicants as measured by SAT/ACT scores and high school GPA. However, the negative relationship between teaching interest and academic achievement is greatly attenuated once we account for the selectivity of institutions to which applicants apply, suggesting that ambition or a desire for prestige is a more salient predictor of (a lack of) teaching interest, rather than academic achievement, per se. Supporting that interpretation, we find that students interested in teaching are rated by their teacher-recommenders as having greater concern for others but lower self-confidence and intellectual promise.

We then proceed to identify which careers are most similar to K–12 teaching, where similarity is conceptualized based on the observable characteristics of applicants, including demographics, academics, and teacher-recommender ratings. We identify several alternative career paths that attract similar students, including therapy, psychology, nursing, social work, and school counseling. Except for nursing, each of these careers has seen a decline in interest over the past decade, including a 20% decline for teaching. Like teaching, interest in these careers is concentrated among women, students rated as more altruistic, and students with lower academic achievement who apply to less selective institutions. Notably, however, there is far greater racial/ethnic diversity in these alternative careers, which suggests that the lack of diversity in teaching does not simply reflect a more general lack of interest in lower-paid "helping" careers. Instead, our results suggest that there are reasons specific to the teaching profession that must be identified and addressed to ameliorate racial/ethnic representation gaps. By contrast, the pattern of lower interest among higher-achieving students is comparable or less severe for teaching than similar careers.

Finally, we examine where students interested in teaching are most likely to apply to college. Prospective teachers tend to apply to mid-sized, public, master's-level universities that are both close to home and have less selective admissions. Interest in teaching is substantially lower among applicants to HBCUs and PBIs, even after accounting for applicants' demographic and academic characteristics.

Ultimately, our results provide important new information about the early teacher pipeline, but also underscore the need to better understand the development and malleability of students' interest in the teaching profession.

The Stubborn Composition of the Teaching Profession

There are long-standing concerns about the academic and demographic composition of the teacher workforce. K–12 teaching has consistently and disproportionately attracted college students with lower academic achievement, as well as white and female students (Bartanen & Kwok, 2023; Ingersoll et al., 2021; NCES, 2018). Lortie's seminal sociological work described teaching as a historically gendered profession, shaped by norms that framed it as women's work that offered limited incentives for men or high-achievers to enter or stay (Lortie, 1975). More recently, racial and ethnic representation gaps have drawn significant policy and research attention, given the growing diversity of the student population and evidence highlighting the benefits of a diverse teacher workforce (Dee, 2004; Gershenson et al., 2022). Although the proportion of nonwhite teachers has increased over time, it has not outpaced the increasing proportion of nonwhite students in K–12 public schools (Grissom et al., 2015). Despite some promising evidence from the early 2010s that the academic qualifications of teacher candidates were improving (Lankford et al., 2014), the profession has continued to attract disproportionately lower-achieving students. Compared to racial and ethnic disparities, the underrepresentation of men and academically high-achieving individuals in teaching has received less policy and research attention, despite similarly persistent patterns. More broadly, there is growing concern that the overall health of the teaching profession is deteriorating, amid falling prestige and interest in the field and persistent challenges in staffing certain "hard-to-staff" roles and environments, such as special education positions in high-poverty schools (Edwards et al., 2024; Kraft & Lyon, 2024; Nguyen et al., 2022).

Given the stubborn characteristics of the teaching workforce, meaningful changes to the academic and demographic characteristics of K–12 teachers will likely require changes in who becomes a teacher. Currently, roughly three-quarters of new teachers enter the profession through "traditional" university-based teacher education programs (TEPs), with the remaining quarter entering through "alternative" certification programs (ACPs), which are mainly operated by for-profit and non-profit companies and largely serve individuals who already have a bachelor's degree. While the share of alternatively certified teachers is growing over time, existing research demonstrates that ACPs tend to attract a more racially diverse set of individuals (Matsko et al., 2021; Redding, 2021), suggesting they may offer one pathway toward diversifying the teaching workforce. However, TEPs remain the primary route to the profession in most states and continue to produce the vast majority of new teachers. The composition of TEPs largely mirrors the existing workforce (Redding & Baker, 2019), yet we know far less about the underlying factors that shape career choices in teaching and the extent to which these compositional disparities reflect pre-existing differences in how various demographic and academic groups view teaching as a career option. Understanding these career choice processes is essential for designing policies or interventions that can effectively broaden the appeal of teaching across different populations, particularly within traditional preparation programs. To contextualize this challenge, we review existing research on who is interested in teaching and what motivates their career decisions.

Who is Interested in Teaching?

Prior research on interest in teaching follows two broad lines. The first relatively more established line explores teacher motivation, or the reasons that individuals choose to become a teacher. Generally, this literature documents that U.S. teachers are drawn to teaching for altruistic (desire to help others or society) and intrinsic (enjoyment of the job) reasons (Bartanen et al., 2024; Kwok et al., 2022). By contrast, extrinsic motivators (e.g., salary) likely serve to push individuals *away* from teaching. In particular, teachers' low pay relative to other college-educated careers may contribute to the underselection of men (who tend to be more responsive to extrinsic motivation) and high-achieving students (whose outside options may be stronger) (Lortie, 1975). However, key limitations of much of the evidence includes a reliance on self-reported measures taken at a single time point and samples of individuals who have already selected into teaching.

A second line of research documents the characteristics of those interested in teaching, occupational choice more broadly, and how interest in teaching has changed over time. Generally, teaching interest is greater among white and female students (Cooc & Kim, 2023; Hanushek & Pace, 1995), as well as students with lower SAT or ACT scores

(ACT, Inc., 2014; Bartanen & Kwok, 2023), suggesting that the overrepresentation of these groups in teaching is at least in part a function of differences in interest. However, Bartanen and Kwok (2023) find that race and gender gaps in teacher education enrollment are substantially greater than gaps in teaching interest. Similarly, Cooc and Kim (2023) find that controlling for teaching career expectations in 9th grade only minimally attenuates race and gender gaps in who majors in education in college. In sum, it is clear that there are differences—by race/ethnicity, gender, and academic achievement—in teaching interest that emerge well before individuals commit to career decisions. It is less clear whether representational disparities in teacher education and the teaching profession are mostly or completely driven by interest. Further, we have little direct evidence about the antecedents and malleability of these interest gaps.

These patterns of teaching interest are further influenced by broader economic and labor market conditions. Economic forces, including the profession's relative stability during economic downturns and varying opportunity costs of entering the profession, influence who chooses teaching as a career. Research demonstrates that teacher supply strengthens during economic recessions (Nagler et al., 2020; Rucinski, 2023), indicating that compensation and career stability are important drivers of entry into teaching. Studies of occupational and major choice among college students find that while expected earnings matter, non-pecuniary factors such as job enjoyment may be even more influential, particularly for women (Arcidiacono et al., 2020; Wiswall & Zafar, 2015; Zafar, 2013), which likely contributes to gender disparities in the occupation. These findings collectively suggest that individuals pursuing teaching are relatively less sensitive to compensation, while placing greater value on intrinsic job satisfaction and the stability that the profession offers.

Parallel to concerns about the composition of the K–12 workforce is evidence that interest in the teaching profession is declining. Several studies using varied samples and interest measures document a drop in interest in the years leading up to the COVID-19 pandemic (Bartanen & Kwok, 2023; Croft et al., 2018; Kraft & Lyon, 2024). Bartanen and Kwok (2023) find a sharp drop in teaching interest among applicants to a large state university in Texas between 2009 and 2020 and, notably, the declines were largely consistent across subgroups. Similarly, Croft et al. (2018) find a decline among ACT test-takers in the relative popularity of an education major between 2007 and 2017. These declines in interest correspond with recent decreases in enrollment and completion counts from teacher education programs (e.g., Harper et al., 2023; Partelow, 2019). While Kraft and Lyon (2024) note that K–12 teaching has experienced declines (and subsequent rebounds) in interest and prestige in prior decades, they conclude that, "The current state of the teaching profession is at or near its lowest levels in 50 years." They further suggest the current decline started around 2010 and appear to be driven by multiple factors, including stagnant teacher wages, the rising cost of college, perceived loses in teacher authority and job security, and new policies and accompanying rhetoric targeting teachers' unions.

In sum, the extant literature underscores the importance of understanding interest in teaching. On one hand, we have relatively clear evidence from multiple sources that groups currently underrepresented in K–12 teaching—men, people of color, and high-achieving individuals—also have lower interest in teaching and that interest in teaching, broadly, has declined in recent years (though evidence from the post-pandemic period remains limited). On the other hand, our understanding of who is interested in teaching remains relatively superficial, relying primarily on basic demographic and academic characteristics that may miss important nuance captured by personality traits and other factors. Additionally, there is limited research on what in-school factors may cultivate teaching interest, whether students interested in teaching pursue different educational pathways, and how teaching interest compares to other career paths.

The Current Study

Given these limitations in our current understanding of interest in teaching, our study aims to address three specific gaps. First, beyond basic demographic and academic characteristics, we know very little about the individuals interested in teaching, which may limit the efficacy of efforts to recruit potential teachers. Identifying other characteristics, such as more detailed demographic, academic, or personality traits, could greatly improve our understanding of who is likely (and unlikely) to pursue a teaching career. Understanding personality traits, in particular, may be beneficial given some work linking them to teacher effectiveness and retention (Goldhaber & Ronfeldt, 2020; Guarino et al., 2006). For instance, Rockoff et al. (2011) examined teachers' cognitive (e.g., academic achievement) and non-cognitive skills (e.g., extroversion, conscientiousness) and found that both types of skills were related to student achievement, with non-cognitive skills also associated with subjective evaluations and retention. Additional studies further highlight the potential value of examining these types of personality characteristics (Bastian et al., 2017; Klassen et al., 2011; Roloff et al., 2020; Roloff Henoch et al., 2015; Savage et al., 2021).

Second, there is little information about the institutions of higher education where prospective teachers apply. Learning more about where individuals are more interested in teaching could also inform recruitment efforts. Previous studies of teaching interest have largely ignored institutional context (Bartanen & Kwok, 2023; Cooc & Kim, 2023; Croft et al., 2018; Hanushek & Pace, 1995), despite the prominent role of universities as the primary certification route for new teachers. Our data include millions of applications to nearly 1,000 colleges and universities, allowing us to observe the average characteristics of institutions where potential teachers are likely enrolling.

Third, there is little work that studies interest in teaching alongside other career paths, meaning that we do not know the extent to which persistent compositional disparities for teachers are unique to the teaching profession or whether they are just one example of a broader phenomenon among lower-paying, "helping" careers (e.g., social work). Identifying career paths similar to teaching in terms of student characteristics could also be valuable from a recruitment perspective, helping preparation programs understand their closest competition. Few studies empirically document which careers attract similar types of students as teaching, particularly leveraging information beyond basic demographic characteristics. Thus, we aim to identify careers similar to teaching and examine whether the compositional challenges in K–12 teaching appear elsewhere.

Data

We analyze data provided by the Common Application ("Common App"), which is a centralized platform that allows students to apply to many post-secondary institutions with a single application. Our sample includes all 64 million college applications submitted via the Common App by 11.5 million applicants from 2014 to 2025.[1] The applicant data include self-reported information on applicant gender, race/ethnicity, high school GPA, standardized exam scores (e.g., SAT or ACT), first generation status, fee waiver eligibility, and the income quintile of their ZIP Code. We can also observe the full set of anonymized member institutions to which each applicant submits an application.[2] Starting in 2017, we also have data from teacher-recommenders who, in addition to submitting letters of recommendation, are asked to rate applicants on 15 items relating to academic and personality characteristics, such as *intellectual promise*, *self-confidence*, and *concern for others*. In the available years, 68% of applicants have at least one submitted recommendation, though not all provided ratings. Overall, 51% of applicants have quantitative ratings, with 28% rated by exactly one teacher, 20% by two, and 3% by three or more.

To construct our measure of interest in teaching, we use a required question on the Common App about applicant career interest. Applicants select one mutually exclusive career[3] out of 50 options, including, for example, "engineer", "veterinarian," and "undecided".[4] To identify applicants that are interested in teaching, we construct a variable that takes on the value of one if an applicant selected "teacher or administrator (elementary)" or "teacher or administrator (secondary)" from this drop-down menu and

[1] The time dimension of the data is the "application season," which spans across two calendar years. For simplicity, we refer to years, where the year corresponds to the trailing year in the season. For example, the year 2023 corresponds to the 2022–23 application season, where most students will matriculate in the fall of 2023.

[2] Prior to our receipt of the data, identifying member institution information (e.g., name, location, IPEDS code) is removed to maintain the anonymity of institutions. However, each institution is assigned a unique static random identifier and for each applicant we receive a list of the identifiers of institutions to which they submitted an application.

[3] This mutually exclusive metric is somewhat different than those used in other studies measuring interest in teaching. For example, Bartanen and Kwok (2023) use an interest in teaching metric that allows candidates to select multiple careers they may be interested in pursuing. Kraft and Lyon (2024) generate a similar measure of interest in teaching to the one we use in this study using data from the Cooperative Institutional Research Program (CIRP) The Freshman Survey (among other data sources). This nationally Representative survey of college freshman asks students to select their intended career from a list with over 30 options.

[4] Applicants can also choose "other" and subsequently write in their own response. Approximately 11% of the sample do this, though we do not make use of these responses in our analysis.

zero otherwise.[5] We interpret this as a measure of applicant interest in teaching at the time of applying to college.[6] While obviously non-binding and subject to change, prior work shows that a similar interest measure on college applications was highly predictive of both choosing an initial teacher certification major and entering a teacher education program (Bartanen & Kwok, 2023). We use this same applicant career interest to examine how prospective teachers compare to students interested in other careers. We consolidate very small (less than 0.1% of applicants) careers into the "other" category to reduce the original 50 options to 37 careers, not including "other" and "undecided."[7]

We also merge the Common App data with publicly available information from the National Center for Education Statistics (NCES) to describe applicant high schools and the characteristics of postsecondary institutions that accept the Common App ("members"). Data on applicants' high schools come from the Common Core of Data (CCD) and Private School Universe Survey (PSS). To describe member institutions, the anonymized member data include information from the Integrated Postsecondary Education Data System (IPEDS).[8] Together, these data sources allow us to understand the composition of the applicants and members that submitted and accepted, respectively, applications via the Common App from 2014 to 2025.

During our study period, the Common App dramatically expanded its member pool, changing the types of institutions that accept applications via the platform. Panel A of

[5] The options in the drop-down changed in 2015. In 2014, we use the "Elementary education and teaching" and "Education" choices to flag applicants that expressed interest in a career in teaching. This is not likely to affect our results as the change mostly consists of renaming categories and consolidating small categories. Furthermore, the number of overall categories remained relatively stable at 58 in 2014 versus 47 in 2015. In 2017, "chef" and "hospitality management" were added, and in 2019 "semi-skilled worker" was removed. Otherwise, the categories have remained consistent.

[6] This question is from the "profile" section of the Common Application, meaning that applicants cannot select different career interests for specific applications that they submit. While applicants' career interest response is provided along with their other submitted information, we have no information about whether and how members might use this response for admissions purposes.

[7] The careers consolidated into "other" include: Clergy (minister, priest), Clergy (other religious), College administrator/staff, Farmer or rancher, Homemaker (full-time), Laborer, Laborer (unskilled), School principal or superintendent, Semi-skilled worker.

[8] Specifically, we requested a limited set of institutional characteristics (e.g., Carnegie classification) that were merged to the member data by the Common App prior to anonymization (and our receipt of the data). Also prior to our receipt, noise infusion was applied to certain continuous variables (e.g., mean SAT of admitted students) to further maintain member institution anonymity.

Table A1 demonstrates this change via summary statistics of Common App members over time. On average, member institutions in 2025 are less selective, larger, and have lower average standardized exam scores and graduation rates than in 2014. For example, the share of member institutions under public control more than doubled from 14% to 31%. During this time, the Common App also drastically increased its presence geographically, expanding into less selective members in the southern United States. Public reports from the Common App corroborate membership changes across these dimensions (Hughes et al., 2024). An expanding member pool led to different types of students submitting applications through the platform in 2025 compared to 2014. Panel B of Table A1 shows summary statistics of Common App applicants over time. In 2014, applicants were more likely to be white and less likely to apply to be first generation or fee waiver eligible than in 2025. Applicants were also much more likely to be from the Northeast (40% in 2014 vs. 27% in 2025) and less likely to be from the South (24% in 2014 vs. 38% in 2025).

The Common App sample, while clearly advantageous in terms of size and richness, comes with some important limitations. First, students submitting college applications through the Common App are not a random sample of the college-intending population. In any given year the Common App sample likely understates the level of interest in K–12 teaching nationally because Common App members are more likely to be selective institutions and students applying to selective institutions are less likely to be interested in teaching. Second, the Common App added many new member institutions over the study period and these members are less selective (relative to older members), on average, such that the applicant sample likely includes an increasing share of students who are interested in teaching. This second dimension is particularly important because observed changes over time in teaching interest in our sample may conflate the actual change in teaching interest in the population with compositional changes in our sample.

We view these limitations as most germane to understanding the level of teaching interest and its change over time, neither of which are the primary aims of our analysis. Instead, we are most interested in what *predicts* interest in a K–12 teaching career. Here, the primary threat is that the correlations we estimate (e.g., differences in teaching interest by race/ethnicity) do not generalize well to the population of college aspirants. We believe this threat is less concerning, particularly given the broad (and increasing) diversity of the Common App in terms of member institutions and applicants. Nonetheless, in analyses that examine changes over time in teaching interest, we implement a weighting procedure that accounts for the changing composition of the Common App sample across years. This procedure is described in Appendix C.

Methods

Our analysis begins by predicting interest in K–12 teaching as a function of the characteristics of applicants. We estimate via logistic regression models of the general form:

$$\text{Interest}_{it} = \mathbf{X}_i\beta + \tau_t + \varepsilon_{it} \tag{1}$$

where Interest_{it} is a binary indicator for whether applicant i in season t is interested in teaching (i.e., chose "Teacher or administrator" [elementary or secondary] in response to the career interest question). We predict interest as a function of observable characteristics $\mathbf{X}_i$ and include application season fixed effects τ_t. We use heteroskedasticity-robust standard errors but omit them from our tables for readability as essentially all coefficients are precisely estimated given the large sample sizes. To facilitate interpretation, we report exponentiated coefficients (odds ratios), which are a close approximation of the risk ratio when the base rate of the outcome is less than 10% (Zhang & Yu, 1998). In our case, 3–4% of applicants are interested in teaching in each season.[9]

The vector of applicant characteristics $\mathbf{X}_i$ includes gender, race/ethnicity, first-generation college student, quintile of the median household income for the applicant's zip code, Common App fee waiver eligibility, quintile of high school GPA, SAT composite score, a measure of application selectivity (described below), the total number of Common App applications submitted by the applicant, region (Northeast, Midwest, South, or West), and high school locale type (city, suburb, town, or rural). The measure of application selectivity is constructed using each applicant's full portfolio of applications. Specifically,

[9] Results from least squares (linear probability) models are very similar in qualitative terms, but we prefer the interpretive ease of risk ratios. Additionally, which least squares models are well-suited to the inclusion of high-dimensional fixed effects (e.g., high school FE or application institution FE), our estimates are highly stable across model specifications.

we construct the quintile of applicants' median application rank. The application rank is derived from the 2023 IPEDS via principal components analysis using the following variables: admissions rate, public institution, graduation rate, and average SAT score of admitted students. Each institution's rank is the first principal component, then we take the median value for each applicant (e.g., if an applicant submitted three applications, we take their second-ranked institution).

In subsequent analyses, we estimate adjusted versions of the baseline model described by Equation 1. To examine the relationship between teaching interest and ratings from teacher-recommenders, we shift the unit of observation from *applicant* to *applicant-by-recommendation*. We weight each observation by $1/N_i$, where N_i is the total number of recommendations submitted for applicant i. Each of the 15 ratings has seven possible levels, ranging from "below average" to "top few." We linearize then standardize this ordinal scale after confirming that a non-parametric model yields essentially the same results. We estimate a single model that includes all 15 ratings simultaneously, despite the fact that the inter-item correlation is very high (0.77). The large amount of data affords us precise coefficient estimates despite this multicollinearity.

We also examine where those interested in teaching submit applications. Again, this analysis parallels Equation 1 except that it shifts the unit of observation from *applicant* to *application* and we weight each observation by $1/N_i$, where N_i is the total number of applications submitted by applicant i. We include the following member characteristics in our models: control-by-Carnegie classification (e.g., private doctoral, public master's), enrollment size, distance from applicant's home to institution, mean SAT of admitted students, acceptance rate, graduation rate, mean earnings of graduates 10 years after graduating, median student loan debt upon entering repayment, a binary indicator for whether the institution is approved by the state for teacher certification, and whether the institution is a minority-serving institution (MSI)[10] or women's college.

Beyond predicting interest in teaching, we also aim to understand which careers are

[10] We include a vector of indicators for the following MSI types: historically Black college/university (HBCU), predominantly Black institution (PBI), Alaskan-Native or Native Hawaiian-serving institution, Asian American and Native American Pacific Islander-serving institution, Hispanic-serving institution, Native American non-tribal institution.

most similar to teaching, where similarity is conceptualized in terms of the characteristics of applicants. In other words, we identify careers that draw observably similar applicants. We consider three sets of characteristics: demographics, academics, and teacher ratings. To quantify career j's (e.g., nurse) similarity to teaching, we estimate a multinomial logistic regression model where the dependent variable is one of three outcomes: interested in teaching, interested in career j, or interested in neither. Using "interested in neither" as the base category, we obtain vectors of coefficients for career j and teaching, respectively. We then compute the euclidean distance between these vectors, which serves as a measure of similarity (where smaller distance indicates greater similarity). We repeat this process for all careers, then normalize the distances to form a 0–100 dissimilarity scale. Appendix B provides a more detailed description of our approach.

In addition to plotting each of the 37 alternative careers (including "undecided") along these dimensions (dissimilarity to teaching in terms of demographics, academics, and teacher ratings), we select a subset of the most similar careers to compare to teaching in greater depth. To do this, we shift Equation 1 to a multinomial logistic regression. This approach allows us to examine the extent to which patterns of differential teaching interest by applicant characteristics play out similarly for other careers.

Results

Who is interested in teaching?

Table 1 shows results from logistic regression models predicting teaching interest with applicant characteristics. The coefficients are presented as odds ratios, which are a close approximation of risk ratios when the outcome incidence is low (Zhang & Yu, 1998), as is the case here. Column 1 shows a series of simple regressions where each characteristic is entered separately, whereas columns 2 and 3 show multiple regression results that include all of the characteristics simultaneously. Since many of the characteristics are correlated (e.g., SAT and GPA), the multiple regression results parse out which are most salient in terms of predicting teaching interest. In addition to our baseline model specification (column 2), we also show results that include member characteristics (column 3), which allows for a comparison of applicants who apply to similar colleges.

Race/ethnicity and gender are both strong predictors of teaching interest. Men are about one-third as likely as women to be interested in teaching, which roughly mirrors the current 1:3 male-to-female ratio of the K–12 teacher workforce. The stability of this coefficient across specification demonstrates that the gender gap in teaching interest is not explained by any other observable characteristics. Similarly, White students are more interested in teaching than all other racial/ethnic groups, while Asian students are the least interested (less than half as likely as White students, on average). As with gender, these racial/ethnic differences are largely unexplained by applicant and college characteristics. However, controlling for applicant characteristics increases the magnitude of the Black–White interest gap and decreases the Asian–White gap, and Black students are the least interested in K–12 teaching (roughly one-third as likely as White students), on average, in the fully specified models. Despite being proportionally small racial/ethnic groups, we can also obtain reasonably precise estimates for teaching interest among American Indian or Alaska Native (AIAN), Native Hawaiian or Pacific Islander (NHPI), and Multiracial students. Similar to other racial/ethnic minorities, we find that these groups are substantially less interested in K–12 teaching than White applicants. The magnitude of the disparities are somewhat smaller than for Black and Asian students. Latino, NHPI, and Multiracial students are one-third less likely to be interested compared to White students, and AIAN are one-quarter less likely.

Family background, as measured by first-generation status, zip code household income quintile, and eligibility for a Common App fee waiver, are far less predictive of teaching interest, particularly when accounting for other characteristics. For example, first-generation applicants are approximately 30% more likely to be interested in teaching, but only 3% more likely when controlling for the full set of applicant characteristics. Similarly, applicants from low-income zip codes are the least likely to be interested in teaching, but this relationship disappears in the multiple regression models. Fee waiver eligibility is not a meaningful predictor of teaching interest in any specification. These modest-to-null relationships largely track with Bartanen and Kwok (2023), who find only marginal differences in teaching interest by household income and parental education.

Lower-achieving applicants in terms of GPA and SAT scores are more likely to be interested in teaching. Much of these gradients attenuate, however, in the multiple regression models. Specifically, controlling for application selectivity is what drives nearly all of this attenuation. As shown in column 1, those applying to more selective colleges are far less likely to be interested in teaching, and this relationship holds (though slightly attenuates) in the multiple regression models. Relatedly, applicants who submit more applications (via Common App) have lower teaching interest. One interpretation of the salience of application selectivity is that it proxies for traits (e.g., ambition, a desire for prestige, or lower risk aversion) or circumstances (e.g., family expectations for a high-paying or high-status career) that are not fully captured by academic achievement. We return to this idea further below.

The last two variables we examine in Table 1 are applicant region and locale, the latter of which corresponds to the applicant's high school, since we do not observe home addresses. Descriptively, students from the Northeast have the highest K–12 teaching interest, slightly above the Midwest ($OR = 0.86$) and well above the South (0.58) and West (0.56). Accounting for applicants' other characteristics (column 2) reduces the magnitude of the gaps for the South and West, suggesting some of the regional differences are due to selection. We observe further attenuation of the gaps in column 3 when comparing applicants who apply to institutions with similar characteristics. Notably, however, teaching interest among students from the South remains meaningfully below students from other regions even in the full models. Turning to locale, we find that students attending town and rural high schools are the most likely to be interested in teaching, followed by suburban and city (least likely). Again, much of these differences appear to be explained by applicants' demographic and academic characteristics. In the multiple regression models, students from city high schools are 10–15% less likely to be interested in teaching than those from other locale types.

We next leverage a unique feature of the Common App data, which is that it contains ratings of applicants from their high school teacher-recommenders across a range of academic and non-academic constructs. These ratings afford us a different window through which to examine interest in teaching and inform our interpretation above concerning selection into teaching based on measures of academic achievement. Figure 1 plots odds ratios from two logistic regression models that predict interest in teaching as a function of these ratings, which we standardize. In one model, we include the vector of ratings on their own, while the other adds controls for the student characteristics we examined in Table 1.

We find that students judged higher in *Concern for others* are more likely to be interested in teaching, and this is largely not explained by any of the student characteristics we considered previously. Higher scores in *Leadership*, *Integrity*, and *Productive discussion* are also associated with greater teaching interest, though these coefficients are smaller in magnitude. By contrast, students rated higher in *Intellectual promise*, *Self-confidence*, *Academic achievement*, and *Reaction to setbacks* are less likely to be interested in teaching. Particularly for *Intellectual promise* and *Academic achievement*, these relationships attenuate when controlling for student characteristics, which makes sense because there are explicit measures of these constructs in the data. Interestingly, the relationship with *Concern for others* also shrinks, though it remains the item with the strongest partial correlation in terms of predicting K–12 teaching interest. Here, the attenuation is mostly driven by gender, as men are both less interested in teaching and receive lower ratings for *Concern for others*.

Which careers are similar to teaching?

Figure 2 plots 37 career interest options (including "undecided") in terms of their similarity to teaching. Specifically, we examine which careers attract students with similar demographic characteristics (x-axis), academic credentials (y-axis), and teacher ratings (color). We also show the relative size of these career interest groups, where larger circles indicate more students in that group. For example, 13% of applicants are undecided, while only 0.1% are interested in becoming a chef. Teaching (3.5%) is roughly the same size as "Business owner" (3.6%). Accordingly, the careers most similar to teaching are represented by circles closer to the bottom left corner that are also blue (rather than orange).

Roughly, we observe four groups of careers. First, there are a handful of careers that attract similar students to teaching, including therapist, psychologist, hospitality, social worker, and school counselor. Each of these are similar across all three dimensions (demographics, academics, and teacher ratings). Nursing is also somewhat similar, particularly in terms of academic characteristics (its larger demographic difference is driven by an even greater gender disparity than teaching). These careers are likely the closest competitors to teaching. A second cluster, located at the opposite end (top right) of Figure 2, includes engineer and computer programmer. These two STEM careers are the least similar to teaching, drawing students with very different demographic and academic characteristics. Specifically, they attract far more men and nonwhite students, as well as students with higher GPAs and SAT scores. This pattern is consistent with findings that STEM positions are among the most difficult teaching vacancies to fill in schools.

Third is a set of highly professionalized careers, including scientist/researcher, college teacher, government, doctor, and foreign service. These careers are more similar to teaching than STEM in terms of demographics because of a more even gender split. Like STEM, however, they attract students with very strong academic qualifications, while teaching does not. A fourth set of careers, including business, sales, law enforcement, and military, draw students with somewhat similar academic characteristics but have greater representation of male and nonwhite students.

Given our focus in understanding careers similar to teaching—and, relatedly, those which otherwise-inclined students might choose instead of teaching—we leverage the time dimension of our data to examine how interest in teaching and similar careers has changed from 2015–2025. We choose 6 similar careers based on the metrics in Figure 2, giving some preference to more popular career interests (e.g., psychologist with 2.2% of applicants instead of hospitality with 0.14% of applicants). Figure 3 shows these results. Specifically, we use 2015 as a reference point and plot the relative change over the past decade for each career (see Appendix Figure A1 for the absolute change). We observe a steady decline in K–12 teaching interest totaling 20% over the period, from 3.6% of applicants in 2015 to 2.9% in 2025. While there is a slightly more pronounced drop in the first application year of the pandemic, the post-pandemic years largely maintain a pre-existing trend of declining teaching interest among college applicants (Bartanen & Kwok, 2023; Kraft & Lyon, 2024). Appendix Figure C2 shows this trend disaggregated by various applicant characteristics. We find little evidence that the decline in teaching interest is driven by particular types of applicants.

While teaching experiences the largest absolute decline over this period, the 20%

relative decline is similar for therapist, social worker, and school counselor. Psychologist and veterinarian see modest increases. In stark contrast to teaching is nursing, where we see a 25% *increase* in interest over the period, even after a dip in the early pandemic years. Together, Figure 2 and Figure 3 suggest that nursing, in particular, is drawing increased interest from students who might otherwise be interested in teaching. To probe this pattern more deeply, we examine the actual career interest choices of applicants who have a high predicted probability of teaching interest, defined here as the top 10% of the sample. To obtain a predicted probability for each applicant, we estimate our baseline logistic regression model (i.e., column 2 of Table 1) using only the 2015 season, then apply those coefficients to applicants from all seasons seasons. Next, we restrict the sample to applicants in the top 10% and remaining top 50% of predicted probability of teaching interest, respectively, and tabulate their actual career interest choices.

Table 2 shows these tabulations for the 2015, 2020, and 2025.[11] In 2015, nursing and teaching are equally likely among those with the highest propensity of teaching interest (11% each), but we see a decline in teaching interest in 2020 (10.5%) and 2025 (9.7%) alongside an increase in nursing interest (13.0% and 13.4%). Among this group, we also see increased interest in veterinarian, lawyer, business owner, and dentist, as well as in applicants choosing "other" (perhaps reflecting growth in careers that are not well captured by this relatively static list of options). Notably, the decline in teaching interest is similar in absolute terms—and much larger in relative terms—among those in the remaining top 50% of predicted teaching interest. Among this group, 5.0% were actually interested in teaching in 2015 compared to 4.0% in 2025, while nursing interest jumps from 6.6% to 11.3%. Overall, Table 2 is consistent with the hypothesis that nursing serves as an increasingly dominant alternative career path for individuals who would have pursued teaching.

Next, we estimate a multinomial logistic regression model using teaching, similar careers, and undecided, relative to a base category that includes anything else. This allows us to compare teaching directly to these other substitutes. We focus on demographic and academic characteristics, as there were few substantive differences in teacher ratings among these groups. Table 3 shows that interest in teaching is far less racially/ethnically diverse

[11] Results for the bottom 50% of predicted teaching interest are shown in Table A2.

than other similar careers, evidenced by the much smaller risk ratios for the race/ethnicity groups in column 1 (teaching). For example, Black or African American applicants are one-third as likely as White applicants ($RRR = 0.34$) to be interested in teaching relative to the base category. This is substantially smaller than for school counselor ($RRR = 0.82$), nurse (1.13), therapist (0.88), psychologist (0.94), and social worker (0.95). Similar patterns play out across each racial/ethnic group. In fact, White students comprise 68% of those interested in teaching, which is higher than any other career interest except for conservationist (76%) and farmer (81%), both of which are very small groups (0.3% and 0.06% of applicants, respectively).

By contrast, stratification by gender and academic achievement is either comparable or in some cases smaller for teaching than these similar careers. Male interest in teaching is actually greater than for counselor, nurse, psychologist, social worker, and veterinarian. GPA and SAT gradients for teaching are also comparable or flatter, and for some careers (school counselor, nurse, therapist) the negative selection on SAT score is substantially greater than teaching. Application selectivity looks fairly similar except for psychologist, which has a flatter gradient, and therapist and veterinarian, where there is (negative) selection at higher SAT scores but not at lower SAT scores. However, those interested in teaching are relatively more likely to submit few applications, along with prospective veterinarians.

Where do prospective teachers apply to college?

The final part of our analysis examines which colleges have greater applicant interest in teaching. Table 4 shows logistic regression results across multiple specifications predicting teaching interest as a function of institutional characteristics. Column 1 stacks together simple regression results that include each variable separately. Column 2 is a multiple regression model with no applicant characteristics and column 3 adds these characteristics. Several patterns emerge. First, students interested in teaching are more likely to apply to smaller (i.e., fewer than 10,000 students), non-doctoral, public institutions. For example, column 1 shows that interest in teaching is roughly 250% greater among those applying to public master's level institutions compared to public doctoral institutions. By contrast, it is roughly half as prevalent among those applying to private doctoral institutions. Of course, much of these patterns likely reflects our previous analyses showing that those interested in teaching have lower academic achievement and less selective application behavior. Accordingly, many of the differences in teaching interest as a function of institutional characteristics in column 1 either attenuate or change direction in the multiple regression models without (column 2) and with (column 3) applicant characteristics. However, interest in teaching remains substantially greater in public master's level institutions even after controlling for applicant and other institutional characteristics.

We also find that teaching interest is greater among applicants who apply to institutions close to home, demonstrating the "draw of home" phenomenon (Boyd et al., 2005) early on in the teacher pipeline. Descriptively, institutions with greater applicant interest in teaching have lower graduation rates, but this is completely driven by selection, as the pattern reverses in the multiple regression models. Similarly, these institutions produce graduates with lower earnings and higher debt, but the magnitudes are small in the fully specified models. Perhaps unsurprisingly, teaching interest is greater at institutions that are approved by their state for teacher certification. Finally, applicants to minority-serving institutions—particularly HBCUs and PBIs—have lower teaching interest, even after accounting for their demographic and academic characteristics.

Table 5 shows how these patterns compare to the careers similar to teaching. Specifically, we again estimate a multinomial logistic regression model where the dependent variable takes a different value for teaching, undecided, and the six similar careers, relative to a base category of everything else. Greater interest at public master's and lower enrollment institutions is the most pronounced for teaching, though also appears for school counseling and social work. Similarly, the draw of home pattern is largest in magnitude for teaching, though school counseling and nursing are very similar. Most remaining patterns are similar across these careers, with a few exceptions. Notably, lower interest among those applying to HBCUs is most pronounced for teaching, though the pattern appears (in smaller magnitude) for all similar careers except psychologist.

Discussion

Concerns about the composition of the K–12 teacher workforce and the overall health of the profession highlight the need to better understand pathways to teaching. In particular, recent evidence suggests that compositional disparities—by demographics and academic achievement—begin to appear well before college students make decisions about their major or career path. However, we still have relatively little large-scale evidence about who is potentially interested in teaching and how the teaching profession compares to other career paths that students might be considering. Leveraging college application data from 11.5 million unique applicants over the past decade, the current paper provides the most detailed quantitative information to date on interest in teaching. Our analysis identified which applicant characteristics predict interest in becoming a teacher and used those results to classify the careers most similar to (and different from) teaching. We then documented how interest in teaching and similar careers has changed over time and how interest varied across different types of post-secondary institutions.

Relative to the overall composition of college applicants, prospective teachers are substantially more likely to be female, white, first-generation college students, and have lower academic achievement as measured by GPA and SAT/ACT scores. They tend to submit fewer college applications and apply to less selective, small or mid-sized public institutions that are closer to their home. An important addendum here, however, is that teaching interest appears to be greater among less ambitious applicants. While previous studies document negative associations between teaching interest and both SAT/ACT scores and high school GPA (ACT, Inc., 2014; Bartanen & Kwok, 2023), we find that students' application behavior largely explains these patterns. That is, students who apply to more selective institutions are substantially less likely to be interested in K–12 teaching, and accounting for this relationship largely attenuates the correlation between interest and SAT scores (and completely for GPA). While this evidence should be considered suggestive (particularly insofar as application selectivity is a reasonable proxy for ambition), we find some corroborating evidence from applicants' teacher recommendations. Specifically, applicants rated as having more intellectual promise and self-confidence are less likely to be interested in teaching, while those rated as having greater concern for others are more interested. The latter relationship dovetails with previous findings that altruism is a salient motivator for becoming a teacher (Bartanen et al., 2024; Brookhart & Freeman, 1992; Lortie, 1975).

We also find that K–12 teaching attracts a similar set of students to other female-prevalent “helping” careers, including social work, nursing, therapy, and psychology. Most different are highly professionalized and STEM careers, including engineer, doctor, and scientist/researcher. We document a consistent decline in teaching interest over the study period, continuing through the pandemic years and amounting to a 20% drop between 2015 and 2025. In relative terms, this decline is similar to social worker, therapist, and school psychologist. By contrast, nursing interest increased by 25% over the period. These results contribute to a growing evidence base documenting an erosion of the attractiveness of the teaching profession in recent years (Auguste et al., 2010; Bartanen & Kwok, 2023; Croft et al., 2018; Kraft & Lyon, 2024). However, parallel declines in some similar careers raise the question of whether the decline in teaching interest reflects something specific to the public education system or that teaching is merely one case in a broader labor market phenomenon.

While teaching’s declining interest problem may not be unique, we do find that racial/ethnic disparities in teaching interest are substantially worse than careers that attract otherwise similar students, such as counseling, social work, and nursing. This finding suggests that K–12 teaching’s longstanding struggle to recruit racially diverse teachers may not just be a symptom of broader labor market dynamics, but that there are reasons more specific to the K–12 education system or teacher training that inhibit a more representative workforce. Notably, we find lower interest in teaching among applicants to HBCUs and minority-serving institutions, even when accounting for applicants’ own demographic characteristics. By contrast, gender and academic achievement gaps are actually smaller for teaching than similar career paths. While teaching interest is substantially greater among applicants with lower SAT scores, this gradient is somewhat flatter than for school counseling, therapy, nursing, and social work, suggesting that teaching recruits a stronger set of students in terms of academics than would otherwise be expected.

Reflecting on these key results and what they might tell us about the teaching profession, we are cautious to speculate too far beyond the warrant afforded by our empirical analysis. Broad, descriptive quantitative studies such as this one are ultimately most useful for documenting large-scale patterns and raising questions or hypotheses that can then be examined more rigorously by future work. To that end, we put forth a couple of ideas that are consistent with—even if not directly confirmed by—our findings. The first is that one's own experience with the K–12 education system is an important driver of interest in teaching (Lortie, 1975). In particular, the lack of racial/ethnic diversity in teaching interest may be a vicious cycle wherein nonwhite students are far less likely to be taught by teachers who share their background (Redding, 2019), reducing teaching's salience as a viable or desirable career path and helping to perpetuate representation gaps. This representation–reproduction hypothesis could be tested empirically using state-level longitudinal data systems that follow individuals from their K–12 schooling to workforce outcomes.

It is also possible that representation gaps, per se, are not the salient mechanism. Instead, interest in teaching may arise from having positive experiences in school, including academic success or supportive relationships with teachers or other school personnel. For example, our results suggest that K–12 teaching attracts students with a stronger academic profile than social work or school counseling (which have similar economic returns to teaching)—driven in particular by comparatively lower interest among students with low high school GPAs and SAT scores. Relatedly, while fee waiver eligibility and residing in a zip code with low median household incomes (our best proxies for applicants' socioeconomic status) were unrelated to interest in teaching, they are associated with substantially greater interest in social work, school counseling, and nursing. These careers also had far greater racial/ethnic proportionality.

In line with this interpretation, one possible explanation is that nonwhite students or students from low-income backgrounds are more likely to have positive interactions with roles such as social work, school counseling, and nursing than with teachers. Critical scholarship suggests that many students of color experience K–12 schooling through what Ferguson (2000) and Meiners (2007) term "carceral logics"—disciplinary practices and surveillance structures that disproportionately target them, thereby framing schools as punitive rather than empowering spaces. This aligns with work by Wun (2016) and Morris (2016) showing how such experiences can alienate students from the educational system, even if they are committed to serving youth in other capacities. In addition, the underrepresentation of teachers of color (Ladson-Billings, 1994; Redding, 2019) may further limit opportunities for racial/ethnic role-modeling.

While we believe our study makes several contributions, we also face a number of important limitations. First, our sample comes from the Common App, which represents a more selective set of institutions such that the applicants we observe are not fully representative of the full college-going population. Notably, we likely do not observe many applicants to community colleges, less selective four-year colleges (unless they applied to a Common App member through the Common App portal), and minority-serving institutions including HBCUs. This limitation is likely most salient for interpreting our results on interest in teaching and its change over time. While we have taken care to avoid conflating changes in interest with compositional changes in our sample, it remains likely that we are understating the overall level of teaching interest in the population. Similarly, our findings concerning lower teaching interest among applicants to HBCUs, PBIs, and other MSIs come from only a handful (through increasing in recent years) of Common App members, which may not represent well the population of these institutions.[12]

A related limitation is that we only observe applications submitted through the Common App system, which means that we do not know whether applicants applied to institutions through other means, such as a statewide admissions platform (e.g., ApplyTexas) or an institution-specific application. This introduces measurement error into our application selectivity measures, which are a key predictor of teaching interest in this study. The magnitude and nature of this measurement error is unclear, though we have no reason to suspect that it differentially affects applicants who are interested in teaching. Further, our application selectivity measure is based on a relative ranking of each applicant's median application, which may make it fairly robust to missing data.

[12] According to the National Center for Education Statistics, there were 99 HBCUs in 2022. Included in our sample are 6 in 2014, 10 in 2020, and 39 in 2025.

Finally, it is important to reiterate that the current study is one concerning *interest in teaching at the time of college application*. While our application data are immensely rich, we cannot observe how interest changes over time (e.g., as students progress through K–12 school and college) or how interest translates into actually becoming a teacher. However, there is prior evidence linking interest at college application/entry to subsequent teacher pipeline milestones, including becoming a teacher (Bartanen & Kwok, 2023; Hanushek & Pace, 1995), suggesting that interest patterns documented here are likely to mirror actual labor market and teacher supply outcomes.

In building our understanding of interest in teaching, this study also points to several important avenues for future research. It is clear that at least some of the observed demographic and academic disparities in who becomes a teacher reflect differences in interest at the time of college application. What remains unclear is why these interest differences arise and whether interest is malleable either before or during college. Perhaps more than any other career, students receive repeated and intense exposure to the work of K–12 teachers, which undoubtedly shapes their perception of and disposition towards this career. Studying how students' schooling experiences, including interactions or relationships with individual teachers, shapes subsequent teaching interest could provide answers to many of the questions raised here. Additionally, the differences in teaching interest by region and locale that we document here are important to study more closely. We show that students from city high schools tend to have lower interest, as do those from the South and West. A complete investigation of these patterns is beyond the scope of the current analysis, but we hope to pursue them in future work.

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Table 1

Interest in Teaching and Applicant Characteristics

	(1)	(2)	(3)
Applicant Characteristics			
Male	0.36**	0.36**	0.36**
Race/ethnicity (Base=White)			
American Indian or Alaska Native	0.83**	0.74**	0.80**
Asian	0.28**	0.43**	0.46**
Black or African American	0.44**	0.37**	0.40**
Latino	0.68**	0.64**	0.66**
Native Hawaiian or Pacific Islander	0.64**	0.65**	0.66**
Multiracial	0.62**	0.67**	0.69**
First-generation	1.30**	1.03**	1.02**
Zip Code HH Income Quintile (Base = 3rd Quintile)			
1st	0.82**	0.99	0.99
2nd	0.97**	1.01	1.00
4th	0.99	0.99	1.00
5th	0.90**	1.03**	1.06**
Fee Waiver Eligible	0.97**	1.00	1.02**
GPA Quintile (Base = 3rd Quintile)			
Lowest	1.12**	1.03**	1.04**
2nd	1.06**	1.02**	1.02**
4th	0.81**	0.94**	0.94**
Highest	0.62**	0.90**	0.89**
SAT Composite Score (Base = 1200 to 1290)			
Less than 1100	1.52**	1.20**	1.17**
1100 to 1190	1.29**	1.09**	1.08**
1300 to 1390	0.70**	0.90**	0.91**
1400 to 1490	0.43**	0.78**	0.80**
1500 to 1600	0.23**	0.64**	0.68**
Missing	1.33**	1.14**	1.11**
Application Selectivity Quintile (Base = 3rd Quintile)			
Lowest	1.73**	1.62**	1.51**
2nd	1.40**	1.33**	1.28**
4th	0.58**	0.66**	0.70**
Highest	0.27**	0.40**	0.49**
Number of Applications Submitted (Base = 4 to 8)			
1	1.24**	1.21**	1.23**
2 or 3	1.20**	1.16**	1.15**
More than 8	0.63**	0.78**	0.80**
Region (Base = Northeast)			
Midwest	0.86**	0.86**	0.99
South	0.58**	0.65**	0.74**
West	0.56**	0.71**	0.91**
Locale (Base = Suburb)			
City	0.68**	0.86**	0.88**
Town	1.26**	1.04**	1.01
Rural	1.19**	1.02**	0.98**
Year Fixed Effects	✓	✓	✓
Separate Regressions	✓		
Member Characteristics			✓

Notes: Results show exponentiated coefficient estimates (odds ratios) from logistic regression models where the dependent variable is a binary indicator for whether the applicant chose K–12 teaching as their career interest. There are roughly 9 million applicants (columns 1 and 2) and 46 million applications (column 3). Column 1 stacks separate regressions denoted by horizontal lines. Columns 2 and 3 show results from a single model. For columns 1 and 2, the unit of observation is applicant. For column 3, the unit of observation is application and we weight applications by 1 over the total number of applications submitted by the applicant. $^{*}p < 0.01$, $^{**}p < 0.001$

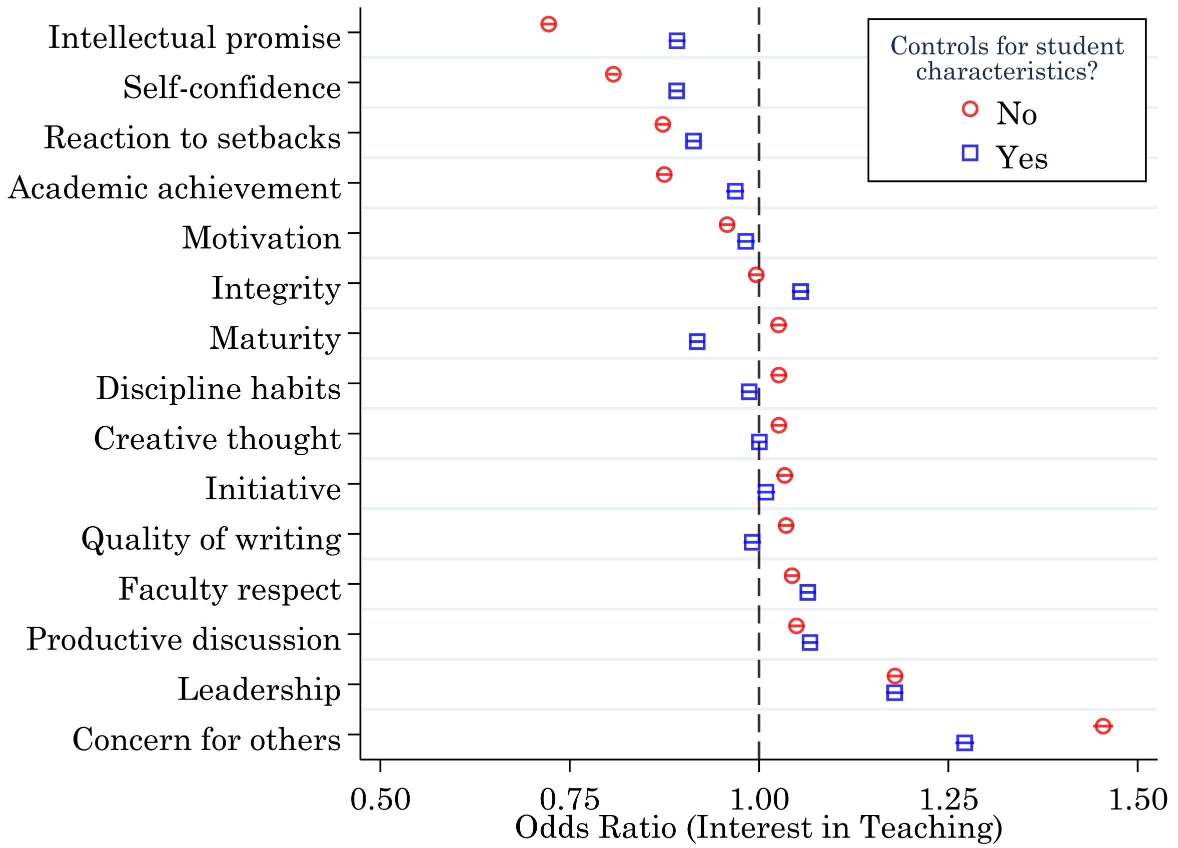
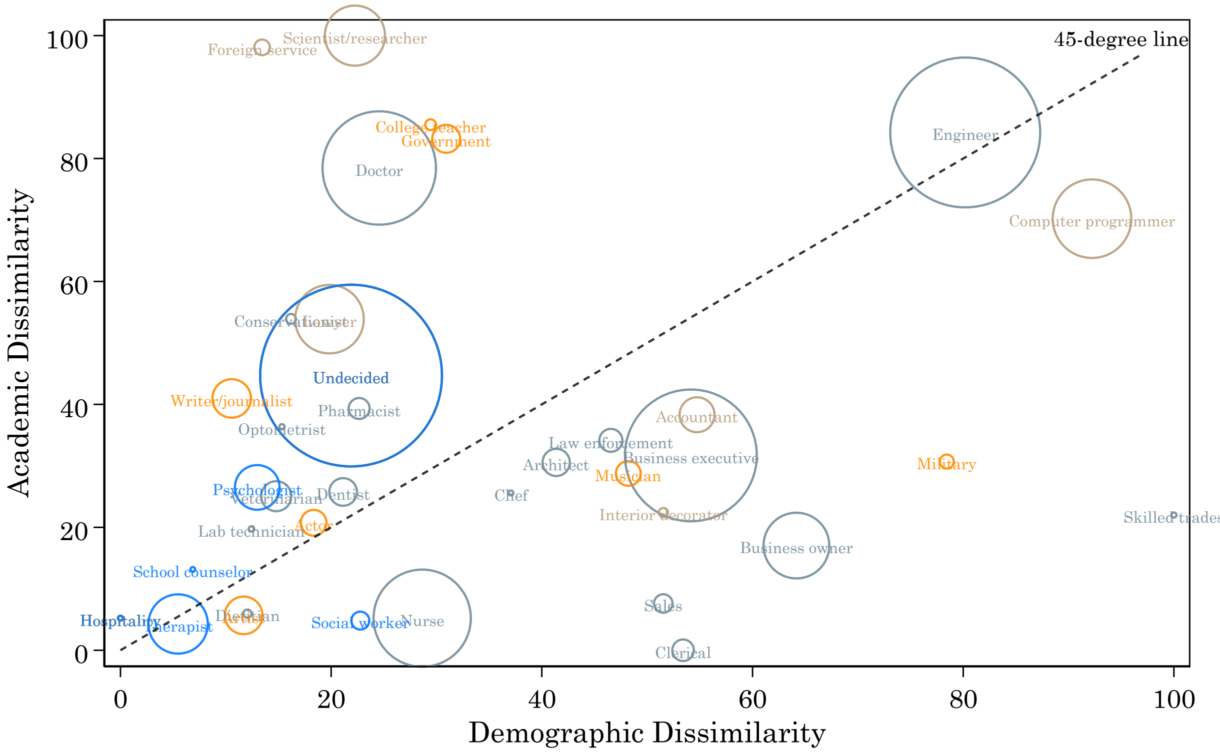


Figure 1

Interest in Teaching and Teacher-Recommender Ratings

Note: Figure displays the relationship (odds ratio) between standardized teacher ratings and applicants' interest in teaching from two logistic regression models. Red (circles) and blue (squares) coefficients, respectively, are estimated in different models where the dependent variable is a binary indicator for interest in teaching. Both models include fixed effects for application season. The blue (squares) coefficients come from a model that includes the vector of applicant characteristics (those from Table 1, column 2). The x-axis shows the odds ratio corresponding to a 1 SD change in the rating indicated by the y-axis, holding constant all other ratings. Error bars show 95% confidence intervals. Ratings were standardized within each application season, and observations were weighted by the inverse of the number of recommendations per applicant.



Color indicates teacher ratings (blue=similar, orange=dissimilar). Size indicates frequency of career interest.

Figure 2

Careers Similar to Teaching

Note: Figure compares K–12 teaching to other careers based on the characteristics of applicants. See Appendix B for details on the construction of dissimilarity indices.

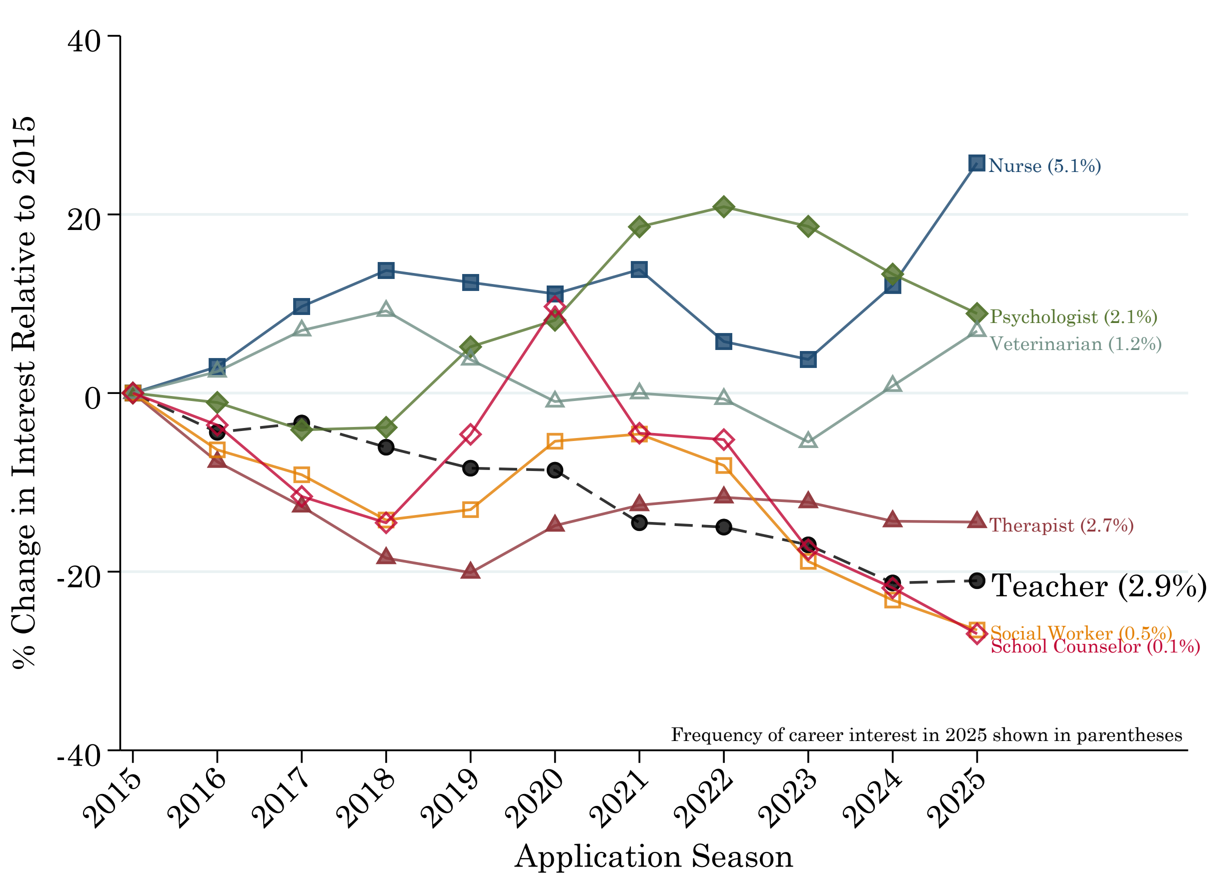


Figure 3

Interest in Teaching and Similar Careers by Application Season

Note: Figure plots the change in applicant career interest by application season relative to its frequency in 2015. We omit 2014 because it used a different set of career interests. K–12 teacher and similar careers are shown. See the main text for a description of how similar careers were chosen. To account for the changing composition of applicants over time, we employ weights generated from coarsened exact matching. See Appendix C for details on this procedure. We report in parentheses each career's percentage of applicants in 2025 (e.g., 2.9% of applicants chose teacher as their career interest in 2025). See Figure A1 for a version of this plot that shows the absolute (instead of relative) change.

Table 2

Actual Career Interests Among Applicants With High Predicted Probability of Interest in Teaching

	Top 10%			Remaining Top 50%		
	2015	2020	2025	2015	2020	2025
Other	16.1	16.5	20.3	13.3	14.4	17.5
Undecided	14.8	12.8	11.4	15.3	12.8	10.6
Nurse	11.1	13.0	13.4	6.6	8.8	11.3
Teacher	11.0	10.5	9.7	5.0	4.6	4.0
Therapist	6.2	5.7	5.4	4.5	4.1	4.1
Business executive	5.4	4.6	4.6	8.5	7.6	7.5
Psychologist	3.4	3.5	3.2	2.7	2.8	2.8
Artist	3.1	3.0	2.7	1.9	2.2	1.8
Doctor	3.1	3.8	2.4	6.4	6.3	4.4
Writer/Journalist	2.4	1.6	1.2	2.8	1.9	1.3
Veterinarian	2.0	2.3	2.6	1.6	1.8	2.0
Social worker	1.8	1.9	1.4	1.1	1.1	0.8
Scientist	1.8	1.7	1.5	2.6	2.5	2.0
Lawyer	1.7	2.3	2.8	2.8	3.5	4.3
Law enforcement	1.6	1.8	1.2	1.8	1.6	1.1
Accountant	1.6	1.1	1.1	2.0	1.6	1.6
Business owner	1.4	1.8	2.4	2.3	2.8	3.7
Engineer	1.4	1.5	1.6	5.9	5.5	5.2
Pharmacist	1.3	0.6	0.6	1.5	0.9	0.8
Actor	1.2	1.0	0.8	1.5	1.4	0.9
Musician	1.0	0.8	0.7	1.2	1.1	0.8
Dietitian	0.9	0.5	0.5	0.5	0.3	0.3
Dentist	0.9	1.2	1.5	1.0	1.3	1.8
Sales	0.8	0.6	0.8	0.7	0.7	1.0
Interior decorator	0.6	0.9	1.0	0.3	0.4	0.5
Clerical	0.5	0.8	1.0	0.6	1.0	1.2
School counselor	0.4	0.4	0.3	0.2	0.2	0.1
Architect	0.4	0.7	0.9	0.7	1.1	1.5
Computer programmer	0.4	0.6	0.6	1.7	2.3	2.0
Government	0.3	0.5	0.3	0.8	1.0	0.6
Foreign service	0.3	0.2	0.1	0.8	0.4	0.2
Conservationist	0.3	0.5	0.5	0.3	0.5	0.4
Lab technician	0.2	0.3	0.4	0.1	0.2	0.3
College teacher	0.2	0.1	0.2	0.3	0.3	0.2
Optometrist	0.2	0.1	0.1	0.2	0.2	0.2
Military	0.1	0.3	0.2	0.4	0.5	0.4
Skilled trades	0.1	0.1	0.1	0.1	0.2	0.3
Chef	0.0	0.2	0.3	0.0	0.2	0.3
Hospitality	0.0	0.4	0.3	0.0	0.2	0.2

Notes: Table plots the frequency (percentage) of applicants in an application season (columns) who choose a particular career interest response (rows). The subgroups (top 10% and remaining 50%) are determined by the predicted probability of teaching interest based on coefficients from a model predicting a binary indicator of interest in teaching as a function of applicant characteristics using the 2015 sample. This model is used to make an out-of-sample prediction for 2020 and 2025 applicants.

Table 3

Predicting Interest in Teaching and Similar Careers

	Teach (1)	Sch Coun (2)	Nurse (3)	Therap (4)	Psych (5)	Soc Work (6)	Vet (7)	Undec (8)
Applicant Characteristics								
Male	0.27**	0.22**	0.13**	0.43**	0.21**	0.14**	0.18**	0.71**
Race/ethnicity (Base=White)								
American Indian or Alaska Native	0.69**	0.77	0.96	0.88**	0.86**	0.97	1.10	0.72**
Asian	0.39**	0.52**	1.13**	0.68**	0.68**	0.61**	0.49**	0.60**
Black or African American	0.34**	0.82**	1.13**	0.88**	0.94**	0.95**	0.74**	0.51**
Latino	0.61**	0.90**	1.02**	0.83**	1.00	0.95**	1.04**	0.77**
Native Hawaiian or Pacific Islander	0.63**	1.26	1.28**	1.08	0.74**	1.12	0.74**	0.78**
Multiracial	0.65**	0.77**	0.90**	0.93**	1.03*	0.98	0.96**	0.88**
First-generation	1.05**	1.06*	1.33**	0.91**	1.06**	1.17**	1.15**	0.89**
Zip Code HH Income Quintile (Base = 3rd Quintile)								
1st	1.01	1.19**	1.07**	0.98	1.02	1.14**	1.08**	1.08**
2nd	1.02	1.03	1.04**	1.01	1.00	1.03	1.06**	1.04**
4th	0.99	0.97	0.99*	0.98*	0.99	0.96*	0.92**	1.01
5th	1.03**	1.00	0.94**	0.97**	1.02*	0.96*	0.82**	1.11**
Fee Waiver Eligible	1.00	1.26**	1.15**	0.86**	1.02**	1.46**	1.09**	0.89**
GPA Quintile (Base = 3rd Quintile)								
Lowest	1.04**	1.31**	0.95**	0.96**	1.14**	1.42**	1.00	1.12**
2nd	1.03**	1.10**	0.97**	0.98**	1.06**	1.14**	0.98	1.04**
4th	0.92**	0.89**	0.98**	1.00	0.88**	0.83**	0.97**	0.96**
Highest	0.87**	0.83**	0.95**	1.01	0.83**	0.76**	0.96**	0.91**
SAT Composite Score (Base = 1200 to 1290)								
Less than 1100	1.27**	1.74**	1.43**	1.36**	1.07**	1.43**	1.14**	1.01
1100 to 1190	1.12**	1.34**	1.18**	1.19**	1.07**	1.13**	1.04**	1.01
1300 to 1390	0.88**	0.90	0.80**	0.78**	0.91**	0.91**	0.94**	0.99
1400 to 1490	0.75**	0.57**	0.55**	0.53**	0.74**	0.77**	0.90**	1.00
1500 to 1600	0.61**	0.58**	0.41**	0.30**	0.50**	0.72**	0.73**	0.98**
Missing	1.20**	1.68**	1.29**	1.18**	1.00	1.39**	1.02	1.14**
Application Selectivity Quintile (Base = 3rd Quintile)								
Lowest	1.77**	1.71**	1.51**	1.14**	1.10**	1.83**	1.05**	1.15**
2nd	1.38**	1.33**	1.25**	1.15**	1.02**	1.32**	1.02*	1.04**
4th	0.61**	0.65**	0.52**	0.58**	0.90**	0.74**	0.96**	0.90**
Highest	0.36**	0.33**	0.23**	0.30**	0.77**	0.55**	0.44**	0.95**
Number of Applications Submitted (Base = 4 to 8)								
1	1.20**	1.09**	1.12**	1.06**	0.90**	1.09**	1.25**	0.88**
2 or 3	1.14**	1.00	1.03**	0.99	0.94**	1.02	1.14**	0.89**
More than 8	0.78**	0.90**	0.99*	0.90**	1.01	0.91**	0.82**	1.12**
Region (Base = Northeast)								
Midwest	0.83**	0.65**	0.98**	0.94**	0.94**	0.95**	1.01	0.85**
South	0.61**	0.48**	0.87**	0.94**	0.96**	0.70**	1.18**	0.73**
West	0.69**	0.83**	0.90**	1.01	1.05**	1.14**	0.96**	0.86**
Locale (Base = Suburb)								
City	0.87**	0.96	0.96**	0.99	1.01	1.04**	0.99	1.16**
Town	1.05**	1.08	0.98*	1.06**	0.99	1.19**	1.15**	0.99
Rural	1.03**	1.04	1.02**	1.04**	0.96**	1.13**	1.26**	0.97**

Notes: Results show exponentiated coefficient estimates (relative risk ratios) from a single multinomial logistic regression model where the base category is not choosing any of the 8 listed career options. $^{*}p < 0.01$, $^{**}p < 0.001$

Table 4

Interest in Teaching and College Characteristics

	(1)	(2)	(3)
Member Characteristics			
Control × Carnegie classification (Base = Public, Doctoral)			
Private, Doctoral	0.55**	0.93**	1.02**
Private, Master's	1.53**	0.88**	0.96**
Public, Master's	2.62**	1.39**	1.45**
Private, Baccalaureate	1.55**	0.94**	1.08**
Public, Baccalaureate	2.21**	0.99	0.99
Institutional Size			
1,000 or fewer	1.63**	1.49**	1.53**
1,000 to 4,999	1.97**	1.54**	1.49**
5,000 to 9,999	1.89**	1.42**	1.35**
10,000 to 19,999	1.26**	1.22**	1.15**
Applicant Distance to Institution (Base = >500 Miles)			
≤50	2.40**	1.59**	1.38**
50 to ≤100	2.41**	1.50**	1.31**
100 to ≤250	1.94**	1.33**	1.24**
250 to ≤500	1.35**	1.12**	1.10**
Mean SAT of Admitted Students (100 points)	0.69**	0.76**	0.90**
Acceptance Rate (10 perc. points)	1.20**	1.04**	0.98**
Graduation rate (10 perc. points)	0.80**	1.22**	1.21**
Mean earnings 10 years post grad (10 log points)	0.82**	0.88**	0.92**
Median debt upon entering repayment (10 log points)	1.05**	1.00**	0.99**
State-approved teacher certification institution	1.82**	1.36**	1.33**
HBCU	0.64**	0.36**	0.70**
Predominantly Black institution	0.74**	0.68**	0.87**
Alaskan-Native or Native Hawaiian-serving institution	1.07	1.32**	1.02
Asian Amer. and Nat. Amer. Pac. Isl.-Serving institution	0.81**	0.92**	0.99
Hispanic-serving institution	1.09**	0.87**	0.97**
Native American non-tribal institution	1.48**	0.67**	0.89*
Women's college	1.20**	1.02	0.85**
Year Fixed Effects	✓	✓	✓
Separate Regressions	✓		
Applicant Characteristics			✓

Notes: Results show exponentiated coefficient estimates (odds ratios) from logistic regression models where the dependent variable is a binary indicator for whether the applicant chose K–12 teaching as their career interest. There are roughly 46 million applications. Column 1 stacks separate regressions denoted by horizontal lines. Columns 2 and 3 show coefficients from a single model. The unit of observation is application and we weight applications by 1 over the total number of applications submitted by the applicant. Column 3 includes applicant characteristics and is the same model as shown in column 3 of Table 1. $^{*}p < 0.01$, $^{**}p < 0.001$

Table 5

College Characteristics for Teaching and Similar Careers

	Teach (1)	Sch Coun (2)	Nurse (3)	Therap (4)	Psych (5)	Soc Work (6)	Vet (7)	Undec (8)
Member Characteristics								
Control × Carnegie classification (Base = Public, Doctoral)								
Private, Doctoral	1.00	1.00	0.89**	1.03**	1.03**	0.99	0.60**	0.98**
Private, Master's	0.98**	1.04	1.13**	1.21**	1.00	0.94**	0.75**	1.06**
Public, Master's	1.47**	1.33**	0.96**	1.02**	1.10**	1.20**	0.72**	1.17**
Private, Baccalaureate	1.14**	1.19**	0.93**	1.26**	1.21**	1.06**	0.94**	1.42**
Public, Baccalaureate	0.99	1.14**	0.87**	1.00	1.10**	1.09**	0.96**	1.25**
Institutional Size								
1,000 or fewer	1.53**	1.42**	0.83**	0.93**	1.16**	1.26**	1.11**	1.02*
1,000 to 4,999	1.54**	1.49**	0.98**	0.97**	1.19**	1.27**	0.95**	1.10**
5,000 to 9,999	1.37**	1.36**	0.99**	1.03**	1.09**	1.18**	0.78**	1.06**
10,000 to 19,999	1.18**	1.18**	1.08**	1.01	1.09**	1.13**	0.88**	1.12**
Applicant Distance to Institution (Base = >500 Miles)								
≤50	1.44**	1.39**	1.38**	1.10**	1.11**	1.12**	0.86**	1.08**
50 to ≤100	1.37**	1.37**	1.34**	1.24**	1.12**	1.13**	0.97**	1.06**
100 to ≤250	1.29**	1.33**	1.23**	1.23**	1.08**	1.08**	0.97**	1.07**
250 to ≤500	1.12**	1.16**	1.16**	1.18**	1.03**	1.04**	0.95**	1.02**
Mean SAT of Admitted Students (100 points)	0.86**	0.86**	0.81**	0.85**	0.94**	0.88**	0.92**	0.98**
Acceptance Rate (10 perc. points)	0.98**	0.99**	0.99**	1.00**	0.99**	0.99**	0.98**	1.01**
Graduation rate (10 perc. points)	1.25**	1.20**	1.07**	1.16**	1.11**	1.15**	1.07**	1.12**
Mean earnings 10 years post grad (10 log points)	0.91**	0.95**	1.05**	0.94**	0.96**	0.93**	0.96**	0.96**
Median debt upon entering repayment (10 log points)	0.99**	1.00	1.01**	1.01**	0.98**	0.99**	0.95**	0.98**
State-approved teacher certification institution	1.38**	1.18**	1.29**	1.15**	1.12**	1.13**	0.80**	1.11**
HBCU	0.66**	0.90**	0.94**	0.76**	1.01	0.83**	0.89**	0.77**
Predominantly Black institution	0.86**	0.93	1.01	0.89**	0.96**	0.74**	0.59**	1.03**
Alaskan-Native or Native Hawaiian-serving institution	1.05	1.11	1.24**	0.92**	0.96	0.88**	1.47**	1.10**
Asian Amer. and Nat. Amer. Pac. Isl.-Serving institution	0.99	1.07**	1.02**	0.95**	1.05**	1.08**	0.79**	1.00
Hispanic-serving institution	0.97**	1.03	1.06**	1.01*	1.04**	0.91**	0.74**	0.98**
Native American non-tribal institution	0.92*	1.01	0.96	1.02	0.93	1.00	1.02	1.19**
Women's college	0.86**	0.87**	1.33**	0.75**	0.96**	1.08**	0.75**	0.90**

Notes: Results show coefficient estimates (relative risk ratios) from a single multinomial logistic regression model where the base category is not choosing any of the 7 listed career options. $^{*}p < 0.01$, $^{**}p < 0.001$

Appendix A
Additional Tables and Figures

Table A1

Common App Descriptive Statistics By Year

	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Panel A: Members												
Control × Carnegie classification												
Public, Doctoral colleges/universities	0.07	0.07	0.07	0.08	0.10	0.11	0.12	0.13	0.13	0.13	0.13	0.13
Private, Doctoral colleges/universities	0.13	0.12	0.12	0.11	0.10	0.10	0.09	0.09	0.08	0.08	0.07	0.07
Public, Masters colleges/universities	0.06	0.06	0.06	0.06	0.06	0.07	0.08	0.08	0.10	0.11	0.12	0.13
Private, Masters colleges/universities	0.26	0.26	0.25	0.25	0.25	0.24	0.24	0.25	0.24	0.24	0.24	0.23
Public, Baccalaureate colleges/universities	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.03	0.03
Private, Baccalaureate colleges/universities	0.37	0.37	0.35	0.34	0.32	0.31	0.31	0.30	0.30	0.30	0.29	0.29
Public, Other	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02
Private, Other	0.10	0.10	0.11	0.13	0.14	0.13	0.12	0.11	0.11	0.09	0.09	0.09
Admissions rate	0.58	0.59	0.61	0.60	0.61	0.62	0.63	0.65	0.67	0.69	0.68	0.69
Minority-Serving Institution	0.10	0.10	0.12	0.12	0.13	0.12	0.12	0.13	0.14	0.16	0.17	0.17
Enrollment total, 1000s	6.25	6.15	6.37	6.71	7.04	7.40	7.60	7.85	7.89	8.06	8.02	7.99
Graduation rate	0.69	0.68	0.67	0.66	0.66	0.66	0.66	0.66	0.64	0.64	0.63	0.62
Mean SAT score	1208	1202	1191	1185	1183	1180	1176	1173	1166	1162	1158	1156
Median ACT score	26.4	26.2	25.9	25.7	25.6	25.4	25.2	25.1	24.9	24.7	24.6	24.5
Panel B: Applicants												
Male	0.45	0.45	0.44	0.44	0.44	0.44	0.44	0.43	0.43	0.44	0.44	0.44
First-generation	0.31	0.32	0.33	0.32	0.32	0.32	0.32	0.31	0.34	0.36	0.35	0.38
Fee waiver eligible	0.22	0.23	0.24	0.25	0.26	0.27	0.27	0.25	0.26	0.32	0.34	0.36
Race/ethnicity												
Missing	0.03	0.05	0.05	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03
American Indian or Alaska Native	0.003	0.003	0.003	0.003	0.002	0.003	0.002	0.002	0.002	0.003	0.003	0.003
Asian	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.11	0.10	0.10
Black or African American	0.09	0.10	0.11	0.11	0.12	0.12	0.12	0.12	0.13	0.13	0.14	0.15
Latino	0.13	0.14	0.14	0.15	0.15	0.16	0.17	0.17	0.17	0.19	0.20	0.21
Native Hawaiian or other Pacific Islander	0.002	0.002	0.002	0.002	0.002	0.001	0.001	0.002	0.002	0.002	0.001	0.001
Two or More Races	0.04	0.04	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
White	0.59	0.57	0.56	0.55	0.54	0.53	0.52	0.52	0.51	0.49	0.47	0.45
Region												
Midwest	0.18	0.18	0.18	0.20	0.21	0.20	0.20	0.20	0.20	0.20	0.20	0.19
Northeast	0.40	0.40	0.39	0.38	0.36	0.35	0.34	0.32	0.31	0.29	0.28	0.27
South	0.24	0.24	0.26	0.26	0.27	0.28	0.30	0.32	0.32	0.34	0.36	0.38
West	0.18	0.18	0.17	0.16	0.16	0.17	0.16	0.17	0.16	0.17	0.16	0.15
Application Selectivity												
Least selective	0.11	0.12	0.14	0.16	0.17	0.18	0.20	0.18	0.21	0.24	0.26	0.28
2nd	0.15	0.16	0.17	0.18	0.19	0.22	0.23	0.21	0.21	0.21	0.22	0.22
3rd	0.21	0.21	0.20	0.21	0.20	0.21	0.20	0.20	0.20	0.19	0.19	0.18
4th	0.21	0.21	0.21	0.20	0.20	0.19	0.19	0.21	0.21	0.20	0.20	0.20
Most selective	0.32	0.30	0.28	0.25	0.24	0.21	0.19	0.19	0.17	0.15	0.14	0.13
High School Region												
City	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33
Suburb	0.53	0.53	0.52	0.52	0.51	0.51	0.51	0.51	0.51	0.50	0.50	0.49
Town	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Rural	0.10	0.10	0.10	0.11	0.11	0.11	0.11	0.11	0.12	0.12	0.12	0.13
N Members	501	523	590	653	710	760	817	855	919	971	1014	1048
N Applicants	646230	691303	753999	810543	874779	925482	962095	1043532	1111644	1186781	1255692	1326464

Notes: Table shows descriptive statistics for Common App members (Panel A) and applicants (Panel B) from 2014 to 2023. Variable means are provided. Control × Carnegie Classification does not sum to one because "Missing" and "Other" categories are excluded from the table. Applicant category does not sum to one because "Other" category is excluded from the table.

Table A2

Actual Career Interests Among Applicants With Low Predicted Probability of Interest in Teaching

	Bottom 50%		
	2015	2020	2025
Other	8.5	10.4	13.0
Undecided	13.6	12.2	9.7
Nurse	1.4	2.0	2.9
Teacher	1.4	1.3	1.1
Therapist	1.8	1.8	2.1
Business executive	10.4	10.0	10.1
Psychologist	1.3	1.5	1.4
Artist	1.0	1.2	1.0
Doctor	11.0	9.3	7.2
Writer/Journalist	2.4	1.7	1.1
Veterinarian	0.7	0.7	0.8
Social worker	0.3	0.3	0.3
Scientist	4.7	4.3	3.3
Lawyer	3.6	4.1	4.6
Law enforcement	0.6	0.7	0.5
Accountant	1.9	1.7	2.1
Business owner	2.9	3.6	4.7
Engineer	17.0	14.9	16.2
Pharmacist	1.1	0.7	0.7
Actor	1.1	1.1	0.8
Musician	1.1	1.2	0.9
Dietitian	0.1	0.1	0.1
Dentist	0.9	0.9	1.3
Sales	0.4	0.6	0.9
Interior decorator	0.0	0.1	0.1
Clerical	0.4	0.8	1.1
School counselor	0.1	0.1	0.0
Architect	0.9	1.3	1.6
Computer programmer	4.7	6.8	6.4
Government	1.7	2.0	1.3
Foreign service	1.3	0.9	0.5
Conservationist	0.2	0.2	0.2
Lab technician	0.1	0.1	0.1
College teacher	0.6	0.5	0.4
Optometrist	0.2	0.1	0.1
Military	0.7	0.6	0.6
Skilled trades	0.1	0.1	0.3
Chef	0.0	0.1	0.2
Hospitality	0.0	0.1	0.1

Notes: Table plots the frequency (percentage) of applicants in an application season (columns) who choose a particular career interest response (rows). The subgroups (top 10% and remaining 50%) are determined by the predicted probability of teaching interest based on coefficients from a model predicting a binary indicator of interest in teaching as a function of applicant characteristics using the 2015 sample. This model is used to make an out-of-sample prediction for 2020 and 2025 applicants.

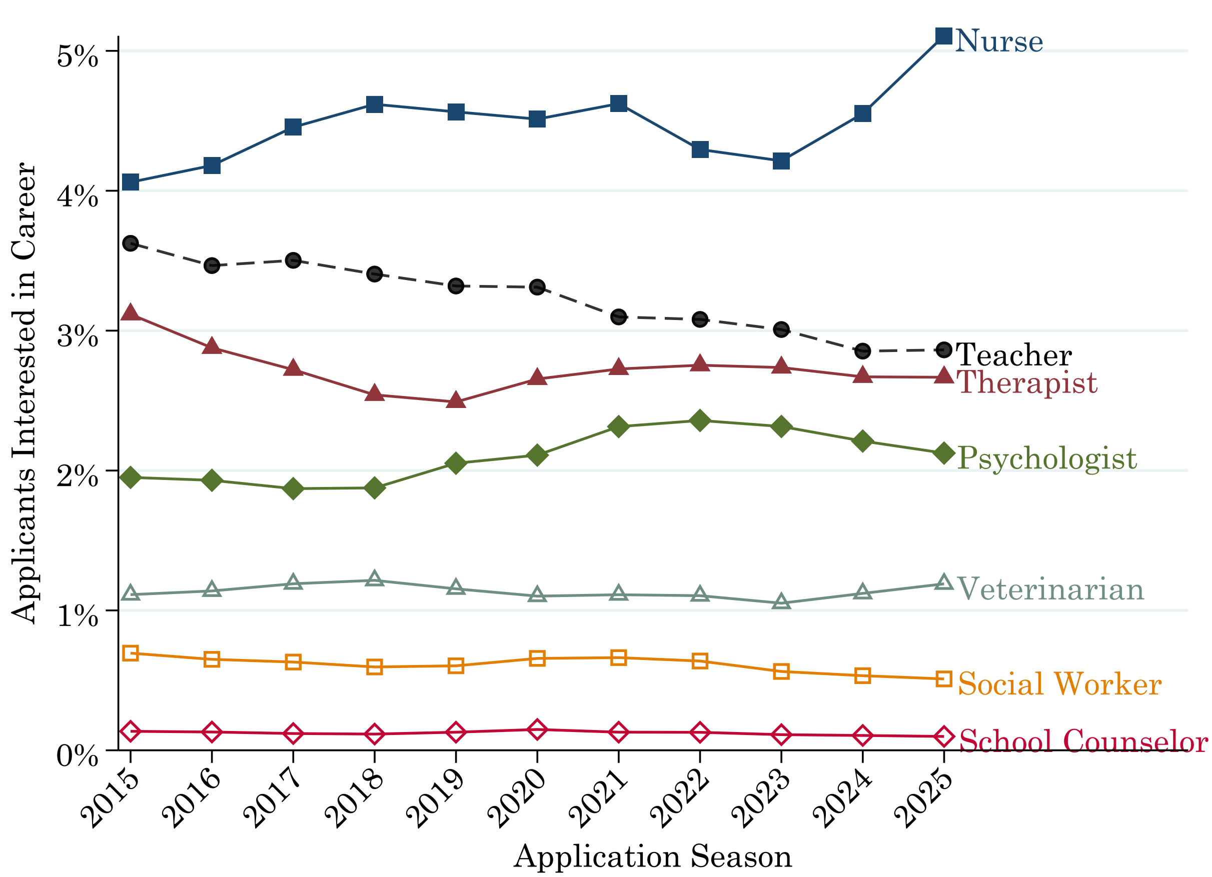


Figure A1

Interest in Teaching and Similar Careers by Application Season

Note: Figure plots the percentage of applicants choosing a particular career interest by application season. We omit 2014 because it used a different set of career interests. K–12 teacher and similar careers are shown. See the main text for a description of how similar careers were chosen. To account for the changing composition of applicants over time, we employ weights generated from coarsened exact matching. See Appendix C for details on this procedure.

Appendix B
Construction of Similarity Indices

Figure 2 plots the similarity of careers to K–12 teaching across three dimensions: academics, demographics, and teacher ratings. To construct these indices, we consolidate coefficient estimates from multinomial logistic regression models that predict interest in teaching, interest in a given career j, and interest in any career that is not teaching or career j as a function of applicant characteristics and ratings from teacher-recommenders. We iterate over this multinomial logistic regression model for all 34 career options (not including teaching). While one could theoretically estimate a single model that yields coefficients for all careers at once, this approach is not computationally feasible.

Each of these 34 multinomial logistic regression models yields two vectors of coefficients for teaching and career j, respectively. Our measure reflects how similar these vectors are to one another. Conceptually, if the vector of coefficients for choosing teaching and career j are similar, that indicates that similar students are choosing these careers, and vice-versa if the vectors are different. To compute similarity, we rely on euclidean distance:

$$Sim_{i,j} = \sqrt{(\beta_1^i - \beta_1^j)^2 + (\beta_2^i - \beta_2^j)^2 + ... + (\beta_n^i - \beta_n^j)^2} \quad \text{(B1)}$$

where $(\beta^i - \beta^j)^2$ is the squared difference between a particular regression coefficient (e.g., coefficient for male student) for teaching (i) and career j. The euclidean distance combines multiple coefficients into a single (dis)similarity measure, where a smaller distance indicates greater similarity. We compute this distance for three sets of coefficients: applicant demographics (gender, race/ethnicity, fee waiver eligibility, quintile of median household income of zip code), academic characteristics (GPA quintile, SAT composite score, application selectivity quintile, number of applications submitted), and teacher-recommender ratings.

An important practical consideration is how to assign weights to the coefficients that form the similarity indices. For example, consider the vector of coefficients for race/ethnicity, where white is the base category. Without explicit weights, the squared difference for all of the racial/ethnic groups' coefficients contribute equally to the euclidean distance, despite the fact that some of the groups are very small. Instead, we want our similarity measure to reflect more heavily differences in coefficients for variables that have a larger variance. By similar logic, we need to account for the fact that variables with multiple categories will have multiple coefficients (thus contributing more heavily to the euclidean distance), whereas a binary or continuous variable will have just one coefficient (thus contributing less). Thus, we take a two step approach prior to computing the euclidean distance. First, we assign weights ex ante to the variables that form a particular measure. These weights are ultimately arbitrary and reflect our best judgment about how to determine the relative importance of measures that form an index. Second, for variables with multiple categories we reweight the coefficients such that the total sums to one (which is then multiplied by the weight decided in step one) and small categories receive less weight. We accomplish the latter by pre-multiplying the coefficients by the product of their mean and standard deviation, then rescaling by a common factor such that the variables sum to one. The weight of each variable forming our indices are shown in Table B1. The weight column shows how we chose to combine different measures into particular index (e.g., demographics). The subweight column shows how categorical variables were weighted based on the adjustments for different group sizes described above.

Table B1
Weights for Similarity Indices

	Weight	Subweight
Demographics		
Gender	33.3%	
Race/ethnicity	33.3%	
American Indian or Alaska Native		.03%
Asian		7.3%
Black or African American		9.2%
Latino		14.3%
Native Hawaiian or Pacific Islander		.01%
Multiracial		2.5%
White (omitted group)		
First-gen	11.1%	
Fee-waiver eligible	11.1%	
Zip Code HH Income Quintile	11.1%	
Lowest		1.3%
2nd		1.9%
3rd		2.7%
4th		5.2%
Highest (omitted group)		
Academics		
SAT Score	50%	
Less than 1100 (omitted group)		
1100 to 1190		11.3%
1200 to 1290		12.7%
1300 to 1390		11.6%
1400 to 1490		9.3%
1500 to 1600		5.0%
High School GPA Quintile	50%	
Lowest		12.8%
2nd		12.9%
3rd (omitted group)		
4th		11.8%
Highest		12.6%
Teacher-recommender ratings		
All items (15 total)	6.7%	

The steps described above yield indices academic, demographic, and ratings indices for each of the 34 non-teaching career interests. We take a final step to normalize each of them on a 0–100 scale based on the range. To do this, we subtract each career's index value by the minimum value and then multiply it by 100 over the range. Table B2 shows the normalized index values for each career interest. These are the values plotted in Figure 2.

Table B2

Dissimilarity Indices (Relative to Teaching)

		Dissimilarity Index		
Career	Frequency	Demographics	Academics	Teacher Ratings
Undecided	0.13	21.9	44.7	13.2
Engineer	0.099	80.2	84.2	28.0
Business_executive	0.084	54.1	31.7	23.4
Doctor	0.070	24.6	78.5	24.2
Nurse	0.058	28.6	5.2	17.7
Computer_programmer	0.044	92.2	70.2	33.7
Lawyer	0.037	19.8	53.9	31.2
Business_owner	0.035	64.2	17.0	24.4
Scientist/researcher	0.032	22.3	100.0	31.7
Therapist	0.031	5.5	4.3	12.9
Psychologist	0.022	13.0	26.5	14.6
Writer/journalist	0.018	10.6	41.0	56.9
Artist	0.018	11.7	5.7	100.0
Accountant	0.016	54.7	38.3	30.4
Veterinarian	0.013	14.8	25.1	16.0
Government	0.012	30.9	83.2	41.6
Dentist	0.012	21.1	25.8	23.8
Architect	0.012	41.4	30.6	25.7
Actor	0.011	18.3	20.7	66.5
Musician	0.010	48.2	28.8	49.5
Law_enforcement	0.0095	46.6	34.2	18.8
Clerical	0.0088	53.4	0.0	23.1
Pharmacist	0.0085	22.7	39.3	26.3
Sales	0.0073	51.5	7.6	25.5
Social_worker	0.0069	22.8	4.8	8.9
Foreign_service	0.0059	13.4	98.1	33.7
Military	0.0051	78.4	30.7	43.8
College_teacher	0.0037	29.4	85.5	49.1
Conservationist	0.0033	16.2	53.9	22.7
Interior_decorator	0.0030	51.5	22.4	32.0
Dietitian	0.0026	12.1	6.0	20.6
Lab_technician	0.0016	12.4	19.7	20.5
Optometrist	0.0015	15.3	36.4	23.8
Skilled_trades	0.0015	100.0	22.0	20.6
Chef	0.0014	37.1	25.6	17.0
Hospitality	0.0014	0.0	5.2	7.6
School_counselor	0.0013	6.9	13.2	0.0

Appendix C
Examining Teaching Interest Over Time

Several prior studies document changes in teaching interest over time, particularly among college students. The past 10 to 15 years, in particular, have shown a decline in teaching interest, suggesting that the health of the teaching profession is at historical lows. Our ten-year panel allows us to replicate these patterns using a large and diverse sample. However, we face two empirical challenges, both stemming from sampling bias: students submitting college applications through the Common App are not a random sample of the college-intending population. First, in any given year the Common App sample likely understates the level of interest in K–12 teaching nationally because Common App members are more likely to be selective institutions and students applying to selective institutions are less likely to be interested in teaching. Second, the Common App added many new member institutions over the study period and these members are less selective (relative to older members), on average, such that the applicant sample likely includes an increasing share of students who are interested in teaching. This second dimension is particularly important because observed changes over time in teaching interest in our sample may conflate the actual change in teaching interest in the population with compositional changes in our sample.

To address this latter form of sampling bias, we construct a consistent sample of Common App applicants across the study period (2014–2025) using a coarsened exact matching (CEM) approach (Iacus et al., 2012). Intuitively, we take the first application season as our target sample and reweight each of the 2015–2025 seasons to match the characteristics of 2014. Our choice to reweight towards 2014 (as opposed to 2025, for example) stems from our belief that the growth in the Common App sample over time is primarily characterized by entry of new types of applicants for whom there may not be good "matches" in early seasons. That is, we believe that common support holds when reweighting later seasons to 2014 but is less plausible when reweighting earlier seasons to later seasons. By narrowing the sample, however, this decision does potentially limit generalizability.

The CEM algorithm follows the same fundamental logic as other matching approaches, such as propensity score matching. However, it ensures balance by restricting the matched sample to strata where both "treatment" (in this case, being in the 2014 season) and comparison units exist. Here, we define strata by the intersection of the following applicant characteristics: gender, race/ethnicity, Common App fee waiver eligible, quintile of high school GPA, high school state/territory, and high school locale type.[13] We also include a measure capturing the portfolio of institutions to which an applicant submits applications. To construct this measure, we first run principal components analysis on the full roster of Common App members for the following institutional characteristics: admit rate, public institution, graduation rate, and average SAT score of enrolled students.[14] We then use the first principal component to rank institutions by selectivity, then determine

[13] We don't use SAT or ACT scores here because of the substantial decrease in reporting (i.e., increase in missingness) among applicants over time.

[14] We run this PCA using 2025 data for all institutions.

the median rank within each applicant (e.g., we use the third institution's rank if an applicant submitted five total applications). Finally, we generate a quintile measure of median application rank across all unique applicants (pooling all seasons).

We run the CEM algorithm for each non-2014 application season. Defined by the variables above, there are between 80,000–100,000 total strata per season, with roughly 45,000 matched strata.[15] We are able to obtain matches for approximately 95% of the 2014 applicant pool. The matched samples include 95% of the 2015 applicant pool and steadily declining to 86% of the 2025 applicant pool, reflecting that new types of applicants are entering the Common App sample over time. Our matching procedure yields a set of matched samples between 2014 and each other respective season, for a total of 11 sets of matched samples. By construction, there is perfect balance on the matched variables in each of these sets. However, because 2014 is matched in each set, there is a practical matter of how to generate a single weight for applicants in the 2014 season. For example, if an applicant in the 2014 season has a match in 2015 but not 2016, they would receive different weights for these two matched samples. For our analysis, we simply use the proportion of times the applicant is matched across the 11 matched samples as their final analytic weight. The mean of this weight is 0.954. Table C1 shows the balance on observables for each application season using the matched samples with the final analytic weight for 2014.

Figure C1 shows the yearly percentage of applicants interested in K–12 teaching with the unweighted and weighted samples. Consistent with our expectations, we observe that the unweighted sample yields a smaller decrease in interest over time because of the compositional shift towards applicants applying to less selective institutions (who tend to have greater teaching interest). Once we obtain a "stable" sample using the CEM weights, we observe a consistent decline over time in teaching interest.

Figure C2 disaggregates this trend by various subgroups, including application selectivity (panel a), race/ethnicity (panel b), high school locale (panel c), and high school region (panel c). These results use the same CEM weights. Note that because these variables are part of the CEM process, balance holds within each of the subgroups. For example, within the Q1 selectivity subgroup, the share of students from city high schools is consistent across application years. As discussed in the main text, Figure C2 shows no evidence that the decline in teaching interest is driven by particular subgroups despite large differences in the *levels* of teaching interest among these subgroups.

[15] The theoretical number of strata is 241,920, based on the possible unique combinations of the included variables. However, most of these combinations have no observed applicants.

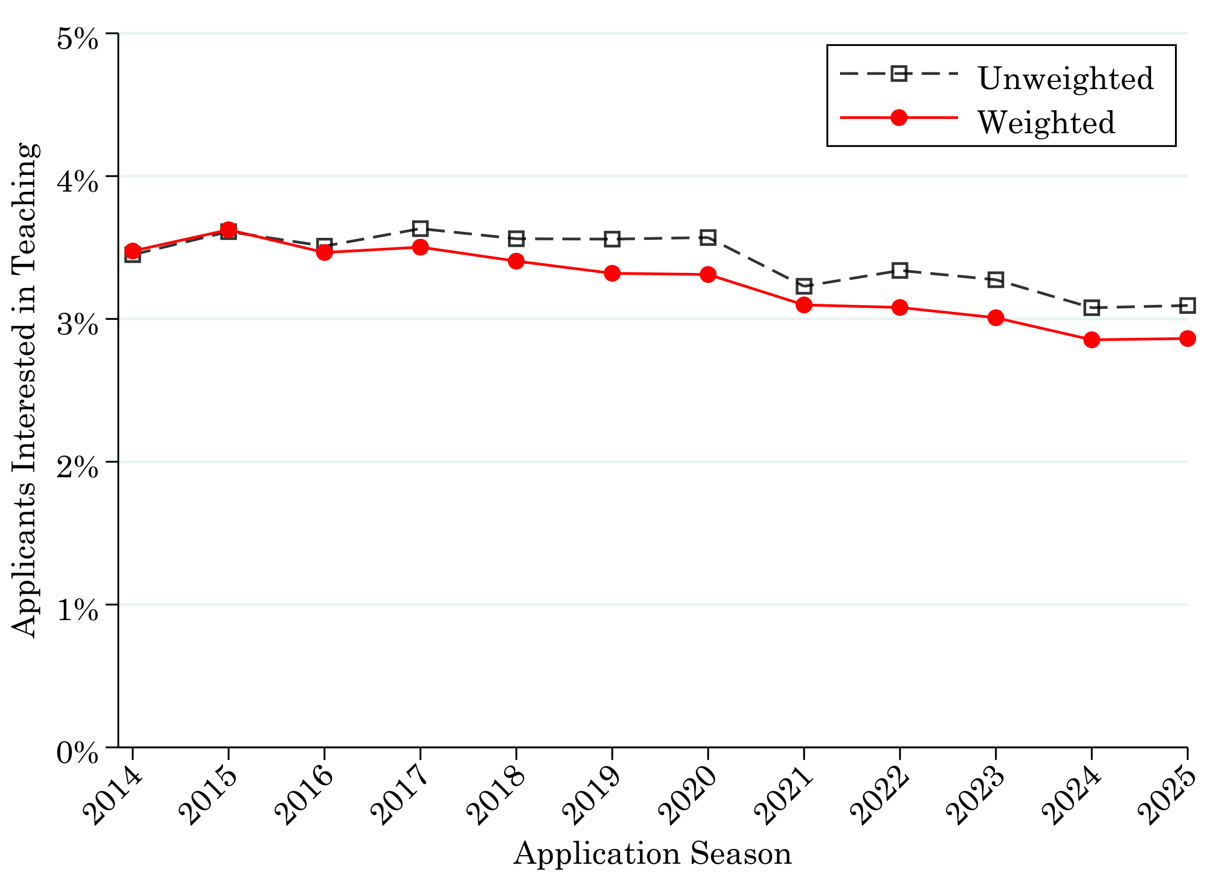


Figure C1

Interest in Teaching Over Time

Note: Figure displays the mean interest in teaching over time. The x-axis represents the application year, while the y-axis shows the proportion of applicants interested in teaching. The blue line corresponds to unweighted data, whereas the red line corresponds to data where applicants in years 2015 to 2023 are weighted to have observable characteristics that match applicants in 2014 using coarsened exact matching (CEM). See Table C1 for results of CEM exercise.

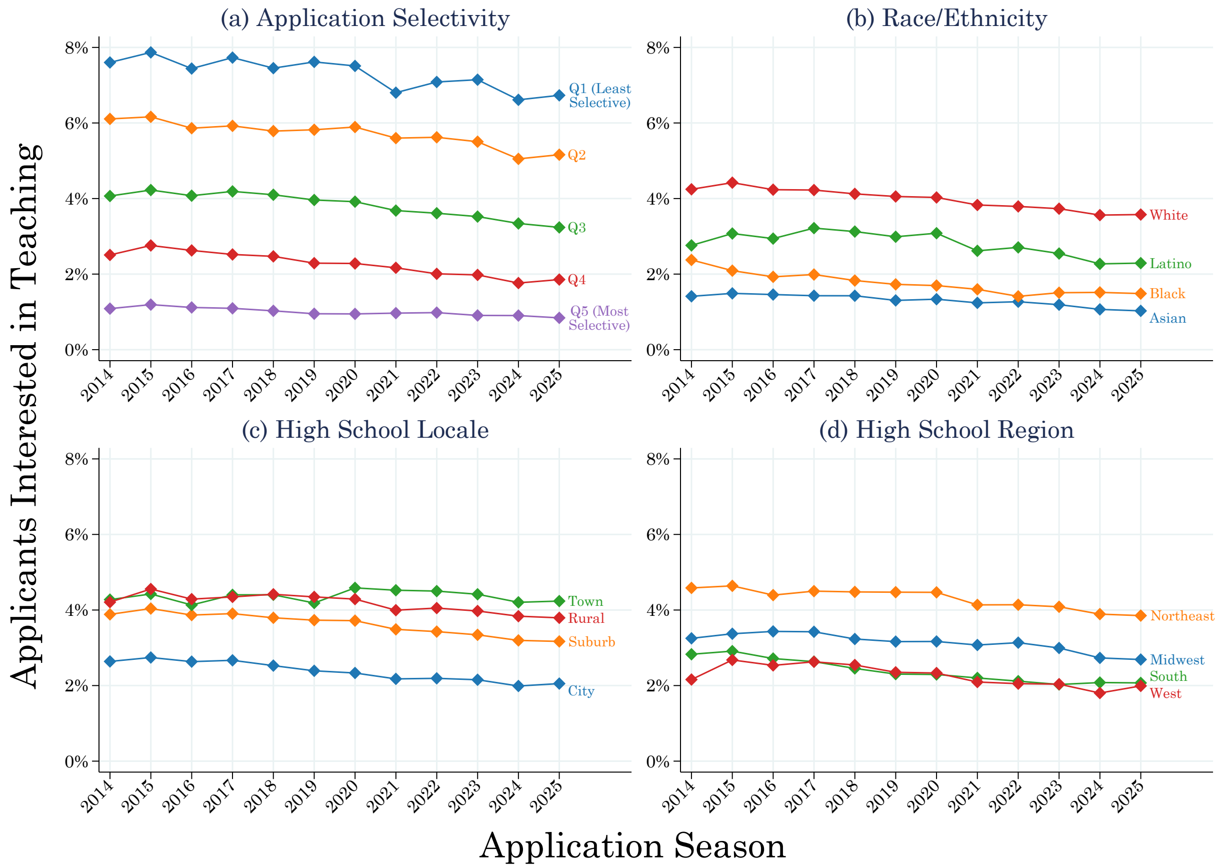


Figure C2

Interest in Teaching Over Time by Subgroups

Note: Figure displays the mean interest in teaching over time. The x-axis represents the application year, while the y-axis shows the proportion of applicants interested in teaching. The blue line corresponds to unweighted data, whereas the red line corresponds to data where applicants in years 2015 to 2023 are weighted to have observable characteristics that match applicants in 2014 using coarsened exact matching (CEM). See Table C1 for results of CEM exercise.

Table C1

Checking Balance After Applying Coarsened Exact Matching Weights

	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Male	0.00	0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Race/ethnicity											
Unknown	-0.00	-0.01*	-0.01	-0.00	-0.01	-0.00	-0.00	0.00	0.01	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
American Indian or Alaska Native	-0.04**	-0.04**	-0.03*	-0.00	-0.01	0.03	0.02	0.01	0.01	-0.03*	-0.03*
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Asian	0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Black or African American	0.00	0.00	0.00	-0.00	0.00	0.00	-0.00	-0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Latinx	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Nat Haw or Pac Isl	-0.01	-0.02	-0.01	-0.03	-0.03	0.00	-0.01	-0.01	0.01	-0.01	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Two or More Races	0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fee waiver eligible	-0.00**	-0.00**	-0.00***	-0.00***	-0.00***	-0.00*	-0.00*	-0.00	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GPA Quintile											
1st	-0.00*	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.00	0.00*	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
2nd	-0.00**	-0.00*	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
3rd	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
5th	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Missing	-0.01***	-0.01**	-0.00**	-0.01**	-0.00*	0.00	0.00	0.00*	0.00*	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
App. Portfolio Difficultly Quintile											
1st	0.00	0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.04***	-0.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
3rd	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.00	0.00	0.00*	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
4th	-0.00*	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.00	0.00	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
5th	-0.01***	-0.00**	-0.00*	-0.00	0.00	0.00	0.00	0.00*	0.01**	-0.04***	-0.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	691303	753999	810543	874779	925482	962095	1043532	1111644	1186781	1255692	1326464
Matched %	95.4	95.0	94.2	93.3	92.1	90.8	90.1	89.2	87.3	86.9	85.9
R^2	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.001	0.001	0.003	0.003

Notes: Heteroskedasticity-robust standard errors shown in parentheses. Each column presents results from an OLS regression where the dependent variable equals 1 if an applicant submitted a Common App application in 2014 and 0 if they submitted in the year shown in the column header. Coarsened exact matching weights are used for comparison year applicants, while 2014 applicant weights equal the proportion of comparison years in which they were successfully matched. Matched % shows the percentage of comparison year applicants matched to 2014 applicants, and N shows the total number of applicants in each comparison year.

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$