THE DETERMINANTS OF MISMATCH BETWEEN STUDENTS AND COLLEGES

Eleanor Wiske Dillon
Jeffrey Andrew Smith

The Determinants of Mismatch Between Students and Colleges
Eleanor Wiske Dillon and Jeffrey Andrew Smith
NBER Working Paper No. 19286
August 2013
JEL No. I23,I24

ABSTRACT

We use the National Longitudinal Survey of Youth 1997 cohort to examine mismatch between student ability and college quality. Mismatch has implications for the design of state higher education systems and for student aid policy. The data indicate substantial amounts of both undermatch (high ability students at low quality colleges) and overmatch (low ability students at high quality colleges). Student application and enrollment decisions, rather than college admission decisions, drive most mismatch. Financial constraints, information, and the public college options facing each student all affect the probability of mismatch. More informed students attend higher quality colleges, even when doing so involves overmatching.

Eleanor Wiske Dillon
Department of Economics
W.P. Carey School of Business
Arizona State University
501 E. Orange Street
Tempe, AZ 85287-9801
ewdillon@asu.edu

Jeffrey Andrew Smith
Department of Economics
University of Michigan
238 Lorch Hall
611 Tappan Street
Ann Arbor, MI 48109-1220
and NBER
econjeff@umich.edu

An online appendix is available at:
http://www.nber.org/data-appendix/w19286

I. Introduction

Students graduating high school in the U.S. can choose to apply to and enroll in a wide variety of colleges. In this paper, we investigate how students of varying abilities sort into colleges of different qualities, with a particular focus on high ability students who choose to attend relatively low quality colleges and low ability students who attend relatively high quality colleges. The literature refers to these choices as "undermatch" (think "underachiever") and "overmatch" (think "overachiever"), respectively. While we follow the literature in using the normatively loaded language of mismatch, we do not take a stand here on the causal effects of mismatch. Instead, we empirically investigate the determinants of undermatch and overmatch using data on a recent cohort of college-goers, interpreting our results within the context of an informal economic model of college choice.

In our informal model, students face real tradeoffs between college quality and cost due to state tuition policies at public universities and price discrimination by private ones. They also worry about the potential benefits and costs of being a relatively weak, or relatively strong, student at their college. A strong student at a weak school may stand out and garner extra faculty attention, or she may exert less effort due to the bad study habits of her peers. A relatively weak student at a strong school may benefit from the extra resources and the strong peers, but may also find herself overwhelmed by the pace of instruction and the level of performance expected. Students also care about dimensions of the college experience other than academics, such as following their high school friends, attending the same school as their parents, or having a religious environment.

We study the sorting of students to colleges that results from students making these tradeoffs, given the information and financial resources available to them and to their families. These choices have important implications not only for

the students themselves but for the taxpayers who subsidize state universities and pay for federal and state student aid programs.

Our work builds on existing research on the extent and determinants of mismatch. Light and Strayer (2000, Table 4) and Black and Smith (2004, Table 4) document the empirical importance of both overmatching and undermatching in the earlier 1979 cohort of the National Longitudinal Survey of Youth. One line of work considers overmatching resulting from affirmative action, e.g. Arcidiacono, Aucejo and Spenner (2012), Bowen and Bok (1998) and Sander and Taylor (2012). Another line of work considers undermatching, focusing specifically on application behavior, as in Avery (2010), Griffith and Rothstein (2009), Howell (2011) and Pallais (2012), or the recruiting efforts of elite colleges, as in Hill and Winston (2010) and Hoxby and Avery (2012). Roderick et al. (2008) and Bowen, Chingos and McPherson (2009) focus on the entire process, including college completion. The literature broadly agrees on the empirical importance of both overmatching and undermatching, and that most mismatch results from where students apply and where they attend conditional on acceptance, rather than from rejection decisions by colleges. The literature does not agree on the effects, if any, of mismatch on academic and/or labor market outcomes.

Relative to the existing literature, we make several contributions. First, we study a nationally representative sample of college-goers from a relatively recent cohort using the data from the National Longitudinal Survey of Youth 1997 cohort (hereinafter NLSY97). The NLSY data have many advantages for our purposes, including a moderately large sample and a variety of useful covariates including student demographics, family background information and the Armed Services Vocational Aptitude Battery (ASVAB). The restricted use data allow us to match in contextual information on student's high schools, on the census tract in which they reside when making the college choice and on the state college system they face, as well as giving us data on what colleges they choose to attend.

Second, we use a different and arguably superior definition of mismatch relative to other studies. Our measure focuses on the difference between a student's percentile in the ability distribution, with ability defined based on her performance on the ASVAB tests, and the percentile of her college in the student-weighted distribution of our college quality index. Third, we separately analyze the determinants of undermatching and overmatching. Fourth, we look at both application choices (though in less detail) and at the first college attended. Fifth, we consider three distinct measures of academic mismatch.

Our approach yields several important findings. We find that substantial fractions of students are both undermatched and overmatched. Perhaps most surprising to us, student decisions drive mismatch in almost all cases. Most students who mismatch either do not apply to a well-matched school or apply and are admitted, but do not enroll. Some students appear to undermatch due to financial constraints, as the probability of undermatch depends on parental wealth. However, many of the factors we examine affect the quality of the college a student attends regardless of her ability, rather than affecting mismatch. Students from the wealthiest families, from neighborhoods where many adults have college degrees, and from high schools where many students go on to college are less likely to be undermatched but also more likely to be overmatched. This suggests that more informed students think that the benefits of improved college quality associated with overmatch overshadow any negative effects. Finally, features of the state university system facing the student affect the probability of mismatch. In particular, having a well-matched public university within 50 miles decreases the probability of both types of mismatch.

The remainder of the paper unfolds as follows: In the next section we outline an informal model of how students and their families decide which colleges to attend. Section III describes our data and Section IV describes our

measures of student ability, college quality and mismatch. Sections V and VI present our empirical findings and Section VII concludes.

II. College choice and college mismatch

This section provides the informal theoretical framework within which we interpret our results. Our informal model draws most heavily on the formal models in Light and Strayer (2000), Arcidiacono (2004) and Stinebrickner and Stinebrickner (2012).

In reality, the process by which students are sorted into schools has several stages and involves choices by both the student and the school. The student first decides which colleges to apply to, then the colleges decide which students to admit, and finally the student chooses among her offers of admission. Students then enroll in their chosen college, learn more about their fit with that college, and may decide to transfer to a different college or to drop out altogether. Our discussion and empirical work implicitly collapse the first three stages into a single choice by the student; we argue in Section V that the data support this simplification.

We assume rational and forward-looking college applicants. Even among such applicants, we expect some students to end up at colleges that do not match their abilities for a variety of reasons, including information constraints, financial constraints, and social considerations, such as where their high school friends choose to attend. Lack of information on the part of either the student or the school could increase the probability of both types of mismatch. The student may not have complete information about the quality of different colleges, or about how her abilities compare with other college applicants. We expect that, on average, students with more educated parents, from better educated and better off neighborhoods, and who attend high schools where more students enroll in a 4-year college will have better information to guide their college choices.

If informed students prefer colleges at which they are well-matched then access to information should lower the probability of mismatching in either direction. However, students may believe, perhaps correctly, that the positive effects of a higher quality college outweigh any effects of overmatching or that the positive effects of being a big fish in a small pond outweigh any negative effects of undermatching. In this case, students with better information about college may be more likely to mismatch in whichever direction they perceive as optimal. In contrast, in the spirit of Manski (1989), relatively uninformed students might try out a college for which they are undermatched or overmatched partly in order to learn about their optimal match.

A student's application may be a poor signal of her actual ability for two reasons. It may randomly misstate her ability if, for example, she had a particularly good or bad day on the SAT. Students may also attempt to strategically misstate their ability with the help of SAT tutors and pricey admissions consultants. If a college misinterprets the student's ability it may admit her to a school for which she is ill-prepared or reject her from a school that would suit her.

In a basic framework where students make (what they perceive to be) the best college match they can subject to their (and their family's) budget, financial constraints will tend to push students toward schools for which they are undermatched, because more elite schools tend to be more expensive. In practice, for strong students from low-income families the extra cost of a top school is largely offset by financial aid, but students do not know their aid offers with certainty when they are applying for schools (e.g. Avery and Turner, 2009). Financially constrained students may also choose a nearby college to reduce travel costs or avoid the cost of living away from home. Again, this will tend to increase undermatching more than overmatching because the students have an incentive to attend a closer school even if they are undermatched for it, but

schools generally have no incentive to accept weaker students just because they live nearby.

Features of the state university system can also generate mismatch in either direction. Most state colleges offer discounted tuition to state residents, making them (often quite substantially) less expensive than other options. We expect students to trade off lower price for match quality at the margin, increasing the probability of mismatch for students who have no well-matched college within their state university system. Because some state colleges are required to have different admission thresholds for in-state students, students who constrain themselves to the state system may end up either overmatched or undermatched.

Finally, students may appear mismatched with their college because they based their choice on other factors. Students may choose a college that is good for their major, for example engineering or art, even if it appears to be a poor match on overall quality. Students may be recruited to colleges based on skills, such as athletics or music, not included in our measure of ability. Students may choose to go to the college that their friends plan to attend, or their parents attended, or whose football team they like, or that provides a desired religious environment. We do not observe these types of skills and preferences in our data, so we will code the student as mismatched, even though she may have matched well in a broader sense.

III. Data

We use the National Longitudinal Survey of Youth 1997 Cohort (NLSY97) data, which samples the population of Americans born between 1980 and 1984. The first interview was in 1997 with follow-up interviews each year since. The majority of the sample graduated high school and made their college choice between 1999 and 2002. 87 percent of the un-weighted sample graduated high school or got a GED. Of these high school graduates, 38 percent started at a four-

year college after high school. We focus on students who start at a 4-year college but also present analyses pooling 2-year and 4-year college starters. Appendix Table 1 lists our sample restrictions and the associated sample losses. The NLSY97 sample includes both a representative cross-section and an over-sample of black and Hispanic youths. We combine these samples in our analyses. We use probability of inclusion (in the overall NLSY97 sample) weights, constructed by the NLSY, to combine the two samples, and also to control for differing sampling and response rates in different regions of the U.S. and by age, gender, race-ethnicity groups.

One of the main strengths of the NLSY97 data lies in the rich set of individual and family covariates it provides. Using the restricted access geocode data provides additional information on the identities of colleges attended and allows the use of contextual information based on the respondent's residential location. Appendix Table 2 defines the variables we use in our analysis, which also include some variables from the double-secret high school survey data, which can be accessed only at the Bureau of Labor Statistics offices in Washington, DC.

Many of the variables we use have modest amounts of item non-response. Rather than do listwise deletion of observations when an independent variable is missing, which would cumulatively result in massive sample loss, we recode missing values to zero and include an indicator variable for missing values in our multivariate analyses.

We mostly use standard variables and variable definitions that do not require additional discussion here. Exceptions are the constructed ability, college quality and mismatch variables considered in detail in the next section, and the NLSY97 measures of family income and wealth. The NLSY measures these variables at a single point in time, namely the 1997 interview. As a result, they get measured at different ages for different respondents. In addition, they include only income and wealth for the household in which the respondent resides. Thus, they

will miss parental income and wealth entirely for older respondents with their own households as well as the income and wealth of the non-custodial spouse in the case of parental divorce. Even without these issues, our ideal measures would include the stock of wealth available at the time of the college choice as well as expected future income and wealth. The available measures fall well short of this ideal, which has implications for how we interpret the estimates from these variables in our multivariate analysis.

IV. Student ability, college quality, and mismatch

1. Ability

Our primary measure of student ability is the Armed Forces Vocational Aptitude Battery (ASVAB). The ASVAB is designed for applicants to the U.S. military and was taken by most of the NLSY97 respondents as part of a norming exercise. NLSY respondents took the ASVAB during the first wave of the survey in 1997 and those who took the test were paid $75 for their time. 78% of the sample, and 84% of respondents who started at a 4-year college, completed all portions of the test.

The ASVAB has twelve components, covering both the sorts of skills measured by the SAT such as algebra, geometry, vocabulary, and reading comprehension and other skills such as electronics knowledge and spatial reasoning. The ASVAB is a computer adaptive test, meaning that the difficulty of the questions asked in the latter part of each section of the test depends on how well respondents do on the initial questions in the section. The score for each section reported by the NLSY depends on both the number of questions answered correctly and the difficulty of those questions as estimated from an earlier sample of test takers. The ASVAB offers a somewhat richer measure of ability than the SAT or ACT score, and should be less influenced by variation in preparation

because there was nothing riding on this test for the NLSY participants.[1] The ASVAB score also has the useful feature that colleges do not observe it. We can therefore capture some of the college mismatch generated by colleges having incomplete information.

When survey participants took the ASVAB, they ranged in age from 12 to 18, younger than most of the larger population taking the test. We adjust the scores for age at testing and then take the first principal component of the 12 section scores as our primary measure of ability, which we call ASVAB1. We calculate each respondent's percentile within the sample distribution of college-bound NLSY97 respondents, weighted by their probability of inclusion in the survey.

As shown in Appendix Table 3, the first principal component explains 60% of the total variance in test scores across the 12 sections. The first component places the highest weight on subjects like those on the SAT (or ACT): arithmetic, word knowledge, and paragraph comprehension. Not surprisingly giving the loadings, the correlation between ASVAB1 and the respondent's SAT or ACT score equals 0.81.

The second component, which we call ASVAB2, explains a further 11% of the variance. It places the most weight on the two timed sections of the test: numerical operations and coding speed. Cawley, Heckman, and Vytacil (2001) find that the first two principal components of the ASVAB score both predict later earnings in the NLSY 1979 sample. To construct our measure of mismatch, for which we need a single measure of ability, we use only ASVAB1. However, we include ASVAB2 as an additional variable in our multivariate analyses.

[1] The ASVAB test is not a straightforward measure of "innate" ability because it includes the influences and training that the student has had up to the point she takes the test. See Neal and Johnson (1996) for a more thorough discussion of what the ASVAB test is measuring. We do not mind if the ASVAB also measures intrinsic motivation, as argued by Segal (2012). More broadly, we use the term "ability" quite agnostically to mean the set of skills, innate or otherwise, that students possess around the time of the college choice.

While we prefer our ASVAB-based ability measure to the SAT or ACT scores commonly relied on in the literature, it remains an imperfect measure of ability. Although the ASVAB tests a richer variety of skills than most standardized tests it still does not capture all the abilities that make for a strong college student. Even if it did attempt to measure all relevant abilities, the score from a single ASVAB test would be an imperfect measure of ability because some students will perform above or below their usual level on any given day.

2. College quality

We construct a multifaceted index of college quality by combining measures related to selectivity and college resources. In particular, we combine data from the U.S. Department of Education's Integrated Post-Secondary Education Data System (IPEDS) and U.S. News and World Report, both from 2008.[2] The components of our college quality index are mean SAT score (or mean ACT score converted to the SAT scale) of entering students, percent of applicants rejected, the average salary of all faculty engaged in instruction, and the faculty-student ratio. Our faculty-student ratio includes only undergraduate students and faculty who do not teach exclusively in graduate or professional schools within universities. Most of the NLSY97 respondents started college between 1999 and 2002, somewhat earlier than our college quality measures. 2008 is the earliest year for which we could obtain US News data and the first year that IPEDS reported faculty-student ratios focused only on undergraduates. The other components of our college quality measure are quite stable between 2000 and

---

[2] US News and IPEDS collect many of the same statistics and for the same college in the same year the numbers are often identical. US News has average SAT or ACT scores for the students at a number of schools that do not report test scores to IPEDS. However, US News focuses on selective schools and excludes 2-year colleges altogether. Combining data from the two sources gives us the most complete sample of colleges. We use US News data to fill in average SAT and ACT scores and faculty/student ratios when these statistics are missing from IPEDS. Rejection rates and faculty salaries come only from IPEDS.

11

2008, so we feel the improved data available in 2008 outweigh the measurement error from observing college quality in a later year.

Following Black and Smith (2004), we use the first principal component across these four measures of quality as our quality index. Like Black and Smith (2006), we view our index as providing an estimate of latent college quality, which we view as continuous and one-dimensional. Within this framework, combining multiple proxies for college quality into a single index measures latent quality with less error than using a single proxy (such as the average SAT score of the entering class) or the categorical quality ratings (e.g. from Barron's) used in much of the literature. Our index corresponds well to a priori notions of relative quality. For example, taking one state at random, the University of Michigan lies at the 93rd percentile, Michigan State at the 74th, Wayne State at the 36th, and Eastern Michigan at the 28th. Appendix Table 4 presents the loadings. At the same time, our measure does not capture differences in the quality that different students experience within the same university due to, for example, quality difference across fields of study or participation in honors programs.

This 4-factor quality index is a good measure of the quality of at least somewhat selective 4-year colleges. However, some 4-year colleges and many 2-year colleges do not report the average SAT or ACT scores for their entering classes, often because they do not require these tests as part of their applications. Our baseline measure of college quality, which we only construct for colleges with all four quality measures, disproportionally misses less selective schools. To address this problem, we also construct an alternative 6-factor measure of college quality that includes an indicator for colleges that do not report SAT or ACT scores (setting the average SAT scores to zero for those schools). This alternative index also includes an indicator for admitting all applicants; that is, for having a rejection rate equal to zero. This 6-factor college quality measure is our baseline measure for our analysis combining 2-year and 4-year college starters. We

designed this measure to better capture college quality across both 2-year and 4-year colleges, but it also allows us to include students starting at 4-year schools that do not report SAT scores. Failure to report SAT scores and open admission policies both have negative weights in our college quality factor analysis, so these new schools are mostly in the lower part of the quality distribution.

3. Measuring mismatch

We employ three alternative measures of mismatch. Our primary measure of mismatch combines the student ability and college quality measures just described. We calculate the college's quality percentile across all four-year institutions in the United States included in the IPEDS, weighted by student body size.[3] Because we weight the quality percentile by student body size, a college in the nth percentile is the college that a student in the nth percentile of the ability distribution would attend if there were perfect assortative matching of students and colleges. We consider students mismatched when they deviate substantially from this type of matching. When considering both 2-year and 4-year college starters we calculate student ability percentiles across all 2- and 4-year starters in the NLSY97 sample and calculate weighted college quality percentiles using all 2-year and 4-year colleges in IPEDS and the 6-factor college quality measure.

In practice, substantial gaps between a student's ability percentile and her college's quality percentile are quite common. Table 1A gives the joint distribution of student ability and college quality, including only 4-year college starters. Students concentrate along the diagonal, which indicates a good match, but there are also many mismatched students. The three upper right cells, corresponding to high ability students at low quality colleges, account for 12.5% of the sample, while the three lower left cells, corresponding to low ability students at high quality colleges, account for 12.9%. A comparison of Table 1A

---

[3] Our measure of student body size is full-time equivalent undergraduates.

13

to Table 4 of Black and Smith (2004) reveals (perhaps surprisingly given the recent policy focus on mismatch) no dramatic changes in the joint distribution between the NLSY79 and NLSY97 cohorts.

In much of the following analysis we categorize students as overmatched, well-matched, or undermatched for their college based on the difference between their ability percentile and their college quality percentile. Figure 1 reveals an approximately normal distribution for this difference. We consider students to be undermatched or overmatched, as appropriate, if their percentile difference exceeds 20. These cutoffs assign about a quarter of the sample to each mismatch category. Using binary indicators for mismatch simplifies the analysis and presentation, but loses some information relative to directly studying the differences in the ability and college quality measures. Later on, we examine the sensitivity of our results to changes in the cutoff used to define the binary mismatch indicators.

We construct our second mismatch measure in the same way as the first, but using student SAT score as the measure of ability and the average SAT score of the entering class as the measure of college quality. This measure links us somewhat to the wider literature, which tends to focus on these specific variables (or on discretized versions of them). Table 1B presents the joint distribution using the SAT-based variables. This table reveals less extensive mismatch, as measured by the fraction in the six corner cells, presumably because colleges observe the student's SAT score directly but only observe proxies for ASVAB1.

Our third mismatch measure compares the student's SAT score to the inter-quartile range of SAT scores at the student's college. This measure captures, in a crude but important way, the notion that being a bit different from the average means something different at a college with a very heterogenous (in terms of ability) student body than it means at a college with a very homogenous student

body. To our knowledge, we are the first in this literature to consider variance in student ability in defining mismatch.

Other important studies in the literature, such as Roderick et al. (2008), Bowen et al. (2009), and Smith et al. (2012) create their measures of mismatch by making tables with student test score bins on one axis and college quality bins on the other. For each student test score bin, they then determine the highest quality bin with a high probability of admission. Students in the highest bin get labeled well-matched, with undermatch then defined by the distance (measured in bins) between the bin of the college the student actually enrolled in and the well-matched bin. Relative to these measures, our primary measure employs better (in the sense of less measurement error) measures of both college quality and ability. Our first two measures also have the feature that it is possible for everyone to be well-matched without violating institutional enrollment constraints. This is not the case with the other measures in the literature; for every student to be well-matched by those measures would require a vast expansion in the enrollment capacity of more selective schools. We think this is an unattractive feature. House (2013) surveys the literature on mismatch measures in (much) greater detail, and demonstrates by applying multiple measures to a common data set that the amount of mismatch varies widely depending on the particular measure adopted.

V. Understanding the college choice

1. Application and admission

The youngest members of the NLSY97 cohort, those born in 1983 and 1984, were asked an additional battery of questions around the time they finished high school about the set of colleges to which they applied and the admission decision from each school. Table 2 presents statistics based on these questions.

The top panel of Table 2 shows that just over 30% of students who ended up mismatched with their college had applied to at least one college with which

they would have been well-matched by our definition. Most of those students who applied were also accepted to one of those well-matched schools. The bottom panel reveals that, among students who ended up undermatched, 69% did not apply to any colleges with which they were well-matched. Only 8% applied to at least one well-matched school and were rejected. The remaining 23% of undermatched students were accepted to at least one school with which they were well-matched but chose to attend a college for which they were undermatched. Note that 8% represents an upper bound on the percentage of all students who end up undermatched due to college admissions decisions because even if these students had been admitted to a well-matched college some would still have chosen to go elsewhere. More broadly, these students could have applied to more colleges; the average undermatched student sends only two applications, slightly below the overall average in our sample. Overmatching is equally a consequence of student choices rather than college choices; only 4% of overmatched students applied to a well-matched school and were rejected.

In sum, mismatch overwhelmingly results from choices made by students and their families, not choices made by college admissions offices. This conclusion, though perhaps surprising, represents the standard view in the academic literature; see, e.g. Hoxby and Avery (2012), Griffith and Rothstein (2010), Avery and Turner (2009), and Roderick et al. (2008). It also justifies our framing of the choice as primarily one made by students in the informal model in Section II.

2. Univariate patterns

Tables 3 and 4 describe the characteristics of students and their families by the quality of college they attend and by their match category, respectively. We highlight only a few of the most important univariate patterns, saving most of our attention for the multivariate results to follow.

If unconstrained students (and college admissions officers) prefer to avoid either undermatch or overmatch, then we would expect Table 3 to reveal that variables correlated with student ability correlate positively with college quality. In the imperfect information version of that same world, we would expect to see that variables positively correlated with information quality have higher levels among well-matched students than among mismatched students (i.e. a hill-shaped pattern) in Table 4.

In fact, we find common patterns in the two tables for nearly every variable. Variables that positively correlate with college quality in Table 3 predict more overmatch and less undermatch in Table 4. For example, in Table 3, students attending the highest college quality quartile have more educated parents on average than those attending lower quality colleges. In Table 4, students who are overmatched for their college have more educated parents on average than students who are well-matched to their college, who in turn have more educated parents than students who end up undermatched for their college. Family wealth has a similarly monotone effect. Monotone patterns in Table 4 such as these indicate that these characteristics influence college quality rather than mismatch, a theme that will recur in the multivariate analysis in the next section.

We draw additional measures related to information and guidance from surveys of the high schools attended by the NLSY97 respondents. These measures have the advantage (when viewed as proxies for the quality of the student's information set) of a weaker (but not zero) correlation with family resources than parental education. We consider the share of teachers at the student's high school with advanced degrees and the shares of graduates from their high school (in the class of 1999) who went on to attend a 2-year college and who went on to attend a

4-year college.[4] All three variables have weak positive relationships with college quality.

VI. Multivariate analysis

We estimate separate probit models of undermatching and overmatching conditioning on demographics, multiple measures of ability, family background variables including parental education and family wealth, contextual variables related to the census region or tract in which the student finished high school, variables related to the state university system and variables related to the student's high school. Although we estimate reduced form specifications, we use the informal theory presented above to interpret our findings. For ease of interpretation, we present mean marginal effects (a.k.a. average derivatives of the conditional probability of mismatch) rather than probit coefficients.

1. Baseline specification

Table 5A presents estimates from our baseline specification, which defines mismatch as a difference of more than 20 between the student's percentile in the distribution of ASVAB first principal components and the percentile of their college obtained using the four-factor college quality index. We estimate the baseline specification using the sample of students who start at a four-year college.

In general, the results from our multivariate analysis parallel the unconditional differences presented in Table 4. Consider first the demographic

---

[4] Inspired by Avery (2010) we looked at whether the student's high school offered college counseling as well. Virtually every high school answered "yes" to this question. The survey did not ask further questions about guidance quantity or quality. We also considered high school teacher experience and salaries, high school graduation rates, the share of the graduating class that took the SAT or ACT, and the availability of Advanced Placement (AP) classes. The three variables included in the tables were selected because of their clear conceptual link to information about college and relatively strong relationship to observed college choices. Frequent item non-response thwarted our attempts to create an index combining multiple variables from the high school survey.

variables at the top of the table. We find a lower probability of undermatching for male students, but little difference in overmatching. Race-based affirmative action programs should increase the probability of overmatch for minority students, conditional on their measured ability. We do not find evidence of this effect for either blacks or Hispanics. In contrast, students in the "other" category, mostly Asians, have a substantially higher probability (0.08) of overmatching and a correspondingly lower probability (-0.11) of undermatching. We also went looking for "quality-quantity" tradeoffs as in Becker and Lewis (1973) by including the number of household members 18 years old or younger, but the data indicate they do not matter much in this context.

Ability has a mechanical effect on the probability of mismatch. Very able students will have few schools for which they are overmatched and many schools for which they are undermatched. The first principal component of the ASVAB scores, the measure of ability we use to define mismatch, demonstrates this mechanical effect. Increasing a student's ASVAB1 percentile by 10 points decreases her probability of overmatch by about 9 percentage points and increases her probability of undermatch by about 7 percentage points.

Once we control for this first ability measure, however, the other ability measures have the opposite effect: higher high school grades, a higher percentile on the second principal component of the ASVAB scores and a higher SAT percentile all raise a student's probability of ending up overmatched, as defined by her ASVAB1 score, and lower her probability of being undermatched. Thinking about the ASVAB1 variable as an error-ridden measure of each student's latent ability provides one way to think about these results. Under that interpretation, the other ability variables represent three additional error-ridden measures. Conditional on one, a higher value of each of the others suggests higher latent ability. Students and colleges observe two of these other measures, namely SAT scores and grades (and perhaps things that proxy for the third, ASVAB2),

which suggests that they should also affect application and acceptance decisions, just as we find here. Put differently, a student with good grades and SAT scores may truly be a good match for a high-quality school, but we will consider her overmatched if she scored poorly on the ASVAB.

Now consider our family background variables: household wealth in 1997, starting college late, parental education, classes outside of regular school, and having a computer at home. We include wealth in the form of indicators for quartiles, with the lowest quartile as the reference group. To our surprise, the wealth variables do not generate much explanatory action. Students from the wealthiest households have a statistically significantly lower probability of undermatching of about 0.03, presumably reflecting their parents' ability and interest in buying their way into a higher quality college. We find some evidence, significant at the ten percent level, of a lower probability of overmatching at the third wealth quartile, which may represent parents too poor for full out-of-state or private tuition but too well off for much financial aid. Alternatively, it may represent selection: students from the bottom wealth quartile are less likely to attend college at all – in Table 3 the average college attendee is in the 3rd quartile – but those who do may be particularly motivated or subject to some affirmative action by higher quality schools. Starting college more than 12 months after graduating from high school raises the undermatch probability by five percentage points. We think of starting late as (among other things) another indicator of financial constraints.

Not at all surprisingly, parental education plays a key role in driving college choices. We find a U-shaped pattern in regard to parental education and the probability of overmatching. Those with the least educated parents and those with the most educated parents have the highest conditional probabilities of overmatching; both groups exceed the omitted group – the highest parental education is completed high school – by over five percentage points. The opposite

pattern holds for undermatching, with students with the most and least educated parents having substantially lower probabilities of undermatching. These patterns suggest a combination of disadvantage-based affirmative action at the lower end of the parental education distribution and the pursuit of college quality at the upper end. The effects of having less-educated parents may again reflect selection: students from households where no parent completed high school are unlikely to attend college, but those who do may have strong unobserved qualities like motivation. Our concerns about measurement error in the family wealth variables lead us to interpret the education variables partly as proxies for wealth, but they also surely capture differences in tastes for education among households as well as differences in information related to college application and choice.

Our final family background variables measure whether the student took courses outside of school and/or had a computer in the home. We interpret these variables as rough proxies for parental enthusiasm about, and willingness to invest in, education. Other than having had courses outside of school having a negative effect on undermatching, we do not find much here.

Our measures of context include indicators for three of the four census regions (the Midwest is the omitted region), a rural residence indicator and variables measuring log median income and the percent of adults with a four-year college degree in the student's census tract. The region variables matter. Students in the northeast have a 16 percentage point higher probability of overmatching and an 11 percentage point lower probability of undermatching than students in the Midwest. Perhaps more surprisingly, students in the south and west also have lower probabilities of undermatching than those in the Midwest. We suspect that some of the regional differences in our estimates spring from regional differences in the relative importance of state and private colleges. In contrast, we find little effect of living in a rural area, though we might expect one if colleges devote less recruiting effort to rural high schools, as in Hoxby and Avery (2012).

The variables measuring income and education at the census tract level both positively affect overmatching and negatively affect undermatching, though only the education effects are precisely estimated. A standard deviation increase in the share of adults with a BA, a change of nine percentage points on an average of 21%, increases the probability of overmatch by two percentage points and lowers the probability of undermatch by three percentage points. These variables capture a mix of primary and secondary school quality (via residential sorting as well as voting behavior), information about college, and social pressure directed toward higher college quality. Given the wealth of variables we condition on at the student level, the importance of the census tract level education variable surprised us.

Among the variables drawn from the high school survey, the fraction of teachers with an advanced degree has no clear effect (and a zero point estimate for overmatching). This finding comports with a large literature – e.g. Rivkin, Hanushek and Kain (2005) – that finds that teacher advanced degrees have little effect on student outcomes. High school student characteristics do matter in our analysis. The probability of overmatching increases in the fraction of students going on to either two-year colleges or four-year colleges. Both variables also decrease the probability of undermatching, though the estimates have smaller magnitudes and less precision than for overmatching. The fraction going to a four-year variable likely reflects better information and guidance, as well as students following their friends. The fraction going to a two-year variable we find more puzzling, though it may reflect a more select group of students, and thus a group of students more likely to overmatch, going on to four-year college within the high school. Taken together, the positive effects of parental education along with measures of information about college on the probability of overmatch suggest that more informed students (and their families) prefer to overmatch. That is, they view the benefits of attending a higher quality college as outweighing any

possible costs of mismatch. Manski and Wise (1983) also find that students prefer colleges where the average SAT score is slightly higher than their own.

The final set of covariates summarizes state higher education policy. Average four year in-state tuition at public colleges (entered in log form to allow for a non-linear relationship) decreases the probability of both overmatching and undermatching, though the latter effect does not attain statistical significance. This pattern may indicate that states with relatively high four-year tuition do a better job of matching students to colleges, perhaps because the system offers more choices of quality and location. Or it may be that lower in-state tuition induces students at the margin to remain in-state and in the public sector rather than seeking better matches in the private sector or in other states. The negative effect on undermatching may result from high four-year college prices pushing some students to be undermatched at a two-year school rather than at a four-year school.

A more obvious interpretation follows our finding that having a public four-year that is a good match within 50 miles (and within the state) leads to almost a five percentage point decrease in the probability of undermatching. This suggests that a desire to live nearby, whether to save money by living at home or to stay near family and high school friends plays a key role in driving undermatching. The effect on overmatching is small and not statistically significant, but in the expected sign. Similarly straightforward to understand is that having a matched private within 50 miles reduces the probability of undermatching as well, by nearly five percentage points. Students make tradeoffs between tuition, travel and room and board costs, and quality at the margin in reasonable ways. Less easy to interpret is the strong positive effect of having a well-matched private college within 50 miles on the probability of overmatching, which it increases by 0.106. Taken together, our findings on the substantively important role of distance in college application and enrollment generally parallel

those in the broader literature: see e.g. Griffith and Rothstein (2009) and Turley (2009).

2. Including students who start at two-year colleges

In addition to attending a lower-quality 4-year college, students can also end up undermatched by starting at a 2-year college. Reynolds (2012) and Long and Kurlaender (2009) show that students who start at a two-year college with the goal of obtaining a four-year degree represent a substantively important group (albeit one with a low probability of ever attaining a four-year degree). This section reports on what happens when we expand our analysis to include two-year starters using the 6-factor college quality index. For this analysis, we follow Reynolds (2012) and include only 2-year college starters who indicate an intention to complete a 4-year college degree at the time they start college.[5] When we use the 6-factor measure of college quality and construct percentiles of college quality across a pooled sample of 2- and 4-year schools, 70% of the 2-year schools are in the lowest quality quartile and almost none are in the top half of the quality distribution. This broadly comports with Stange's (2012) analysis of community college quality; see e.g. his Table 1.

Table 5B presents our analysis of mismatch among all college starters. The percentiles of ability and college quality, and thus our definitions of mismatch, are now constructed using the set of all 2-year and 4-year colleges in IPEDS and all 2-year and 4-year college starters in the NLSY97. In general, the qualitative results parallel those in Table 5A, and even the average derivatives themselves often do not change by much. We highlight the most interesting changes in our discussion here.

First, note that adding in students who start at a 2-year college increases the sample size substantially from 2,125 to 3,805. Second, both black and

---

[5] We provide details on how we construct this filter in the on-line appendix.

Hispanic students are now more likely to be overmatched for their college, not less, and less likely to be undermatched, a pattern consistent with affirmative action. Third, students from families in the top half of the wealth distribution are now more likely to be overmatched than students from less wealthy families as well as less likely to be undermatched. Fourth, the probability of overmatching is now (roughly) monotone in parental education, but quite non-linear, with all of the action at the margin between high school completion and some college. Since this analysis includes many more less-selective colleges, this shift supports the sample selection interpretation of the positive relationship between the lowest parental education group and the probability of overmatching in our baseline analysis. Fifth, 4-year in-state tuition at public colleges now has a (much) stronger negative effect on undermatching than on overmatching. Higher 2-year state tuition, which we include in this model for the first time, decreases overmatching and increases undermatching. We expected the reverse, with lower 2-year tuition pushing people to the 2-year system and thus toward undermatching in some cases. In-state 2-year and 4-year tuition are tightly correlated across states and may partially reflect the breadth and quality of in-state college options. Finally, the percentage of the student's high school class going on to a 2-year college switches from imprecisely decreasing undermatching to strongly increasing it and decreasing overmatch. This results from the fact that what in Table 5A was pushing people out of the sample now pushes them into undermatching when we include the 2-year schools. For a similar reason, the percentage of the high school class going on to a 4-year school now has a much larger deterrent effect on undermatching.

Re-estimating the percentiles including the 2-year group increases the amount of underlying quality spanned by a given percentile difference. This in turn means that re-estimating the percentiles will change the coding of the mismatch variables even in the top part of the distribution, as some high ability

students who were more than 20 percentile points away from their college before will not be after the re-estimation. Online Appendix Table OA-1 presents our multivariate analysis using the 6-factor college quality measure, but constructing the college quality and ability percentiles from only the sample of 4-year colleges and starters. The first set of results includes only 4-year starters, although the sample still increases somewhat because we can include students who start at 4-year colleges that do not report SAT scores, while the second includes all starters. The results parallel those obtained when including all college starters and recalculating the percentiles, suggesting that the differences between this specification and our baseline have more to do with the sample expansion than with the redefinition of mismatch.

3. Alternative measures of mismatch

Table 5C presents our findings using our two alternative definitions of mismatch. Consider first the two left columns of Table 5C, which display estimates from the definition based solely on the student's SAT score relative to the average SAT score of the incoming class at her college. This multivariate analysis corresponds to the joint distribution in Table 1B, discussed above. This definition of mismatch relies on an ability measure observed by colleges, so it does not capture the mismatch that arises because colleges have imperfect information about the true ability of applicants or because students misestimate their own abilities relative to other college applicants. Additionally, the SAT score embodies some of the guidance students have about applying for college if this information leads them to put extra effort into preparing for (or re-taking) the SAT or ACT exams. On the other hand, SAT scores measure ability closer to the time of college application. Because of the high stakes of the SAT, there is less risk than in the ASVAB of under-measuring ability because students have not taken the test seriously.

Perhaps most importantly, this analysis requires that we limit the sample to students reporting an SAT score, which they do by allowing the NLSY to view

a high school transcript that includes standardized test scores. As a result, the sample size falls from 2,125 to 1,279.[6] The loss comes from two different missing data processes: about half comes from students not releasing their transcripts to the NLSY and about half comes from schools not providing SAT scores on transcripts that do get released.

Many of the estimates in the SAT analysis in Table 5C differ substantially in magnitude and/or precision from the corresponding estimates in Table 5A. But in only a handful of cases does the average derivative estimate attain statistical significance in the two analyses, but with different signs. We confine our remarks here to these cases. First, as expected, the mechanical effect of ability on mismatch moves from the ASVAB1 percentile, which now has a positive effect on overmatching, to the SAT percentile, which now has a negative effect on overmatching and a positive effect on undermatching. Being in the south census region goes from having a positive effect on overmatching in Table 5A to a negative effect in Table 5B, possibly due to issues with the ACT to SAT score translation, though the South is a mixed SAT / ACT region. Finally, the patterns related to parental education change around a bit. In the SAT analysis, unlike the analysis in Table 5A, the probability of overmatching increases monotonically in parental education, while the probability of undermatching continues to have a hill shape with the maximum for students whose most educated parent is a high school completer. The change may reflect different investments in preparation for the SAT or ACT.

As described in Section IV, our third measure of mismatch exploits data from the IPEDS on the inter-quartile range (IQR) of the SAT scores in the

---

[6] The survey also includes self-reported SAT/ACT scores. We prefer the transcript measures for two reasons. The self-reported SAT scores are given in 100-point bins, which would add substantial measurement error. The SAT scores reported on transcripts by the high schools fall within these self-reported bins for only 70% of respondents and below the bin for 25% of respondents, suggesting a pattern of score inflation in the self reports.

entering class at different colleges. In this analysis, we continue to use SAT scores as the measure of student ability but define mismatch for each student as having an own SAT score outside the inter-quartile range for the college. This measure captures the notion that having an SAT score different from the mean by some absolute amount means something substantively different at a college whose students have highly varying SAT scores than it does at a college where students' SAT scores cluster in a narrow band around the mean. The right-hand side of Table 5C presents the estimates using this definition of mismatch; note that we lose some observations due to item non-response for the SAT quartiles in the IPEDS data. Contrary to our expectations, the big picture of the results does not change much relative to the estimates on the left-hand side of Table 5C, though particular estimates do move around, sometimes non-trivially, and become more or less precise. The most surprising change concerns the parental education variables, which have much less effect on the probability of overmatching in this specification, essentially zero for students whose best educated parent has completed at least high school. We conjecture that the underlying mechanism has to do with changes in who gets coded as mismatched in states with more heterogeneous flagships.

4. Match quality versus college quality

We tested the null hypotheses that, for each variable in our empirical model, the sum of the average derivative in the probit for overmatching and the negative of the average derivative in the probit for undermatching equals zero. In substance, this null corresponds to symmetric effects, meaning that analyses that impose symmetry do not miss much. Online appendix Table OA-9 presents these results. We reject the null for only two of the 30 coefficients at the five percent level: living in the south census region and having a well-matched public college within 50 miles. The latter we expected, the former corresponds to a monotone but non-linear relationship. As we would expect to reject one or two by chance, and

because underlying non-linearities in the relationship between our constructed ability and college quality indices may cloud the interpretation of the tests, we do not want to over-emphasize these findings. Still, we were surprised. In an important sense, students and their families care about college quality, not match quality.

5. Additional sensitivity analyses

We conducted a wide variety of sensitivity analyses related to our baseline specification, a handful of which merit explicit mention here. Appendix Table OA-3 presents results from defining mismatch as in Table 5A, but with 10 and 30 percentile point differences, rather than 20. Changing the cutoff used to define mismatch does not change the qualitative findings.

To test the sensitivity of the results to removing students who could not be undermatched under the 20 percentile point definition because their ASVAB percentile was too low, or who could not be overmatched because it was too high, we repeated the analysis using only students with ASVAB percentiles in (20,80). Restricting the sample in this way does not change the qualitative results as shown in Table OA-4.

Inspired by Das and Imberman (2012), who find higher returns to attending private colleges conditioning on college quality as measured by average SAT score, we repeated the analysis excluding students at private universities. Restricting our sample to public universities, which often have simple and binding admission cut-off rules, also makes our selection on observed variables assumption particularly plausible. However, Table OA-5 reveals that this, too, does not change the qualitative findings.

Noting that Black and Smith (2004, 2006) perform their analyses separately for men and women, we thought we should too. Table OA-6 presents those results; once again, the qualitative patterns, much to our surprise in this case, do not change. We also looked at subgroups defined by race/ethnicity and

by parental education and including interactions between race/ethnicity and gender and other key variables. In all cases, the results (not reported) paralleled the results for the full sample in Table 5A.

Concerned about interpreting the results from multiple measures of ability all conditional on one another (i.e. ASVAB1, ASVAB2, high school grades and SAT score in the baseline model), we estimated a model including only one ability measure, namely ASVAB1. As revealed in Table OA-7, this does not change the qualitative results. Concerned about the NLSY97 wealth measure, in Table OA-8 we estimated specifications including wealth in log form, rather than as indicators for quartiles, and including income, also in log form, in place of wealth. The qualitative results remain unmoved.

VII. Conclusion

Our analysis of college application and attendance using the NLSY-97 sample of recent college entrants yielded five main findings. First, using our definition of academic mismatch between students and colleges, we find substantively important amounts of both undermatching and overmatching, though not noticeably more than was present in the earlier NLSY-79 cohort. Second, this mismatch largely results from choices made by students and their families, not by college admissions offices. The vast majority of students who end up mismatched either did not apply to any well-matched schools or were accepted to at least one well-matched school but attended a mismatched school instead. Third, we find some evidence that financial constraints lead some students to undermatch, as students from the wealthiest families undermatch less often.

Fourth, information matters, though not in the way we expected it to. We thought more informed students would have a lower probability of both types of mismatch. Instead we found that our proxies for information lower the probability of undermatching but raise the probability of overmatching. We interpret this as

evidence that informed students and their families believe that the benefits of college quality more than compensate for any possible costs of overmatch.

Fifth, we find that students with a well-matched public college within 50 miles are less likely to mismatch in either direction. In-state tuition policies often make attending a home state college much less expensive than other options; and a nearby college allows living at home or, at least, lower travel costs to visit. At the margin, students trade off these costs against match and quality in reasonable ways. This supports our view of the reasonableness of looking at mismatch from the viewpoint of rational, but possibly ill-informed, students and parents.

We close with two big picture points. First, just because we find evidence that more informed students and their families think college quality trumps concerns about overmatch does not make it so. Students and parents believe lots of things contrary to the evidence; this particular belief might belong to that set. In fact, given the mixed findings in the small existing (academic, rather than anecdotal) literature – see, e.g. Alon and Tienda (2005), Arcidiacono et al. (2012), Arcidiacono et al. (2013), Black, Daniel and Smith (2005, Table A.7), Bowen et al. (2009), Light and Strayer (2000), and Sander and Taylor (2012) – students deciding where to attend college will have to wait a while to get a clear signal regarding the evidence. We have our own paper, Dillon and Smith (2013) underway on this topic, building on the data and findings in this paper.

Second, the optimal amount of mismatch does not equal zero. Sallee, Resch and Courant (2008) show that in a simple model of university systems with a fixed cost of establishing each university and complementarity in production between expenditures per student and student ability, the optimal system consists of exact matching as we have defined it: i.e. a set of colleges ordered by quality where the top quality college serves the most able students, the second best college serves the next most able students and so on. Specific, and not unreasonable, assumptions about peer effects among students yield a similar

optimal system design. These models play an important role as a conceptual benchmark but they, like our own academically oriented definition of mismatch, miss important features of the real world. As emphasized in e.g. Smith (2008) both students and colleges have many other dimensions besides the academic on which they might care to match. Models and empirical studies that treat these other dimensions seriously await future work.

References

Alon, Sigal and Marta Tienda (2005): "Assessing the `Mismatch' Hypothesis: Differences in College Graduation Rates by Institutional Selectivity", *Sociology of Education,* 78, pp. 294-315.

Arcidiacono, Peter (2004): "Ability Sorting and the Returns to College Major," *Journal of Econometrics,* 121, pp. 343-375.

Arcidiacono, Peter, Esteban Aucejo and V. Joseph Hotz (2013): "University Differences in the Graduation of Minorities in STEM Fields: Evidence from California," Unpublished manuscript, Duke University.

Arcidiacono, Peter, Esteban Aucejo and Ken Spenner (2012): "What Happens After Enrollment? An Analysis of the Time Path of Racial Differences in GPA and Major Choice," *IZA Journal of Labor Economics,* 1:5.

Avery, Chrisotpher (2010): "The Effects of College Counseling on High-Achieving, Low-Income Students," NBER Working Paper No. 16359.

Avery, Christopher and Sarah Turner (2009): "Playing the College Application Game: Critical Moves and the Link to Socio-Economic Circumstances," University of Virginia Working Paper.

Becker, Gary and H. Gregg Lewis (1973): "On the Interaction between the Quantity and Quality of Children," *Journal of Political Economy* 81(2, part 2), pp. S279-S288.

Black, Dan, Kermit Daniel and Jeffrey Smith (2005): "College Quality and Wages in the United States," *German Economic Review,* 6(3), pp. 415-443.

Black, Dan and Jeffrey Smith (2004): "How Robust is the Evidence on the Effects of College Quality? Evidence from Matching," *Journal of Econometrics,* 121(1), pp. 99-124.

Black, Dan and Jeffrey Smith (2006): "Evaluating the Returns to College Quality with Multiple Proxies for Quality," *Journal of Labor Economics,* 24(3), pp. 701-728.

33

Bowen William and Derek Bok (1998): *The Shape of the River: Long-Term Consequences of Considering Race in College and University Admissions*, Princeton, NJ: Princeton University Press.

Bowen, William, Matthew Chingos, and Michael McPherson (2009): *Crossing the Finish Line: Completing College at America's Public Universities*, Princeton, NJ: Princeton University Press.

Cawley, John, James Heckman, and Edward Vytlacil (2001): "Three Observations on Wages and Measured Cognitive Ability," *Labor Economics*, 8(4), pp. 419-442.

Das, Shreyasee and Scott Imberman (2012): "What is the Return to Attending a Non-Elite Private College," Unpublished manuscript, Michigan State University.

Dillon, Eleanor and Jeffrey Smith (2013): "The Consequences of Mismatch between Student Ability and College Quality," Unpublished manuscript, University of Michigan.

Griffith, Amanda and Donna Rothstein (2009): "Can't Get Here from There: The Decision to Apply to a Selective Institution," *Economics of Education Review*, 28(5), pp. 620-628.

Hill, Catharine and Gordon Winston (2012): "Low-Income Students and Highly Selective Private Colleges: Geography, Searching, and Recruiting," *Economics of Education Review*, 29, pp. 495-503.

House, Emily (2013): "Exploring the Undermatch Phenomenon in Michigan," Unpublished manuscript, University of Michigan.

Howell, Jessica (2011): "Assessing the Impact of Eliminating Affirmative Action in Higher Education," *Journal of Labor Economics*, 28(1), pp. 113-166.

Hoxby, Caroline and Christopher Avery (2012): "The Missing `One-Offs': The Hidden Supply of High-Achieving, Low Income Students," NBER Working Paper No. 18586.

Light, Audrey and Wayne Strayer (2000): "Determinants of College Completion: School Quality or Student Ability?" *Journal of Human Resources*, 35(2), pp. 299-332.

Long, Bridget Terry and Michal Kurlaender (2009): "Do Community Colleges

Provide a Viable Pathway to a Baccalaureate Degree?" *Educational Evaluation and Policy Analysis*, 31(1), pp. 30-53.

Manski, Charles (1989): "Schooling as Experimentation: A Re-Appraisal of the Postsecondary Dropout Phenomenon," *Economics of Education Review* 8(4), pp. 305-312.

Manski, Charles and David Wise (1983): *College Choice in America*, Cambridge: Harvard University Press.

Neal, Derek and William Johnson (1996): "The Role of Premarket Factors in Black-White Wage Differences," *Journal of Political Economy*, 104(5), pp. 869-895.

Pallais, Amanda (2012): "Small Differences that Matter: Mistakes in Applying to College," Unpublished Manuscript, MIT.

Reynolds, C. Lockwood (2012): "Where to Attend? Estimates of the Effects of Beginning College at a Two-Year Institution," *Economics of Education Review*, 31(4), pp. 345-362.

Rivkin, Steven, Eric Hanushek, and John Kain (2005): "Teachers, Schools and Academic Achievement," *Econometrica*, 73(2), pp. 417-458.

Roderick, Melissa, Jenny Nagaoka, Vanessa Coca, and Eliza Moeller with Karen Roddie, Jamiliyah Gilliam, and Desmond Patton (2008): *From High School to the Future: Potholes on the Road to the Future*. Chicago, IL: Consortium on Chicago School Research.

Sallee, James, Alexandra Resch and Paul Courant (2008): "On the Optimal Allocation of Students and Resources in a System of Higher Education," *The B.E. Journal of Economic Analysis & Policy (Advances)*, 8(1), Article 11.

Sander, Richard and Stuart Taylor (2012): *Mismatch: How Affirmative Action Hurts Students It's Intended to Help, and Why Universities Won't Admit It*, New York: Basic Books.

Segal, Carmit (2012): "Working When No One is Watching: Motivation, Test Scores, and Economic Success," *Management Science*, 58(8), pp. 1438-1457.

Smith, Jeffrey (2008): "Heterogeneity and Higher Education." In Michael

McPherson and Morton Schapiro, eds. *Succeeding in College: What it Means and How to Make it Happen.* New York: College Board, pp. 131-144.

Smith, Jonathan, Matea Pender and Jessica Howell (2012): "The Full Extent of Student-College Academic Undermatch," Unpublished manuscript, the College Board.

Stange, Kevin (2012): "Ability Sorting and the Importance of College Quality to Student Achievement: Evidence from Community Colleges," *Education Finance and Policy,* 7(1), pp. 74-105.

Stinebrickner, Todd and Ralph Stinebrickner (2012): "Learning about Academic Ability and the College Dropout Decision," *Journal of Labor Economics,* 30(4), pp. 707-748.

Turley, Ruth (2009): "College Proximity: Mapping Access to Opportunity," *Sociology of Education,* 82, pp. 126-146.

Table 1A: Joint distribution of college quality and ability—NLSY97, four-year starters

Ability Quartiles	College Quality Quartiles				Total
	1st Quartile (lowest)	2nd Quartile	3rd Quartile	4th Quartile (highest)	
1st Quartile (lowest)	11.7 (42.2) [44.7]	8.0 (29.1) [30.6]	5.2 (18.6) [20.4]	2.8 (10.1) [12.5]	(100.0) (N=547)
2nd Quartile	6.5 (26.3) [25.0]	7.2 (28.9) [27.3]	6.7 (26.9) [26.5]	4.5 (17.9) [20.0]	(100.0) (N=491)
3rd Quartile	5.4 (22.2) [20.7]	6.1 (24.9) [23.1]	7.3 (30.1) [29.1]	5.6 (22.8) [24.9]	(100.0) (N=482)
4th Quartile (highest)	2.5 (10.9) [9.7]	5.0 (21.7) [19.0]	6.1 (26.3) [24.0]	9.5 (41.1) [42.6]	(100.0) (N=457)
Total	[100.0] [N=517]	[100.0] [N=520]	[100.0] [N=499]	[100.0] [N=441]	100.0 N=1,977

Each cell contains the overall percentage, (the row percentage), and [the column percentage]. College quality is measured by the 4-factor index. Ability is measured by the first principal component of the ASVAB scores. All results are weighted as described in the text.

Table 1B: **Joint Distribution of SAT college quality and ability—NLSY97, four-year starters**

Ability Quartiles	College Quality Quartiles				Total
	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile	
1st Quartile	10.2 (51.9) [45.0]	5.2 (26.3) [23.5]	2.8 (14.5) [10.7]	1.4 (7.2) [4.9]	(100.0) (N=334.3)
2nd Quartile	6.9 (24.8) [30.6]	8.4 (30.2) [38.5]	8.1 (29.0) [30.6]	4.5 (16.0) [15.3]	(100.0) (N=476)
3rd Quartile	3.7 (14.5) [16.2]	5.0 (19.8) [22.8]	8.5 (33.7) [32.1]	8.1 (32.1) [27.8]	(100.0) (N=431.2)
4th Quartile	1.8 (6.7) [8.2]	3.3 (12.2) [15.2]	7.0 (25.7) [26.6]	15.1 (55.3) [52.0]	(100.0) (N=466.7)
Total	[100.0] [N=385.4]	[100.0] [N=374.2]	[100.0] [N=451.9]	[100.0] [N=496.6]	100.0 N=1708.1

Each cell contains the overall percentage, (the row percentage), and [the column percentage]. College quality is measured by the average SAT score of the entering class. Ability is measured by the student's SAT score. All results are weighted as described in the text.

Table 2: College applications and mismatch

	Ended up overmatched	Ended up well-matched	Ended up undermatched
N	207	374	208
Mean number of applications	2.9	2.5	2.1
% applied to over	100.0%	17.3%	9.8%
% applied to well	32.3%	100.0%	30.6%
% applied to under	3.2%	16.6%	100.0%
% accepted to over	100.0%	11.5%	4.7%
% accepted to well	27.9%	100.0%	22.5%
% accepted to under	3.2%	16.6%	100.0%

Share of mismatched who:	Overmatched	Undermatched
Didn't apply to a good match	67.7%	69.4%
Applied to a good match but didn't get in	4.4%	8.0%
Were accepted to a good match but didn't attend	27.9%	22.5%

Note: Only the younger NLSY97 respondents were asked questions about college applications. Of the 2,125 respondents who started at a 4-year college and for whom we have a measure of match with their college, 789 are included in this table. Of the remainder, 1,275 (95% of the missing) are excluded because they were born in 1980, 1981, or 1982. Another 41 (3% of the missing) are ineligible for the application section for other reasons. The remaining 21 are missing because they were eligible but did not answer any application questions. Both panels use weights as described in the text.

Table 3: **Average characteristics of students by college choice, four-year starters**

	College Attendees	College quality quartile			
		1, lowest	2	3	4, highest
N	2,125	591	564	513	457
Male	45%	42%	44%	45%	49%
Black	11%	17%	13%	8%	5%
Hispanic	6%	7%	7%	4%	7%
Other (not white)	6%	2%	5%	6%	11%
Household members age 18 or under	2.2	2.3	2.2	2.1	2.3
ASVAB 1 percentile	52%	40%	47%	58%	66%
ASVAB 2 percentile	51%	46%	49%	50%	57%
High school GPA percentile	53%	44%	51%	58%	63%
SAT percentile	53%	36%	47%	59%	70%
Household wealth in 1997	$183,185	$127,025	$163,161	$206,554	$249,978
Wealth quartile 1 (lowest)	10%	14%	8%	8%	9%
Wealth quartile 2	18%	24%	20%	14%	12%
Wealth quartile 3	28%	29%	28%	30%	21%
Wealth quartile 4 (highest)	45%	33%	44%	49%	58%
Started college late	9%	16%	9%	6%	5%
No parent completed high school	3%	4%	3%	1%	2%
At least one parent grad. high sch.	18%	24%	23%	14%	8%
At least one parent has some college	26%	31%	26%	23%	23%
At least one parent completed college	54%	41%	48%	62%	67%
Took classes outside of school	39%	32%	34%	45%	47%
Had computer at home	80%	72%	80%	83%	86%
Northeast region	21%	12%	15%	23%	36%
South region	30%	35%	25%	31%	30%
Midwest region	32%	35%	36%	35%	19%
West region	17%	17%	24%	11%	16%
Rural	18%	30%	14%	17%	9%
Median income in census tract	$35,867	$31,991	$35,423	$36,984	$40,153
% Adults w/college deg. in tract	21%	18%	20%	22%	24%
% of HS teachers with adv degr	56%	52%	57%	56%	61%
% of HS class to 2-year	18%	16%	19%	18%	18%
% of HS class to 4-year	56%	51%	54%	57%	61%
Avg. 4-year in-state tuition	$3,017	$2,906	$2,880	$3,126	$3,192
Matched public 4-year in 50 mi	52%	45%	49%	53%	61%
Matched private 4-year in 50 mi	66%	53%	64%	68%	81%

Notes: This table describes the characteristics of students at each college quality quartile. For example, the third row shows the percent of students attending each college type who are male. All results are weighted as described in the text. Ability percentiles are among 4-year college starters, with the ASVAB measures adjusted by age when taking the test. In-state tuition is measured in the year each student graduated from high school, deflated to 1997 dollars.

Table 4: **Average characteristics of students by match quality, four-year starters**

	College Attendees	Very Overmatched	Well-matched	Very Undermatched
N	2,125	531	1009	585
Male	45%	36%	44%	53%
Black	11%	18%	12%	5%
Hispanic	6%	8%	6%	4%
Other (not white)	6%	9%	6%	3%
Household members age 18 or under	2.2	2.2	2.2	2.2
ASVAB 1 percentile	52%	30%	51%	70%
ASVAB 2 percentile	51%	56%	52%	44%
High school GPA percentile	53%	47%	53%	59%
SAT percentile	53%	42%	52%	63%
Household wealth in 1997	$183,185	$174,149	$193,628	$173,298
Wealth quartile 1 (lowest)	10%	15%	9%	8%
Wealth quartile 2	18%	20%	17%	18%
Wealth quartile 3	28%	24%	28%	29%
Wealth quartile 4 (highest)	45%	41%	46%	46%
Started college late	9%	9%	9%	9%
No parent completed high school	3%	5%	2%	1%
At least one parent graduated high school	18%	17%	16%	20%
At least one parent has some college	26%	27%	25%	26%
At least one parent completed college	54%	51%	56%	53%
Took classes outside of school	39%	34%	42%	39%
Had computer at home	80%	76%	81%	83%
Northeast region	21%	32%	21%	12%
South region	30%	33%	33%	25%
Midwest region	32%	21%	29%	44%
West region	17%	15%	17%	19%
Rural	18%	12%	17%	24%
Median income in census tract	$35,867	$37,982	$36,345	$33,674
% Adults w/college deg. in tract	21%	23%	22%	19%
% of HS teachers with adv degr	56%	58%	57%	54%
% of HS class to 2-year	18%	19%	18%	17%
% of HS class to 4-year	56%	57%	56%	54%
Avg. 4-year in-state tuition	$3,017	$3,069	$3,031	$2,958
Matched public 4-year in 50 mi	52%	63%	58%	33%
Matched private 4-year in 50 mi	66%	83%	69%	49%

Notes: This table describes the characteristics of all college attendees (in the first column) and of students in each mismatch category. For example, the third row shows the percent of all students and of students in each match category who are male. All results are weighted as described in the text. Ability percentiles are among 4-year college starters, with the ASVAB measures adjusted by age when taking the test. In-state tuition is measured in the year each student graduated from high school, deflated to 1997 dollars.

Table 5A: Determinants of mismatch, 4-factor CQ index and ASVAB ability, four-year starters

	Overmatched	Undermatched
Male	-0.005 (0.011)	**-0.021 (0.009)**
Black	-0.016 (0.014)	0.003 (0.015)
Hispanic	0.009 (0.017)	-0.019 (0.017)
Other (not white)	**0.084 (0.025)**	**-0.110 (0.017)**
Household members 18 or under	-0.003 (0.004)	-0.005 (0.004)
ASVAB1 percentile	**-0.874 (0.097)**	**0.715 (0.020)**
ASVAB2 percentile	**0.065 (0.021)**	**-0.091 (0.017)**
High school GPA percentile	**0.141 (0.028)**	**-0.110 (0.021)**
SAT percentile	**0.234 (0.039)**	**-0.121 (0.026)**
Wealth quartile 2	-0.009 (0.020)	0.010 (0.020)
Wealth quartile 3	-0.032 (0.019)	-0.012 (0.018)
Wealth quartile 4	0.004 (0.020)	**-0.034 (0.017)**
Started college late	**-0.045 (0.017)**	**0.053 (0.017)**
No parent completed high school	**0.056 (0.028)**	**-0.060 (0.026)**
At least one parent has some col.	**0.037 (0.016)**	**-0.041 (0.012)**
At least one par. completed col.	**0.054 (0.016)**	**-0.080 (0.011)**
Took classes outside of school	0.006 (0.013)	**-0.024 (0.011)**
Had computer at home	-0.013 (0.015)	0.018 (0.015)
Northeast region	**0.164 (0.028)**	**-0.110 (0.010)**
South region	**0.041 (0.015)**	**-0.082 (0.011)**
West region	-0.009 (0.019)	**-0.037 (0.014)**
Rural	-0.002 (0.016)	0.003 (0.013)
Log median income in tract	0.050 (0.029)	-0.027 (0.032)
% adults w/college deg. in tract	**0.225 (0.100)**	**-0.374 (0.082)**
% of HS teachers with adv degree	-0.000 (0.026)	-0.027 (0.024)
% of HS class to 2-year	**0.155 (0.058)**	-0.066 (0.046)
% of HS class to 4-year	**0.121 (0.036)**	-0.047 (0.028)
Log avg. 4-year in-state tuition	**-0.064 (0.027)**	-0.034 (0.022)
Matched public 4-year in 50 mi	-0.015 (0.010)	**-0.052 (0.008)**
Matched private 4-year in 50 mi	**0.106 (0.022)**	**-0.047 (0.010)**
N	2,125	2,125
Pseudo R2	0.279	0.284

Notes: Mean marginal effects (a.k.a. average derivatives) reported. Estimates statistically different from zero at the five percent level appear in bold. Having a well-matched public and private school nearby is determined based on the dependent variable's definition of match for each pair of regressions. The omitted parental education category is at least one parent completed high school. Estimates are weighted as described in the text.

Table 5B: Determinants of mismatch, CQ index and ASVAB ability, all starters

|	Overmatched	Undermatched
Male	0.007 (0.007)	**-0.034 (0.008)**
Black	**0.084 (0.012)**	**-0.110 (0.010)**
Hispanic	**0.026 (0.011)**	**-0.051 (0.011)**
Other (not white)	**0.049 (0.016)**	**-0.088 (0.014)**
Household members 18 or under	-0.005 (0.003)	**0.009 (0.003)**
ASVAB 1 percentile	**-0.742 (0.075)**	**0.797 (0.016)**
ASVAB 2 percentile	**0.080 (0.015)**	**-0.120 (0.014)**
High school GPA percentile	**0.175 (0.023)**	**-0.205 (0.017)**
SAT percentile	**0.062 (0.022)**	**-0.187 (0.022)**
Wealth quartile 2	-0.012 (0.011)	0.020 (0.014)
Wealth quartile 3	**0.031 (0.013)**	-0.000 (0.013)
Wealth quartile 4	0.024 (0.013)	**-0.045 (0.013)**
Started college late	**-0.090 (0.011)**	**0.115 (0.011)**
No parent completed high school	0.017 (0.013)	**-0.040 (0.018)**
At least one parent has some col.	0.011 (0.009)	0.006 (0.010)
At least one par. completed col.	**0.027 (0.010)**	**-0.057 (0.009)**
Took classes outside of school	-0.006 (0.009)	**-0.030 (0.009)**
Had computer at home	**0.042 (0.011)**	-0.020 (0.011)
Northeast region	**0.148 (0.024)**	**-0.067 (0.010)**
South region	**0.021 (0.010)**	**0.029 (0.011)**
West region	-0.009 (0.013)	0.009 (0.014)
Rural	-0.000 (0.011)	-0.012 (0.010)
Log median income in tract	0.011 (0.023)	**-0.143 (0.026)**
% adults w/college deg. in tract	**0.310 (0.082)**	-0.104 (0.064)
% of HS teachers with adv degree	**0.063 (0.019)**	0.036 (0.019)
% of HS class to 2-year	**-0.202 (0.039)**	**0.271 (0.033)**
% of HS class to 4-year	0.018 (0.021)	**-0.078 (0.023)**
Log avg. 4-year in-state tuition	-0.003 (0.020)	**-0.071 (0.021)**
Log avg. 2-year in-state tuition	**-0.043 (0.012)**	**0.032 (0.011)**
Matched public college in 50 mi	-0.000 (0.009)	**-0.053 (0.008)**
Matched private college in 50 mi	**0.075 (0.015)**	**0.023 (0.010)**
N	3,805	3,805
Pseudo R2	0.278	0.284

Notes: Mean marginal effects (a.k.a. average derivatives) reported. Estimates statistically different from zero at the five percent level appear in bold. Having a well-matched public and private school nearby is determined based on the dependent variable's definition of match for each pair of regressions. Estimates are weighted as described in the text.

Table 5C: Determinants of mismatch, SAT mismatch, four-year starters

	> 20 percentage point gap		Not in college's inter-quartile range	
	Overmatched	Undermatched	Overmatched	Undermatched
Male	**0.056 (0.007)**	**-0.037 (0.006)**	**0.094 (0.014)**	-0.006 (0.004)
Black	**-0.083 (0.010)**	**0.073 (0.010)**	**-0.050 (0.021)**	0.055 (0.011)
Hispanic	**-0.044 (0.010)**	0.002 (0.011)	-0.031 (0.027)	-0.014 (0.009)
Other (not white)	**0.085 (0.013)**	0.017 (0.011)	**0.089 (0.024)**	0.006 (0.008)
Household members 18 or under	**-0.021 (0.003)**	-0.001 (0.003)	**-0.016 (0.007)**	**-0.006 (0.002)**
ASVAB 1 percentile	**0.084 (0.017)**	**0.071 (0.017)**	-0.060 (0.039)	**0.029 (0.013)**
ASVAB 2 percentile	**0.082 (0.011)**	**-0.079 (0.011)**	**0.127 (0.026)**	0.004 (0.007)
High school GPA percentile	**0.241 (0.017)**	**-0.074 (0.014)**	**0.248 (0.030)**	**-0.019 (0.009)**
SAT percentile	**-0.923 (0.051)**	**0.465 (0.043)**	**-1.152 (0.042)**	**0.280 (0.054)**
Wealth quartile 2	**-0.102 (0.011)**	0.002 (0.012)	**-0.098 (0.030)**	0.012 (0.010)
Wealth quartile 3	**-0.147 (0.012)**	0.011 (0.012)	**-0.125 (0.030)**	**0.020 (0.010)**
Wealth quartile 4	**-0.050 (0.010)**	**-0.043 (0.011)**	-0.056 (0.029)	0.004 (0.008)
Started college late	**-0.161 (0.013)**	-0.011 (0.011)	**-0.119 (0.034)**	0.006 (0.008)
No parent completed high school	**-0.076 (0.014)**	**-0.133 (0.020)**	-0.077 (0.042)	**-0.046 (0.016)**
At least one parent has some col.	**0.039 (0.008)**	**-0.048 (0.007)**	0.001 (0.018)	**-0.021 (0.006)**
At least one par. completed col.	**0.042 (0.009)**	**-0.044 (0.007)**	0.007 (0.019)	**-0.018 (0.006)**
Took classes outside of school	**0.044 (0.008)**	**-0.014 (0.007)**	0.017 (0.019)	**-0.010 (0.005)**
Had computer at home	**-0.068 (0.009)**	**0.053 (0.011)**	**-0.044 (0.022)**	**0.017 (0.007)**
Northeast region	**0.023 (0.009)**	**0.052 (0.010)**	**0.050 (0.020)**	0.004 (0.006)
South region	**-0.044 (0.008)**	-0.006 (0.007)	**-0.058 (0.019)**	-0.009 (0.005)
West region	**-0.064 (0.010)**	0.014 (0.009)	**-0.116 (0.028)**	-0.012 (0.007)
Rural	0.005 (0.008)	**0.056 (0.008)**	-0.008 (0.020)	0.001 (0.005)
Log median income in tract	0.005 (0.018)	**0.041 (0.015)**	**0.109 (0.042)**	0.008 (0.012)
% adults w/college deg. in tract	**0.508 (0.062)**	**-0.246 (0.038)**	**0.296 (0.115)**	**-0.096 (0.027)**
% of HS teachers with adv. degree	**-0.090 (0.014)**	0.001 (0.013)	-0.063 (0.034)	-0.012 (0.010)
% of HS class to 4-year	**0.039 (0.015)**	**-0.067 (0.015)**	**0.114 (0.038)**	-0.018 (0.010)
Log avg. 4-year in-state tuition	-0.007 (0.013)	**-0.043 (0.014)**	0.014 (0.033)	**-0.022 (0.011)**
Matched public 4-year in 50 mi	**-0.078 (0.006)**	**-0.041 (0.006)**	**-0.126 (0.015)**	**-0.011 (0.004)**
Matched private 4-year in 50 mi	**0.097 (0.010)**	**-0.024 (0.005)**	-0.007 (0.016)	**-0.014 (0.004)**
N	1,279	1,279	1,245	1,246
Pseudo R2	0.267	0.162	0.379	0.409

Notes: Mean marginal effects (a.k.a. average derivatives) reported. Estimates statistically different from zero at the five percent level appear in bold. Having a well-matched public and private school nearby is determined based on the dependent variable's definition of match for each pair of regressions. Estimates are weighted as described in the text.

Figure 1: Distribution of estimated college mismatch, four-year starters
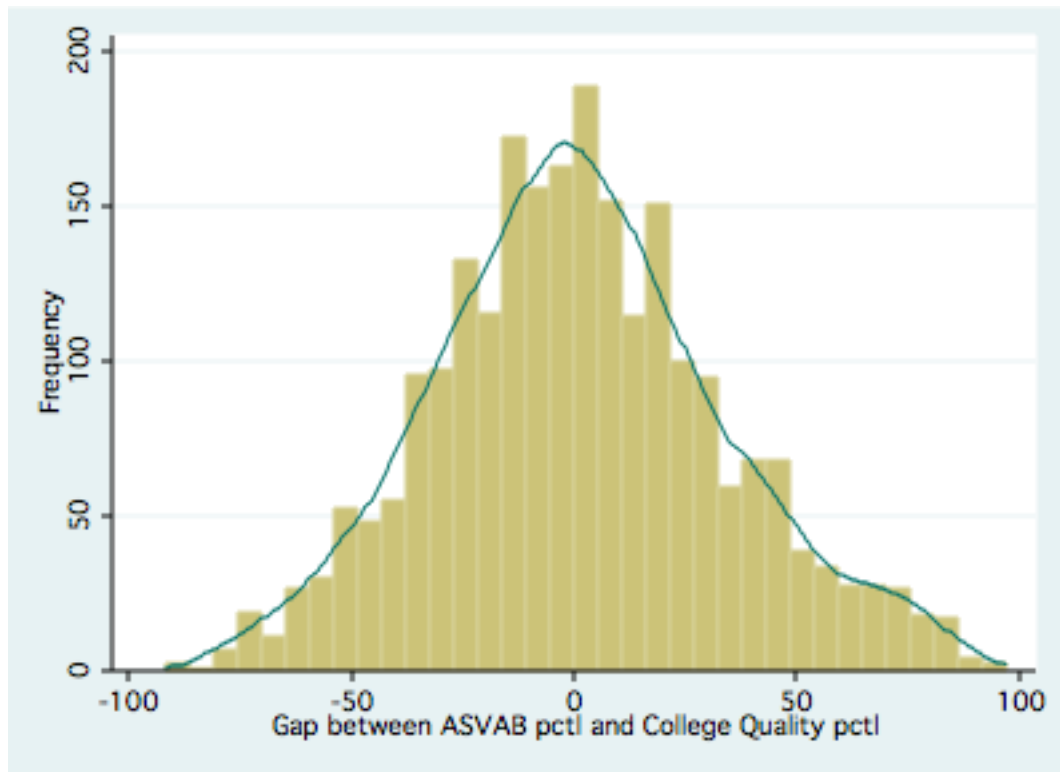
Mismatch defined as student ability percentile minus college quality percentile. Histogram includes estimated kernel density distribution. The distribution is weighted as described in the text.

Appendix Table 1: Sample

Total Observations	8,984
Graduated HS	7,143
Did not graduate HS but got GED	701
Started at a 2-year college*	2,646
Started at a 4-year college*	2,942
Starting college qualities	
Of quality quartile 1	*1,699*
Of quality quartile 2	*1,461*
Of quality quartile 3	*1,212*
Of quality quartile 4	*977*
Missing quality (6-factor index)	*239*
Has quality, but missing ability	*946*
All starters analysis sample**	3,805
Starting college qualities, 4-year only	
Of quality quartile 1	*710*
Of quality quartile 2	*646*
Of quality quartile 3	*609*
Of quality quartile 4	*534*
Missing quality (4-factor index)	*443*
Has quality, but missing ability	*374*
4-year starters analysis sample	2,125

* The 2-year starters include 152 respondents who got a GED and 50 respondents with no recorded high school graduation date or GED. The 4-year starters include 40 respondents who got a GED and 8 respondents with no recorded high school graduation date or GED.
**Analysis sample excludes 598 2-year college starters who, before starting college, reported less than 50% probability that they would eventually obtain a 4-year college degree.
College quality is for the first college attended. For the 4-year starter sample the figures are based on the 4-factor college quality index. For the all starters sample the figures are based on the 6-factor college quality index.

Appendix Table 2: Description of independent variables

Variable	Description
Male	Indicator variable that the respondent is male
Black	Equal to 1 if the respondent lists black as a racial category
Hispanic	Equal to 1 if the respondent lists Hispanic as an ethnic category and doesn't list black as a racial category
Other (not white)	Equal to one if the respondent doesn't list black or white as racial categories or Hispanic as an ethnic category
Household members under 18	Number of children age 18 and under living at the respondent's address in 1997 (including the respondent)
Started college late	Equal to one if the respondent started college more than 12 months after finishing high school.
ASVAB percentile	Percentile over 4-year (or all) college starters in the NLSY97 of the first (ASVAB1) and second (ASVAB2) principal components of the 12 sections of the ASVAB test, taken by NLSY97 respondents in 1997.
High School GPA	From respondent's high school transcript and standardized to a 4-point scale weighted by Carnegie credits. GPA percentile is calculated within our [weighted] sample of college-goers in the same way as the ASVAB percentile.
SAT score	Combined math and verbal SAT scores (max 1600) or the composite score on the ACT converted to the SAT scale from the respondent's high school transcript. SAT percentile is calculated within our [weighted] sample of college-goers in the same way as the ASVAB percentile.
Region of the U.S.	Where the respondent lived in last year of high school
Household wealth	Total 1997 net worth for the household where the respondent lived in 1997. Taken from the parent survey where available or from the youth survey (98.6% from parent survey). We use total wealth across everyone living in the same household as the respondent (respondent may live separately from parents in 1997). 1997 wealth quartiles are calculated within the (weighted) sample.
Parents' education	Highest educational attainment of either of the respondent's resident parents (or only parent in single parent households) as reported in the fall before the respondent finished high school (or earlier if that year is unavailable). We include at most one resident mother and father figure using the following prioritization: biological, adopted, step, or foster.

Log median income in tract	Log median income (from 1990 census) in the census tract where the respondent lived in last year of high school.
% in census tract with BA	The share of the over-25 population that has a 4-year college degree (from 1990 census) in the census tract where the respondent lived during his last year of high school.
Took classes outside of school	From 1997. Equal to one if he or she answered yes to "In a typical week, did you spend any time taking extra classes or lessons for example, music, dance, or foreign language lessons?"
Had computer at home	From the 1997 youth survey. Equal to one if he or she answered yes to "In the past month, has your home usually had a computer?"
Log average 4-year or 2-year in-state tuition.	Average in-state tuition, by year, for public four-year and two-year schools is from the State of Washington Higher Education Coordinating Board. "In-state" tuition for District of Columbia residents is calculated as max(national average in-state tuition, national average out-of-state tuition - $10,000) in accordance with DC Tuition Assistance Grant Program. For each respondent, in-state tuition is the in-state tuition in the fall before he finished high school in the state where he lived that fall. All tuition is CPI-deflated to 1997 dollars.
Well-matched public or private college nearby	Well-matched is defined as having a college of the relevant category whose weighted quality percentile is within 20 percentage points of the student's ASVAB ability percentile (as detailed in the text). Distance is calculated from the zipcode of the respondent's residence in the fall before he finished high school. In the 352 cases where the zipcode that fall was missing, the zipcode from the last available year prior to graduation is used.
% of HS teachers with advanced degrees	From the restricted NLSY97 School Survey, taken from the respondent's last high school. to the survey question "what percent of your teachers have more than a BA?"
% of HS class to four-year or two-year college	From the restricted NLSY97 School Survey. The response from the respondent's last high school to the survey question "by the fall following graduation, about what percent of your 1999 graduating class enrolled in a four-year (two-year) college?"
Rural	Indicates that the respondent did not live within a Metropolitan Statistical Area (MSA) in the fall before she finished high school.

Appendix Table 3: Principal components of the 12 test sections of the ASVAB

	1st Component	2nd Component	Unexplained variance
Eigenvalue	7.18	1.36	
Total variance explained	59.8%	11.3%	
Eigenvectors:			
General Science	0.326	-0.114	21.9%
Arithmetic Reasoning	0.325	0.117	22.2%
Word Knowledge	0.322	-0.038	25.4%
Paragraph Comprehension	0.320	0.114	24.8%
Mathematics Knowledge	0.318	0.239	19.7%
Mechanical Comprehension	0.310	-0.162	27.4%
Electronics Information	0.304	-0.228	26.8%
Assembling Objects	0.273	0.107	45.1%
Shop Information	0.245	-0.462	27.9%
Numerical Operations	0.240	0.444	31.8%
Auto Information	0.225	-0.456	35.6%
Coding Speed	0.223	0.441	37.8%

Note: scores on each test component are adjusted for the age of the respondent when they took the test by regressing the score on age dummies and using the residuals for the principal components analysis. The first two principal components combined explain 71.1% of the total variance of the 12 test section scores.

Appendix Table 4: Principal components of the college quality indices

4-factor college quality index among 4-year colleges

	1st Component	Unexplained variance
Eigenvalue	2.09	
Total variance explained	52.2%	
Eigenvectors:		
Mean SAT	0.588	27.8%
Rejection rate	0.479	52.1%
Faculty/Student ratio	0.359	73.1%
Average faculty salaries	0.544	38.2%

6-factor college quality index among 2- and 4-year colleges

	1st Component	Unexplained variance
Eigenvalue	3.47	
Total variance explained	57.9%	
Eigenvectors:		
Mean SAT	0.500	13.0%
Rejection rate	0.422	38.1%
Faculty/Student ratio	0.145	92.7%
Average faculty salaries	0.310	66.6%
Open admissions	-0.460	26.4%
Does not report SAT	-0.492	15.8%