Gender and the Career Choice Process: The Role of Biased Self-Assessments[1]

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This article develops a supply-side mechanism about how cultural beliefs about gender differentially influence the early career-relevant decisions of men and women. Cultural beliefs about gender are argued to bias individuals' perceptions of their competence at various career-relevant tasks, controlling for actual ability. To the extent that individuals then act on gender-differentiated perceptions when making career decisions, cultural beliefs about gender channel men and women in substantially different career directions. The hypotheses are evaluated by considering how gendered beliefs about mathematics impact individuals' assessments of their own mathematical competence, which, in turn, leads to gender differences in decisions to persist on a path toward a career in science, math, or engineering.

Women and men hold different kinds of jobs, as abundant evidence shows (for reviews, see Reskin 1993; Jacobs 1995*a*; Jacobsen 1994). While explanations of the persistence of sex segregation in paid work remain incomplete, the consequences for gender inequality are clear. The differential occupational distribution of men and women explains the majority of the gender gap in wages (Peterson and Morgan 1995; Treiman and Hartman 1981). Most attempts by sociologists to explain the persistence of sex segregation in the labor force document the importance of demand-side processes, such as statistical discrimination, internal labor markets, and the gendering of job queues (for reviews of this research, see Reskin and Roos 1990; England 1992). Far less attention has been given to supply-

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side processes by which males and females differentially move into various activities associated with different kinds of work (Peterson and Morgan 1995). However, supply-side processes are important because the supply networks from which employers recruit are already segregated by gender (Granovetter and Tilly 1988). Further, sex segregation often emerges early in the path toward many careers. For example, Jacobs (1995*b*) finds that one-third of all women would have to change college majors to be distributed in the same manner as their male counterparts. Since males and females appear to be voluntarily making career-relevant decisions that will carry them, on average, in substantially different occupational directions, it is important to examine these early stages in the supply-side process and ask why men and women make the choices they do.

In this article, I develop and test a simple supply-side mechanism to illustrate how cultural conceptions of gender serve to constrain the early career-relevant choices of men and women. I argue that widely shared cultural beliefs about gender and task competence bias actors' perceptions of their competence at various skills. Focusing on perceptions of competence is crucial for understanding modern stratification systems since the presumption of competence legitimates inequality in achievement-oriented societies such as the United States. When competence at a certain skill is thought to be necessary for a particular career, then gender differences in the perceptions of task competence, over and above actual ability, foster gender differences in commitment to paths leading to that career.

As a specific location of this process, I examine how gender differences in the perception of mathematical competence influence high school and college students' educational decisions that lead to careers in engineering, math, and the physical sciences. As these professions have been especially impervious to the entrance of women (Hanson 1996), they provide a convenient window from which to examine the process by which cultural beliefs about gender differentially influence early career decisions of men and women. Further, since the "quantitative professions" are among the more rewarding financially (Frehill 1997; Babco 1988; Dossey et al. 1988), gender differences in the movement into them has consequences for the continued gender gap in wages. Certainly, discrimination and other structural constraints continue to limit the occupational opportunities available to women. However, a fuller understanding of the persistence of sex segregation in the labor force can be gleaned by also examining the seemingly voluntary processes by which men and women make career-relevant choices.

GENDER AND CAREER CHOICE PROCESSES

The career choice process occurs throughout the life cycle as individuals make a series of decisions that have occupational consequences. Sociologists who examine the processes by which individuals choose careers have focused primarily on later stages when individuals actually choose to enter *jobs* rather than on the decisions to move into activities at earlier stages on the paths leading to specific careers. However, as noted above, gender differences in the selection of activities that constrain occupational choices often occur earlier in the life cycle. This is especially evident in the case of professions like engineering, where a college degree in the field is necessary to pursue a career. Due to the sequence of required classes, the decision to pursue a degree in engineering or the physical sciences must usually be made during the first or second year of college (Seymour and Hewitt 1997). Further, those who fail to take advanced-level math classes in high school are highly unlikely to select college majors in science, math, or engineering (McIlwee and Robinson 1992). Since gender differences in the selection of activities relevant to careers in these fields emerge as early as high school, it is important to examine decisions made at this stage in the life cycle.[2]

Gender and the Path to Math

The ratio of females to males declines as young people move further down the path toward the quantitative professions (McIlwee and Robinson 1992, Catsambis 1994). By high school, males are more likely than females to be enrolled in advanced-level math and science elective classes (AAUW 1992; National Science Board 1993; National Science Foundation 1994). Of the bachelor's degrees earned in 1990, 31.2% of physical science degrees and 13.8% of engineering degrees were awarded to women (Jacobs 1995*b*). In the United States workforce in 1993, only 8% of all engineers and 9% of all physicists were female (National Science Foundation 1996). Thus, in contrast with the vast movement of women into other professions, such as law and medicine, engineering and the physical sciences remain extremely male dominated.

In considering the process by which males and females differentially move into activities relevant to careers in engineering and the physical sciences, it is important to establish what is *not* causing this gender difference. We need to keep in mind that, unlike other systems of difference

[2] Gender differences in career aspirations may, of course, emerge even earlier in the life cycle. However, gender differences in occupationally relevant behavior, such as course enrollment decisions, are minor prior to high school when students begin to choose elective courses.

such as race and class, males and females grow up primarily in mixed-sex families and attend similar kinds of high schools. Since most young people attend coeducational high schools and high schools tend to have very balanced sex ratios, gender differences in career choice are not primarily due to differences in the type of high school attended by males and females. Further, gender differences in the entry into the quantitative professions are not due to differences in family structure or socioeconomic status since males and females are distributed roughly equally across these groups. Finally, a gender difference in the choice of a quantitative college major is not the result of a higher rate of transition from high school to college by males, since females are slightly *more* likely than males to attend college (National Center for Education Statistics 1998). In sum, compared to differences between students of different ethnic groups or social classes, there is considerable similarity in the structural location and resources available to male and female youth. What is puzzling is that a gender gap emerges early in the path toward careers in the quantitative professions in spite of this structural similarity.[3]

While many and varied explanations have been offered for the continued dearth of women in engineering and the physical sciences, most explanations implicate a linkage to mathematics (for a thorough review, see Oakes 1990). Mathematics has been described as the "critical filter" on the path to careers in math, science, and engineering (Sells 1973; Dossey et al. 1988). But, how does this filter serve to remove women disproportionately from the path to the quantitative professions?

Gender and Mathematical Aptitude

One explanation for the shortage of women in the quantitative professions is that males have a biological aptitude for math that females lack (Peng and Jaffe 1979; Rudisill and Morrison 1989; Benbow and Stanley 1980, 1983; Kolata 1980). However, cross-national studies have found wide variation in both the direction and magnitude of mathematical gender dif-

[3] Given the vast differences in social class, type of school attended, and other factors between members of different ethnic groups that have existed historically and continue to the present time, the argument I make here has less to say about the reproduction of inequality by race or ethnicity. This is not to suggest that cultural beliefs about race do not exist or do not influence career decisions, but rather that the differences in resources available to members of different ethnic or racial groups probably overwhelm the impact of cultural beliefs about race in reproducing inequality. Further, whereas males and females mostly grow up together in the same families, members of different race or ethnic groups are much more likely to grow up in different families. Families, for racial or ethnic minorities, can provide insulation or refuge from the dominant white culture. For example, some have suggested that African-American families teach their children ways of resisting hegemonic beliefs (see, e.g., Portes and Wilson 1976).

ferences, casting serious doubt on biological superiority theories (Baker and Jones 1993; Finn 1980; Harnisch 1984). Further, a meta-analysis of over 100 studies demonstrates that gender differences in mathematical performances are small, have declined over time, and vary in direction depending on the mathematical domain (e.g., computation, understanding of mathematical concepts, etc.; Hyde, Fennema, and Lamon 1990). Since analyses of gender differences in math aptitude are often conducted using large national surveys or populations of college freshmen, even differences that are statistically significant are often very small in magnitude (see, e.g., Hyde et al. 1990).[4] Thus, gender differences in actual mathematical competence do not seem to be responsible for the large differences in the numbers of men and women choosing to enter fields requiring some level of mathematical competence. Instead, I argue that cultural beliefs about gender and mathematics differentially influence the movement of males and females along educational and career paths leading to careers in science, math, and engineering. In the next section, I draw upon current understandings of gender as a multilevel system to develop this argument.

CULTURAL BELIEFS AND BIASED SELF-ASSESSMENTS

Gender and Cultural Beliefs

Sociologists have increasingly realized that gender is a multilevel system that consists not only of roles and identities at the individual level, but also includes ways of behaving in relation to one another at the interactional level, and cultural beliefs and distributions of resources at the macrolevel (Ridgeway 1997; Ferree, Lorber, and Hess 1999; Risman 1998). The multilevel nature of this system allows processes that contribute to the reproduction of gender inequality at the macro, micro, and interactional levels to occur simultaneously. In this way, the gender system is overdetermined and represents a powerfully conservative system. While I focus primarily on the role of macrolevel cultural beliefs in perpetuating gender differences in the early career-relevant decisions young people make, processes at the interactional and individual levels undoubtedly also contribute to the outcomes described.

Cultural beliefs about gender (hereafter called "gender beliefs") are the

[4] Using data from the current study, males have significantly higher math test scores than females, although the differences are small in magnitude, less 0.1 of a standard deviation. Males have math scores of 51.7 versus 51.3 for females for the sample used in models 1–3 (see table 1, models 1, 2, and 3). Females, by contrast, have significantly higher math grades. Further, these small gender differences do not account for the large gender differences in decisions relevant to careers in science, math, and engineering, as will be shown in models 4 and 5, presented later in the article.

component of gender stereotypes that contain specific expectations for competence. It is this component, with its specific expectations of competence, that presents special problems for gender equality (Ridgeway and Correll 2000). Gender beliefs are also cultural schemas for interpreting or making sense of the social world. As such, they represent what we think "most people" believe or accept as true about the categories of "men" and "women." In North America, at least, men are widely thought to be more competent than women, except when performing "feminine" tasks (Conway, Pizzamiglio, and Mount 1996; Wagner and Berger 1997; Williams and Best 1990). As we will see below, substantial evidence indicates that mathematical tasks are often stereotyped as "masculine" tasks. Even individuals who do not personally believe that men are more competent than women are likely aware that this belief exists in the culture and expect that others will treat them according to it. This expectation has been shown to modify behavior and bias judgments, as will be described below (Foschi 1996; Steele 1997). I next review the literature that establishes the nature of the gender beliefs associated with mathematics. I then describe how these gender beliefs bias judgments of mathematical competency and, consequently, influence career-relevant choices.

Gender Beliefs about Mathematics

Many studies have shown that students view math as masculine and perceive mathematics to be a male domain (Meece et al. 1982; Fennema and Sherman 1977, 1978; Hyde et al. 1990; Armstrong 1981; Whyte 1986). Likewise, most students believe math and science to be more useful and important for boys and better understood by them (Eccles et al. 1984). A recent ethnographic study of over 300 male and female students who were enrolled in an engineering or science major or had switched out of one paints a detailed picture of the gendered culture of math and science (Seymour and Hewitt 1997). Many of the women in this study said they had difficulty "giving themselves permission" to major in science, math, and engineering, even though they could not explain precisely what had discouraged them (p. 241). They described a dampening effect of a cultural message that suggests that women either could not or should not do math and science.

Collectively, the studies cited above demonstrate that widely shared cultural beliefs do include claims that males are more competent than females at mathematics. While empirical support for actual gender differences in mathematical competence is weak (Baker and Jones 1993; Finn 1980; Harnisch 1984; Hyde et al. 1990), the *belief* of male mathematical superiority itself is widely dispersed in American culture. Exposure to news reports that claim that males have greater natural mathematical ability has been found to increase mothers' stereotypic perceptions of their daughters' mathematical abilities (Jacobs and Eccles 1985). Research also suggests that parents convey different expectations of mathematical success to their male and female children (Frome and Eccles 1998). Likewise, male and female teachers at all grade levels routinely have lower expectations in math for females than for males (AAUW 1992; National Science Foundation 1994). Thus, individuals are exposed to gender beliefs associated with mathematics from various sources (teachers, parents, counselors, published results of standardized test scores by gender), and likely become aware that "most people" believe that males, as a group, are better at math.

Some individuals probably also come to *personally* believe that males are better at math, although girls have been shown to be less likely than boys to hold stereotypic views about mathematics (Hyde et al. 1990). If an individual girl believes that boys are better at math, she might view mathematical competence as inconsistent with a female gender identity, doubt her mathematical ability, and decrease her interest in careers requiring high levels of mathematical proficiency. In this way, personally holding gender stereotypic views in regard to mathematics would be sufficient to produce gender differences in perceptions of mathematical competence and commitment to careers requiring mathematical proficiency. However, personally holding a stereotypic belief is not necessary for the argument I make. Instead, it is only necessary that individuals perceive that *others* hold these gendered beliefs with respect to mathematics, a less stringent assumption. In the next section, I explain why this less stringent assumption is sufficient for the argument I make and describe how cultural beliefs about gender and mathematics differentially influence the early career decisions of males and females.

The Impact of Gender Beliefs on Judgments and Behaviors

Gender beliefs can operate in different ways simultaneously to contribute to the reproduction of gender inequality. It is clear that children learn and internalize gender beliefs and that this internalization affects behavior. However, there is some variation in *what* is internalized. With respect to mathematics, one possibility is that an individual comes to personally believe that boys are better at math than girls. Holding stereotypic beliefs about activities, such as mathematics, has been shown to influence the attitudes and career aspirations of young people (Eccles et al. 1999). The other possibility is that an individual internalizes the belief that "most people" believe boys are more competent than girls at mathematics.

Ridgeway (1997) argues that when gender beliefs are salient they shape behavior most powerfully by affecting people's sense of what *others* expect of them. When males are widely thought to be more competent at a task than females, both males and females in a situation unconsciously expect more competent task performances from men (Berger et al. 1977). This differential performance expectation has been shown to invoke the use of a more lenient standard for evaluating the performances of men in the situation compared to women (Foschi 1989). The use of a more lenient standard to judge male performances causes males to be perceived as having more task ability than females, even when males and females perform at the same objective level (Foschi et al. 1994; Foschi 1996). Thus, when a female enters a situation having internalized the belief that "most people" expect more competent performances from men, even if she does not personally endorse this stereotypic belief, she may still leave the situation with a lower assessment of her ability compared to a male performing at the same level, due to the biasing effect of others expectations.

Recent research by Steele (1997) and Lovaglia et al. (1998) further suggest that when individuals know others expect people of their social category (e.g., women, African-Americans) to do relatively poorly on a task, this knowledge creates anxiety and actually leads to poorer performances. Steele and colleagues (Steele 1997; Spencer, Steele, and Quinn 1999) experimentally manipulated the relevance of a gender belief associated with a task. When subjects were told that males performed better at the task, male subjects outperformed female subjects. However, when subjects were told that previous research had found no gender differences in performing the task, females and males did equally well. Even if subjects did not personally believe that males were better at the task, their awareness that others held this belief heightened their anxiety and had an impact on their performance. This leads to the conclusion that regardless of whether gender beliefs are personally endorsed or internalized as other people's expectations, they often lead to biased self-assessments of ability. I now turn to describing how gender beliefs about mathematics bias perceptions of task competence and, thereby, influence career-relevant decisions.

The Constraining Effect of Gender Beliefs

My general argument is that widely shared cultural beliefs about gender and task competence differentially bias how individual males and females evaluate their own competence at career-relevant tasks. This bias may be the result of the internalization of a cultural belief about gender and mathematics into one's gender identity, or it may be the result of the expectation of others causing males and females to invoke the use of different standards for evaluating their own mathematical success, or

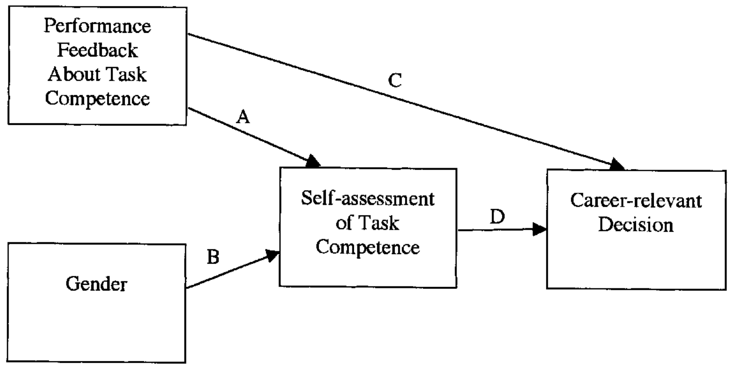

FIG. 1.—The impact of biased self-assessments on career-relevant decisions

both. The predicted outcome, however, is the same: males will overestimate and females will underestimate their own mathematical ability. If, for a given level of achievement, females are less likely than males to perceive that they are good at a task, they should be more likely to reduce their efforts and interests in activities requiring competence at the task, and therefore they should also be less likely to persist on a career path requiring task competence.

It is important to note that gender beliefs are not rigid scripts that individuals are compelled to follow. Indeed, when individuals assess their own competence at a given task, their assessments should depend more on performance information (such as grades or test scores) than on cultural beliefs about gender differences in task competence. However, cultural beliefs provide a context of meaning that modifies or biases the more situationally relevant foreground information, such as the evaluations of task competence by others (Ridgeway 1997; West and Zimmerman 1987). At the individual level, this biasing effect allows individuals considerable variability in the perceptions of their task competence. But, at the aggregate level, it should be sufficient to produce systematic gender differences in perceived task competence.

Figure 1 provides a general sketch of my argument about the impact of these processes on persistence on educational and career paths. To test this model, I propose three hypotheses, which are described in more detail below.

Gender Beliefs and Biased Self-Assessments

In order for a person to continue on a path toward a given career, I assume that she or he must adopt a personal conception of herself or himself as competent at the tasks believed to be necessary for that career path. That is, while many factors certainly influence individual career-relevant decisions and preferences, as a minimum, one must feel competent at the skills or tasks necessary for a given career in order to be commit oneself to pursuing that career. I refer to this personal conception of task competence as a "self-assessment." As depicted in figure 1, positive performance feedback in regard to a given task by legitimate others (such as teachers or supervisors) should increase one's personal self-assessment of task competence. However, cultural beliefs about gender and task competence are argued to provide a framing context (Ridgeway 1997; West and Zimmerman 1987) that biases other information individuals use in assessing their own competence.

In the case of mathematics, when males receive positive feedback about their ability, they should evaluate themselves as skilled at mathematics since a positive evaluation is consistent with both the feedback they received and with societal expectations about their mathematical competency. Conversely, females who receive positive feedback about their mathematical ability should be less likely to perceive that they are skilled at mathematics since this perception is incongruent with widely shared beliefs about gender and mathematics. Research has shown that individuals are more likely to attend to and retain information that confirms stereotypes and to ignore information that contradicts expectations (Hamilton 1981). Further, Foschi (1996; Foschi et al. 1994) has demonstrated that when a cultural belief about a task advantages males (i.e., when males are widely thought to be more competent at the task), both males and females unconsciously use a more lenient standard to evaluate male performances compared to female performances. The use of a more lenient standard ensures that even when they are performing at identical ability levels, males are judged as being more competent or having more task ability than females.

Since widely shared cultural beliefs include claims that males are more competent than females at mathematics, I expect that males are more likely than females performing at the same level to perceive that they are good at mathematics.

HYPOTHESIS 1.—*Males' assessments of their own mathematical competence is higher than females' assessments, controlling for performance feedback about mathematical ability.*

To test the idea that widely shared cultural beliefs about male mathematical superiority leads to gender differences in mathematical self-assessments, it is useful to compare male and female self-assessments for another set of tasks for which cultural beliefs do *not* advantage males. Verbal tasks are used for this purpose. While comparing male and female perceptions of task competence across a wide variety of tasks would provide a better test of this idea, the available data provide these measures only for math and verbal tasks. Previous research is unclear on whether cultural beliefs about verbal tasks advantage females or are gender neutral, but they do not advantage males. Therefore, if male-advantaging cultural beliefs lead to higher self-assessments of mathematical task competence by males, in the absence of male-advantaging beliefs, gender differences in *verbal* self-assessments will either be smaller, nonexistent, or slightly favor females. Thus, I expect males *not* to make higher self-assessments of their verbal competence than females when both perform at the same level. This distinction is important because if males globally assess their competence higher than females at all tasks, regardless of the task's gender association, then gender differences in self-assessments could not predict gender differences in persistence on any *particular* path.

Performance Feedback and Self-Assessments

For both males and females, I expect more positive performance feedback about task ability to lead to higher self-assessments of task competence. However, I expect gender beliefs to influence the extent to which performance feedback affects self-assessments. Males who assess themselves as competent at mathematics can base their assessment, at least partially, on societal expectations, rendering feedback about their competence less important to them than to females, who must base their assessments on something other than societal expectations. Societal expectations of their competence provide males with a sense of confidence in their mathematical ability that makes performance information, either supportive or contradictory to this expectation, less relevant to their self-assessments. In other words, knowing others expect you to do well at a task provides an insulating layer from the constant input of performance feedback common in school and work environments. Conversely, self-assessments will be more contingent on performance feedback in a situation where societal expectations of task competence are lacking. Therefore, I expect that:

HYPOTHESIS 2.—*The effect of performance feedback about mathematical competence on mathematical self-assessment is larger for females than for males.*

Biased Self-Assessments and Career-Relevant Decisions

As previously stated, both males and females must adopt a personal conception of themselves as competent at the tasks believed necessary for a specific career if they are to continue on a path leading toward that career. Therefore, while performance information about task competence undoubtedly has an impact on decisions to move forward on a path leading to a given career (path "C" of fig. 1), self-assessments of task competence will have an effect on career-relevant decisions above and beyond the effects of external indicators of ability (path "D" of fig. 1).[5] Since mathematical competence is assumed to be necessary for persisting on a quantitative career path, I expect that for both males and females:

HYPOTHESIS 3.—*Higher self-assessments of mathematical competence increase the odds of persisting on a path toward a career in a quantitative profession.*

However, if males are more likely than their female counterparts of equal mathematical ability to *believe* they are competent at mathematics (hypothesis 1), and if more positive self-assessments increase the likelihood of continuing on the quantitative career path (hypothesis 3), then gender differences in self-assessments of mathematical competence should partially account for the disproportionately high numbers of males in the quantitative professions.

DATA

The data for this study are from the National Educational Longitudinal Study of 1988 (NELS-88). In 1988, a multistage probability sample of approximately 25,000 eighth grade students, their parents, teachers, and school administrators, from over 1,000 schools was surveyed. A subsample of the students from the base year was again surveyed in 1990, 1992, and 1994, when most were sophomores, seniors, and two years beyond high school, respectively. The students were also given tests in mathematics, reading, social studies, and science, which were developed by the Educational Testing Service. The data set contains over 6,000 variables on each student (see Ingels et al. [1992] for more information on this data set).

While approximately 25,000 students were surveyed in the base year of the NELS-88 study, the subsequent waves were a subsample of the base year and were restricted to those students who continued to be enrolled in the same high school and who were not enrolled in some alternative certification program. Thus, the sample size available at each wave decreases. I utilize three different longitudinal subsamples to test the above hypotheses. The self-assessment hypotheses (hypotheses 1 and 2) are tested using the eighth to tenth grade longitudinal subsample (sample size = 17,424). The hypothesis about the effect of biased self-assess-

[5] Some might wonder why external evidence would have an effect at all if it is not internalized into a self-assessment. However, noninternalized evidence could have an effect in that it can affect how gatekeepers, such as teachers, channel students along career paths.

ments on career-relevant decisions is tested on either the eighth to twelfth grade subsample (sample size = 16,489) or on the eighth grade to two years past high school subsample, depending on whether the decision being made occurs during the senior year of high school or in college. In the latter case, I examine choice of college major, making it necessary to restrict analysis to those students who attended college (sample size = 8,724).[6] The cases are weighted using the appropriate NELS longitudinal sampling weights,[7] and the analyses are conducted on cases for which there is no missing data on variables included in the models.[8] I further restrict my attention to those students who identified themselves as Asian/Pacific Islander, Hispanic, African-American, or white, approximately 99% of the sample.

MODELS AND MEASUREMENTS

Five models are used to test the three hypotheses. The dependent variable in model 1 is mathematical self-assessment, a latent variable described below. The dependent variable in model 2 is verbal self-assessment, also a latent variable. While model 1 tests whether males assess their mathematical competence higher than females, the verbal self-assessment model, model 2, evaluates whether males globally assess their competence higher than females do, regardless of a task's gender association. Taken together, models 1 and 2 provide a test for the idea that widely shared cultural beliefs about gender and task competence have an impact on the perceptions males and females make of their competence at various tasks (hypothesis 1). Model 3 tests the second hypothesis that the *effect* of performance feedback about mathematical competence on mathematical self-assessments is greater for females than for males. To evaluate this hypothesis, separate models are estimated for males and females to test for

[6] A Heckman probit model is used to evaluate the bias introduce by this selection of cases (Van de Ven and Van Pragg 1981).

[7] A different longitudinal sample weight was used for each longitudinal subsample: F1PNLWT, F2PLNLWT, and F3PNLWT for the eighth to tenth grade, eighth to twelfth grade, and eighth to two years after high school subsamples, respectively.

[8] Another possible way of handling the decreasing sample size is to select those students who attended college in the 1994 wave of the data set and use them for all analyses. This approach has the advantage of producing a consistent sample across each model. However, by selecting all of the available cases available at each wave, I retain a larger sample size and prevent the potential bias of selecting only students who went to college, arguably a more academically oriented sample of students. For the sake of comparison, all models were also run on the smaller sample of only those students who were in college two years beyond high school. Results from models estimated on this alternative sample were virtually identical to those presented here.

the interaction effect between gender and performance feedback.[9] In all other models, gender is included as a male dummy variable in order to assess the magnitude and direction of the gender effect on self-assessment and the career choice process. Models 4 and 5 evaluate the effect of biased self-assessments on career-relevant decisions at two different time points (hypothesis 3). All cases were weighted prior to estimating these models.[10] In the next section, I describe how each of the concepts mentioned in the hypotheses is operationalized and measured and how the models are estimated.

Dependent Variables

The latent variable "mathematical self-assessment" measures the extent to which students believe they are skilled at math. Likewise, the latent variable "verbal self-assessment" measures the extent to which students think they are verbally skilled. Three items serve as indicators of mathematical self assessment: "Mathematics is one of my best subjects," "I have always done well in Math," and "I get good marks in Math." Likewise, three items serve as indicators of verbal self-assessment: "I learn things quickly in English," "I get good marks in English," and "English is one of my best subjects." Students were asked to agree or disagree on a six-point scale to these prompts during their sophomore year of high school, the only year in which these items were included in the survey. Confirmatory factor analysis provided support for a two-factor model, measuring distinct math and verbal self-assessment concepts. The math

[9] When models are estimated separately for males and females, the error variances are allowed to vary between the two samples. The other possible way of modeling interactive gender differences is to include one or more interactive terms (the product of gender with the variable of interest) in a model that includes a gender dummy variable and is, therefore, estimated for both males and females. A model estimated with interactive terms constrains the error variances to be equal between the male and female samples. While both modeling schemes produce identical coefficient estimates, tests of significance could vary due to the difference in the assumption regarding the error variances. For comparison, a model with a gender and evidence interaction term was estimated and no substantive differences in tests of significance were found. The models presented here, with male and females modeled separately, have the advantage of allowing for easier comparison of the magnitude of the hypothesized gender difference in the effect of evidence on self-assessments.

[10] Some have argued that sampling weights are not necessary in multivariate analysis if the weight is not a function of the dependent variable, and that weighting in multivariate analysis, at least with the OLS estimator, actually produces inefficient estimates (Winship and Radbill 1994). All models present in this article were also estimated without weights, and the results are highly similar. I also followed the procedure advocated by DuMouchel and Duncan (1983) for assessing whether estimates from weighted and unweighted models are significantly different and found no significant differences. Results are available by request.

items had standardized factor loadings of 0.89, 0.88, and 0.87, respectively. The verbal items had standardized factor loadings of 0.78, 0.85, and 0.82, respectively. When the factor loadings were constrained to be equal in the male and female samples, the chi-square statistics increased insignificantly by 6.63 with 4 degrees of freedom, indicating that the mathematical and verbal self-assessment concepts have the same meaning for males and females.

Models with mathematical or verbal self-assessment as the dependent variable (models 1, 2, and 3) were estimated in a structural equation framework using maximum-likelihood estimation. Models 1 and 2 were estimated simultaneously, and the residuals for the math and verbal assessment latent variables were allowed to correlate.[11] One advantage of structural equation modeling is that equality constraints can be placed on regression coefficients for different groups, such as males and females, to assess whether statistically significant differences in the *size of the effect* of an independent variable on a dependent variable exists between the groups. Importantly, the effect of performance feedback, in the form of math grades, on mathematical self-assessment can be constrained to be equal in the male and female samples to examine whether these constraints statistically improve the fit of the model, allowing for a test of hypothesis 2. The AMOS and MPLUS statistical packages were used to estimate these models (Arbuckle 1997; Muthen and Muthen 1998).[12]

Path persistence, the dependent variable in hypothesis 3, refers to whether or not students move into activities that require a certain level of mathematical competence and are relevant to careers in the quantitative professions. Path persistence is measured at two time points on the educational path leading to careers in science, math, and engineering. First, a calculus enrollment variable measures whether or not a student enrolled in calculus by her or his senior year of high school. This information was taken from students' transcripts. Second, a quantitative major variable indexes whether or not those students who enrolled in a postsecondary educational institution selected a quantitative major in college. Students were asked in an open-ended question to list their college major. The National Center for Educational Statistics (NCES) coded responses into 112 detailed categories. I created a dichotomous measure from this variable where all engineering majors, chemistry, physics, other physical sci-

[11] Allowing the residuals for the two latent variables to be correlated improved the fit of the model ($\chi^2 = 298$; $df = 1$).

[12] These models were also estimated using OLS and robust variance estimators, and no substantive differences in estimates were found. That is, all three methods generated coefficients that were of similar magnitude, and the same coefficients were found to be significant by each method of estimation. Results are available on request.

ences, computer programming, statistics, and mathematics were coded as quantitative and all other majors were coded as nonquantitative.

As the path persistence variables are dichotomous, logistic regression is used to estimate these models (models 4 and 5). Thus, the models estimate the effect of the independent variables, described below, on the likelihood of a student enrolling in high school calculus or choosing a quantitative major.[13]

Independent Variables

The argument that gender affects how students assess their task competence hinges on comparing females and males who are otherwise equal in relevant ways. It is especially important to control for other factors commonly associated with differences in educational attainment. For this reason, all models control for race and parental education. Gender is added as an independent explanatory dummy variable in models 1, 2, 4, and 5. Females constitute the reference category for the gender dummy variable. Gender and race are taken from students' responses on the survey instrument. Race is recoded as a series of dummy variables representing African-Americans, Hispanics, and Asians, with whites serving as the reference category. Parental education was recoded into years of education from a categorical variable where one parent or guardian was asked to describe the highest level of education she or he attained. If applicable, the parent answered the same question for her or his spouse or partner. Responses were averaged if data were available for two parents or guardians.[14]

"Tracking" is the process whereby students are separated by ability into

[13] It might seem more elegant to analyze the entire set of models in a structural equation framework, with the mathematical and verbal self-assessment concepts serving as intervening variables. However, with dichotomous dependent variables, the assumption of normally distributed disturbances is untenable. Muthen (1984) proposed the CVM estimator that can be used to analyze categorical dependent variables in structural equation modeling. However, this estimator makes the strong assumption that the categorical variable reflects the individuals standing on an underlying, normally distributed latent variable. This is not theoretically reasonable in this study. That is, I conceive of the choice to pursue a quantitative or nonquantitative major as inherently categorical. (See West, Finch, and Curran [1995] for more on the CVM estimator.)

[14] The NELS-88 data set also provides a composite index of parent's education, F2PARED, constructed from the parent education variable collected when the student was in the twelfth grade. To avoid causal time ordering problems, I opted to construct my own parent's education variable using data collected from parents when the student was in the eighth grade; i.e., I did not want to have a variable from the twelfth grade predicting the self-assessment outcomes collected at the tenth grade. As parents' education levels are highly stable over the student's high school years, models run using F2PARED in place of my parent's education variable produced identical estimates.

different classes to be taught the same school subject (e.g., honors-level algebra I, academic-level algebra I, regular algebra I).[15] Tracking has been shown to both reflect and reproduce class and racial inequalities in the United States (e.g., see Oakes 1985). Additionally, and relevant to the current study, it is likely that when students make self-assessments of their mathematical or verbal competence, they compare themselves to others in their own mathematics or English classes. In this way, academic tracks represent ability reference groups within which students compare themselves when making self-assessments. This suggests that grades should have the same effect on self-assessments of competence within various levels of academic track placement. For example, a student in a lower track math class earning a B might assess his mathematical competence as high as a student earning a B in a higher track math class does, even though ability was supposedly used to determine track placement. According to the data used in the current study, females are slightly more likely to be in tracks associated with higher academic ability (see table 1). Consequently, females also are more likely to assess their competence in comparison to members of a higher-ability reference group. Gender differences in track placement could, therefore, contribute to gender differences in self-assessments of task competence.

A series of dummy variables was constructed to control for the track of high school math and English classes in which students were enrolled. A dummy variable representing the honors track and one representing the academic track were created for math and English classes using teacher descriptions.[16] The general high school track serves as the reference category. While both honors and academic classes are considered

[15] I use the term "track" to refer to classes students are required to take. The decision to place students in one track or another is usually made by counselors and teachers. Input from students is rare (Oakes 1985). I control for track of required classes when predicting the decision to enroll in calculus, a nonrequired, or elective, class. While being in an honors- or academic-level math track has been shown to increase the odds of choosing to enroll in calculus (Seymour and Hewitt 1997), most students, even those in higher math tracks, do not chose to take calculus. Thus, the decision to enroll in calculus, while influenced by track, represents a choice that students make and one that has occupational consequences.

[16] The teacher data provides two items about the level of each student's classes. The first is a measure of either the student's science or math class. I used this variable to create the math-level dummy variables, even though in about half the cases I had only the student's science level. In a similar fashion, the English-level variable was created from an item from either the student's English or social studies class. In collecting the variables this way, the National Center for Educational Statistics relies on the high correlation between level of math and science (or English and social studies) taken. I, too, assume that in the absence of knowledge of math or English track, science and social studies serve as adequate proxies.

higher ability levels than the general high school math or English class, honors is generally thought to be the highest math or English track.

In comparing the perceptions students make of their ability to perform a task, it is important to control for actual task ability. Task ability (in this case, math and verbal ability) was measured by averaging the eighth and tenth grade scores on the math or verbal standardized tests administered by the Educational Testing Service as part of the NELS-88 survey. Test scores are on a 100-point scale. I use the average of eighth and tenth grade to provide a more stable measure of ability over time.[17] Test scores from the eighth and tenth grades of high school represent the more recent scores available that do not create time-ordering problems in the models estimated. Not surprisingly, there is a high correlation between eighth and tenth grade test scores (0.88 for the mathematics tests and 0.81 for the verbal tests). While many have argued that these types of tests are culturally biased to the advantage of white, middle-class males, to the extent that this bias exists, it means that females and minorities with scores equal to that of white males would, if the bias were removed, actually have *more* ability than their white male counterparts. Thus, any cultural bias would make it harder to find statistically significant differences in self-assessments due to gender or race.

Of primary importance to this study is the effect of performance feedback on students' self-assessments of task competency. Mathematical and verbal performance feedback is measured by using the average math and English grades students received in high school. The NCES created these average grade variables by converting grades taken from students' transcripts to a continuous 13-point scale (with "1" representing the highest grade). This conversion allows grades to be comparable across the various schools attended by students in the NELS study.[18] I converted these values to the commonly used 4.0 grade point average scale ("4.0" being the highest "A" grade) to aid in interpretability. Therefore, a one-unit change in the grade variable represents a grade change of approximately one letter grade. While grading scales or requirements may differ from one school to another, this variation is not problematic in this study since grades are used as an indicator of the feedback provided to students about how others (their teachers) assess their mathematical (or verbal) competence. In other words, it is less important

[17] The longitudinal effects of eighth grade test scores on tenth grade test scores and on the other independent variables were also modeled in the structural equation model. The results were highly similar to the models presented in the article using the average of eighth and tenth grade test scores. Further, I estimated the effects of the eighth grade scores on the dependent variables in models 4 and 5; these effects were found to be largely mediated through tenth grade scores.

[18] Students were drawn from over 1,000 different schools.

whether or not grades actually measure ability or competence, but rather that they are available to students and accepted by them as a legitimate external evaluation of their competence.[19]

English grades and test scores are included in the math self-assessment models, and conversely, math grades and scores are included in the model with the verbal self-assessment dependent variable. This is done to make all models as comparable as possible. Further, it is likely that students make relative comparisons of the performance feedback they receive in various classes when assessing their ability and making career-relevant decisions. If students did not make relative comparisons, then the only performance information that would influence their mathematical self-assessments would be their mathematical grades and scores. However, others have shown that students do make these comparisons, classifying academic subjects, college majors, and even students within college majors as math/nonmath, hard/soft, "techy"/"fuzzy" (Seymour and Hewitt 1997; Montell 1992). If students do compare their math and verbal feedback, and especially if they perceive competency in these two areas to be in tension with each other, then as students receive increasingly higher verbal feedback they might see themselves as less skilled at mathematics, as less of a "techy." Specifically, higher English grades would dampen the mathematical self-assessments students would otherwise make if they instead based their mathematical self-assessments solely on their mathematical performance.[20] Therefore, it is important to control for English performance in the mathematical self-assessment models.

[19] One reviewer asked whether the grade and self-assessment items actually represent distinct concepts. Confirmatory factor analysis indicates that a model where the three math self-assessment items predict the latent variable "mathematical self-assessment" and the math grade item predicts the latent variable "math grades" produces a better fit than a model where the math grade variable is allowed to be a fourth measured variable predicting the latent variable "mathematical self-assessment." This is also true for the verbal self-assessment items and English grade variable. The correlations between the individual math self-assessment items and the math grade variable range from 0.40–0.47, and the correlation between the individual verbal self-assessment items and the English grade variable range from 0.35–0.47.

[20] One possible explanation for this relationship is that with higher English grades students are less likely to believe that their math grades are the result of possessing specific skill or competency in mathematics. For example, students who receive high grades in both English and math might perceive that they are generically good at school, rather than specifically skilled at math or English. Or, consider the scenario where two students receive equal grades in mathematics, both receive higher math grades than English grades, but one student earns better grades in English than the other student does. While both students earned better grades in math than they did in English, the student with lower English grades is presented with more of a contrast between the feedback she or he received in these two areas. She or he, therefore, might make higher assessments of her or his own math competence, even though both had equal math grades.

Finally, the self-assessment items are added as *independent* variables in models 4 and 5 to test the path persistence hypothesis (hypothesis 3). That is, I argue that if self-assessment of mathematical competence differs by gender, this differential perception should be at least partially responsible for the gender differences in the movement of males and females into activities relevant to the quantitative professions. To test this idea, mathematical self-assessment is allowed to predict persistence on the mathematical career path. By adding the mathematical assessment variable as an independent variable in the path persistence models, I expect that the magnitude of the gender effect on path persistence will decrease. The verbal self-assessment variable is also added to these models since students likely use relative assessments of their competence when making career-relevant decisions.

RESULTS AND DISCUSSION

Table 1 provides descriptive statistics for the males and females in the sample for whom there is complete data for each stage of the analysis.[21] The cases were weighted using the appropriate longitudinal probability weights provided in the NELS-88 data set. Not surprisingly, there is a large gap between the number of males and females who elected a quantitative college major. Compared with only 4% of females, 12% of males have majors in engineering, mathematics, or the physical sciences.[22] A smaller gender gap was found in calculus enrollment, where 10% of females and 11% of males had enrolled in calculus by their senior year of high school (see the model 4 column of table 1). The means of the mathematical assessment items do suggest that males are more likely than females to believe they are competent in math. This pattern emerges even though math grades and math test scores are very similar for males and females. Males do not appear to globally assess their competence higher,

[21] Missing data is less than 10% for each variable, with the exception of the calculus enrollment variable, which was missing for approximately 13% of the cases. This variable was taken from students' transcripts, and there is no reason to believe that there should be a pattern to the type of student on which this information was available or missing. To check for biases due to missing data, mathematical assessment models were run on the entire sample, including those who had missing data on some of the variables used in the analysis, using full information maximum-likelihood estimation (see Anderson [1957] for a discussion of ML estimation in the presence of missing data). No substantive differences in the relative magnitude or significance of estimates were found.

[22] Due to the large sample size, virtually all differences in means between males and females are significant. For this reason, I discuss the magnitude of the differences in this section and reserve discussion of significance for the multivariate models to follow.

as the means for the English assessment items are higher for females than for males. Finally, gender differences in the parental education, ethnicity, and math and English class-level variables appear minor, as would be expected. I now turn to the models designed to bring evidence to bear on the hypotheses offered.

Gender Beliefs and Biased Self-Assessments

The first hypothesis is that males assess their mathematical competence higher than females who perform at the same ability level and who receive the same feedback about their mathematical competence. Model 1 provides a test of this hypothesis (see table 2). First, and not surprisingly, higher math grades and test scores increase the level of mathematical self-assessment. Thus, those with more mathematical ability, as measured by test scores, are more likely to believe that they are skilled at mathematics. Further, the more positive the feedback from legitimate others, in the form of math grades, the higher the level of mathematical self-assessment. This is not surprising since evidence of task competence should be highly salient as students make personal assessments of their skill at a given task.[23] However, controlling for these differences in ability and performance feedback, males were found to assess their task competence 0.25 points higher than their female counterparts. Consistent with hypothesis 1, males are more likely to perceive that they are good at math than are those females with equal math grades and test scores.

Since the argument presented suggests that widely shared cultural beliefs about gender and task competence bias males' and females' self-assessments of task competence, it is useful to evaluate the same model for a set of tasks that have different gendered beliefs associated with them. Model 2 is identical to model 1, except the dependent variable is verbal self-assessment. As with the mathematical self-assessment model, differences in ability and performance feedback are controlled. Note that the parameter estimate for the male dummy variable is significant, but negative, meaning that *females* were found to make higher self-assessments of their verbal ability. This indicates that males do not globally assess their task competence higher than females, regardless of the gender association of the task. Instead, cultural beliefs associated with a particular task or field of study bias students' perceptions of their abilities in that field.

[23] One reviewer asked how much of the variation in mathematical self-assessment was explained by the grade variable alone. The r-square for the mathematical self-assessment model with math grade as the only independent variable is 0.245, compared with 0.346 for the complete model presented in table 2.

TABLE 1

MEANS FOR VARIABLES USED IN SUBSEQUENT ANALYSES[a]

	MODELS 1, 2, and 3		MODEL 4		MODEL 5	
DEPENDENT VARIABLES	Females	Males	Females	Males	Females	Males
Math assessment items:						
Math best	3.65 (1.83)	4.11 (1.70)	3.67 (1.82)	4.10 (1.71)	3.78 (1.78)	4.19 (1.67)
Math always	3.85 (1.73)	4.21 (1.60)	3.87 (1.74)	4.19 (1.61)	4.01 (1.69)	4.30 (1.57)
Math marks	4.04 (1.72)	4.29 (1.60)	4.05 (1.73)	4.28 (1.62)	4.19 (1.67)	4.45 (1.53)
English assessment items:						
English best	4.08 (1.63)	3.69 (1.58)	4.08 (1.62)	3.68 (1.58)	4.30 (1.50)	3.86 (1.51)
English quickly	4.70 (1.26)	4.43 (1.30)	4.70 (1.25)	4.44 (1.30)	4.86 (1.14)	4.60 (1.21)
English marks	4.62 (1.40)	4.20 (1.47)	4.63 (1.38)	4.21 (1.47)	4.84 (1.25)	4.43 (1.34)
Enrolled in calculus[b]			.098	.106	.130	.149
Chose quantitative major[b]					.036	.124
Independent variables:						
Math grades	2.13 (.91)	1.99 (.93)	1.97 (.86)	1.82 (.86)	2.10 (.83)	2.01 (.85)
English grades	2.39 (.87)	2.03 (.90)	2.24 (.83)	1.88 (.85)	2.46 (.76)	2.14 (.78)
Math test scores	51.3 (9.37)	51.7 (9.80)	51.4 (9.41)	51.9 (9.91)	53.7 (9.06)	54.5 (9.48)
Verbal test scores	52.3 (9.11)	50.5 (9.46)	52.4 (9.15)	50.6 (9.45)	54.5 (8.71)	52.6 (9.25)

Class level:[b]						
Math honors	.190	.179	.181	.167	.188	.169
Math academic	.477	.475	.479	.466	.541	.533
General math track[c]	.333	.346	.340	.367	.271	.298
English honors	.233	.178	.225	.172	.254	.198
English academic	.380	.407	.386	.394	.421	.437
General English track[c]	.387	.415	.389	.434	.325	.365
Ethnicity:[b]						
Asian	.036	.036	.041	.037	.045	.044
African-American	.112	.111	.109	.102	.103	.084
Hispanic	.096	.085	.089	.080	.077	.076
White[c]	.756	.768	.761	.781	.775	.796
Parent's education in years	13.3 (2.28)	13.6 (2.32)	13.3 (2.28)	13.6 (2.32)	13.7 (2.24)	14.1 (2.32)

SOURCE.—NELS-88.

NOTE.—For models 1, 2, and 3, $N = 6,877$ for females and 6,624 for males; for model 4, $N = 5,876$ for females and 5,681 for males; for model 5, $N = 3,539$ for females and 3,085 for males. SDs are given in parentheses.

[a] Values given are for cases with no missing values on any of the listed variables. All cases are weighted using the NELS sampling weights. See text for a description of the variables and for the wording of the assessment items.

[b] A (0-1) variable. The mean represents the proportion of students in the category indicated by the variable label. Standard deviations are not reported for (0-1) variables.

[c] Omitted reference category.

TABLE 2
MAXIMUM-LIKELIHOOD ESTIMATES OF THE EFFECTS OF GENDER AND OTHER VARIABLES IN A STRUCTURAL EQUATION MODEL OF MATHEMATICAL AND VERBAL SELF-ASSESSMENT[a]

	MODEL 1[d] MATH SELF-ASSESSMENT[e]		MODEL 2[d] VERBAL SELF-ASSESSMENT[e]	
INDEPENDENT VARIABLES	Coefficient	SE	Coefficient	SE
Male	.245*	.025	−.119*	.023
Math grades	.861*	.019	−.325*	.017
Math test scores	.076*	.002	−.001	.002
English grades	−.393*	.020	.754*	.019
Verbal test scores	−.039*	.002	.026*	.002
Class level:[b]				
Math honors	.184*	.042	.175*	.038
Math academic	.056*	.030	.141*	.027
English honors	−.096*	.038	.060*	.035
English academic	.001	.029	−.044*	.026
Ethnicity:[c]				
Asian	.116*	.064	.158*	.058
African-American	.586*	.039	.440*	.036
Hispanic	.077*	.043	.286*	.039
Parent's education (in years)	−.037*	.006	.002	.005

SOURCE.—NELS-88.

NOTE.—Fit statistics: χ^2 = 1,858 (60 *df*); ρ1 (RFI) = .949; IFI (Bollen delta square) = .983; CFI = .982; RMSEA = .047; R^2 = .346 for math assessment and .281 for verbal assessment.

[a] Estimates are based on 6,877 females and 6,624 males.

[b] Math and English class level variables are a series of (0-1) variables, with "the general high school track" serving as the reference category.

[c] Ethnicity is measured as a series of (0-1) variables, with "white" serving as the reference category.

[d] Models 1 and 2 were estimated simultaneously and the residuals for the two assessment variables were allowed to correlate

[e] Mathematical and verbal self-assessment variables are latent variables constructed from 3 math and 3 verbal self-assessment items. The math items have factor loadings of .89, .88, and .87. The verbal items have loadings of .82, .78, and .85. See text for the exact wording of the items.

* $P < .05$, one-tailed test.

While it is beyond the scope of this article to attempt to extend the argument presented to understanding racial or ethnic differences in career choice, it is worth discussing what may appear to be surprising results. Controlling for track of math and English class, grades, test scores, and parents' education, Asians, African-Americans, and Hispanics were found to assess both their math and verbal ability higher than whites. The estimate for the coefficient for the African-American dummy variable is especially notable for its magnitude. Others have shown that African-American students often have more positive attitudes toward education than whites (Portes and Wilson 1976; Catsambis 1994) and have higher self-concepts and higher self-esteem (Coleman 1966; Rosenberg and Simons 1971). Portes and Wilson (1976) have argued that positive attitudes towards self and school represent a real advantage to blacks in facilitating educational success. Espousing positive attitudes may be a strategy that African-American children learn from their families as a partial way of countering the impact of discrimination. The higher self-assessment values for African-Americans found in this study, then, appear consistent with earlier research.

The puzzle is how are African-Americans able to maintain high self-assessments in the face of dominant cultural beliefs that undoubtedly disadvantage them? In other words, why does the cultural belief approach advocated in the current study appear to hold for gender but not for race? It is again worth noting that students from different racial backgrounds grow up mostly in racially homogenous families, compared to the mixed-gender families in which most male and female youth are raised. Further, whereas males and females largely attend school together, members of different racial or ethnic groups are often segregated from each other into different kinds of schools. Growing up in mostly same-race families allows for the family to serve as a site of resistance to dominant cultural beliefs. Families can teach children alternative beliefs to counter hegemonic beliefs. African-Americans, in particular, have been highly successful in delegitimating hegemonic beliefs (see, e.g., MacLeod [1987] 1995). Being isolated in racially segregated schools further reduces the amount of daily exposure students have to hegemonic beliefs compared to what they would confront in more racially integrated schools. In contrast, alternative gender belief systems, such as the present day "girl power" phenomenon, are pitted daily against hegemonic gender beliefs. Thus, even individuals who are exposed to alternative gender beliefs in their families likely have daily exposure to hegemonic gender beliefs.

Performance Feedback and Self-Assessments

The results presented thus far show that males assess their mathematical competence higher than females of equal mathematical ability. But, as stated in hypothesis 2, since cultural beliefs about mathematics advantage males, performance feedback about their task competence should be less important to them in making self-assessments of their mathematical competence. Conversely, performance feedback, in the form of math grades, should have a larger impact on females' self-assessments of their mathematical ability, since they must contend with lower societal expectations of their mathematical competency. To test this hypothesis, I estimate the effects of the independent variables on mathematical self-assessment separately for males and females.

Comparing the male and female regression coefficients for the math grade variable (see model 3, table 3), the larger coefficient for females, 0.97 versus 0.74 for males, suggests that females do rely more on performance feedback about their task competency in making self-assessments. By constraining the math grade coefficients to be equal in the male and female samples and by comparing the fit of this model with the fit of the model where this constraint is relaxed, the gender difference in the *strength of the effect* of math grades on self-assessment was found to be significant.[24] As hypothesized, feedback about their mathematical competence has a significantly larger effect on the mathematical self-assessments of females compared to males.

Model 3 also shows that higher English grades and test scores actually lead to lower levels of mathematical self-assessment for both males and females. Recall that the mathematical self-assessment models control for the feedback students receive about their verbal competence. The logic behind this control is that it is likely that when students assess their mathematical competence, they make *relative* comparisons of the feedback they receive in various school subjects. As mentioned earlier, some have suggested that students perceive competency in math and verbal areas to be in tension with one another (Seymour and Hewitt 1997; Montell 1992). The negative regression coefficients for the English grade variable in the mathematical self-assessment models, and the negative coefficient for the math grade variable in the verbal self-assessment model (model 2), support the idea that students use performance information in relative ways when assessing their specific task competence.

As with math grades, the *effect* of English grades on mathematical self-assessments is significantly larger for females. (However, the effect is more negative for English grades and was more positive for math grades). That is, while higher English grades lead to lower self-assessments of their mathematical ability for all students, controlling for math grades and test scores, the negative effect is larger for females. While the gender difference in the effect of math grades on mathematical self-assessment was hypothesized, the significant gender difference in the effect of English grades was not. One explanation for this unexpected finding is that when individuals are in a situation where societal expectations of their task competence are lacking, they pay heightened attention to all performance feedback in the general environment, in this case the environment of school. Therefore, the process of making relative comparisons of various types of feedback when assessing one's own competence at a specific task,

[24] In SEM modeling, regression coefficients can be constrained to be equal, and a nested model contrast can be made between the constrained and unconstrained model. In this case, the significant chi-square of 31.6 with one degree of freedom suggests that the more constrained model produces a significantly worse fit.

TABLE 3
MAXIMUM-LIKELIHOOD ESTIMATES OF THE EFFECTS OF MATH GRADES AND OTHER VARIABLES IN A STRUCTURAL EQUATION MODEL OF MATHEMATICAL SELF-ASSESSMENT: A COMPARISON OF GENDER DIFFERENCES IN THE REGRESSION COEFFICIENTS[a]

	MODEL 3: MATHEMATICAL SELF-ASSESSMENT			
INDEPENDENT VARIABLES	Females Coefficient	SE	Males Coefficient	SE
Math grades	.967*	.027	.739*	.026
Math test scores	.078*	.003	.072*	.003
English grades	−.490*	.029	−.282*	.028
Verbal test scores	−.040*	.003	−.036*	.003
Class level:[b]				
Math honors	.193*	.059	.178*	.059
Math academic	.016	.042	.087*	.041
English honors	−.129*	.052	−.059	.055
English academic	−.024	.041	.032	.039
Ethnicity:[c]				
Asian	.107	.090	.128	.089
African-American	.623*	.056	.532*	.055
Hispanic	.033	.060	.142*	.061
Parent's education (in years)	−.030*	.008	−.044*	.008

SOURCE.—NELS-88.
NOTE.—Fit statistics: $\chi^2 = 505$ (48 *df*); $\rho 1$ (RFI) = .971; IFI (Bollen delta square) = .994; RMSEA = .038; $R^2 = .361$ for females and .315 for males.
[a] Estimates are based on 6,877 females and 6,624 males.
[b] Math and English class level variables are a series of dummy variables, with "the general high school track" serving as the reference category.
[c] Ethnicity is measured as a series of dummy variables, with "white" serving as the reference category.
* $P < .05$, one-tailed test.

a process which occurs for all students, is amplified under conditions where societal performance expectations are lacking. Widely shared cultural beliefs about gender and mathematics create this type of environment for female students.[25]

Biased Self-Assessments and Career-Relevant Decisions

Gender differences in self-assessments of competence at mathematics become important if they can be linked to gender differences in early career-relevant decisions, in this case, the decision to persist on the path leading

[25] As further support of this idea, verbal self-assessment models were also estimated separately for males and females, and no gender differences were found in the strength of the effects of math or English grades on verbal self-assessments. Recall verbal tasks are not clearly associated with gender differences in societal expectations. While higher English grades lead to higher verbal self-assessments and higher math grades lead to lower verbal self-assessments, indicating again that students use performance feedback in relative ways, no gender difference was found in the strength of the effect of either type of grade on verbal self assessment. Results are available on request.

to careers in the quantitative professions. In model 4a, I examine the impact of gender on enrolling in high school calculus; and in model 4b, I add the self-assessment variables to assess their impact on the gender regression coefficient (see table 4). In model 4a, the coefficient for the male dummy variable is significant and positive. Converting the coefficient into an odds ratio, we see that males are 1.23 times more likely to enroll in calculus than are their otherwise equal female counterparts. Importantly, since mathematical ability is controlled, the gender difference in calculus enrollment cannot be attributed to superior mathematical ability that some claim males possess (Peng and Jaffe 1979; Rudisill and Morrison 1989; Benbow and Stanley 1980, 1983; Kolata 1980).

In model 4b, I add the self-assessment variables to the equation. As hypothesized, higher levels of mathematical self-assessment increase the odds of enrolling in calculus. For every additional point of mathematical self-assessment, the log odds increases by 0.39. The regression coefficient for the verbal self-assessment variable is negative, suggesting that students' decisions to enroll in calculus are based on a relative comparison of their assessments of their math and verbal skills. That is, at any level of mathematical self-assessment, the higher the perception of verbal ability, the lower the odds that a student will enroll in calculus, and vice-versa. Since grades and test scores are controlled, self-assessments of task competence are shown to have an effect on career-relevant decisions over and above actual ability. Of primary interest, the coefficient for the male dummy variable is no longer significant, indicating that the effect of gender on calculus enrollment is, at least partially, the result of gender differences in perceptions of mathematical competence. Put another way, when males and females perceive themselves to be equally mathematically competent, they are equally likely to enroll in calculus.[26]

[26] Since the gender gap in calculus enrollment has narrowed in recent years and is smaller than the gender gap in some advanced elective science classes, such as physics (AAUW 1992), one reviewer suggested that I model physics enrollment, rather than calculus enrollment. I therefore reran models 4a and 4b, changing the dependent variable from calculus enrollment to physics enrollment. I could not, however, change the mathematical self-assessment variable to a science assessment variable because no such variable exists in the NELS data. (The self-assessment items are only asked with regard to math and verbal skills). The results of the physics enrollment models are qualitatively similar. That is, higher mathematical self-assessment contributes to an increased likelihood of enrolling in physics, and gender differences in mathematical self-assessment partially explain this difference. However, the magnitude of the effect of mathematical self-assessment on physics enrollment is smaller than for calculus enrollment. This is not surprising, as we would expect math self-assessment to have an impact on math enrollment more than it would on science enrollment. Even though the calculus gender gap is relatively small, it is especially important for women to enroll in calculus if they are to persist on the path to careers in engineering, math, and science, as will be shown in model 6.

TABLE 4

MAXIMUM-LIKELIHOOD ESTIMATES OF THE EFFECTS OF GENDER AND OTHER VARIABLES IN A LOGISTIC REGRESSION MODEL OF CALCULUS ENROLLMENT.[a]

Independent Variables	Model 4a		Model 4b	
	Coefficient	SE	Coefficient	SE
Male	.211*	.105	.138	.121
Math grades	.594*	.105	.195*	.118
English grades	.344*	.097	.585*	.107
Math test scores	.161*	.011	.143*	.011
Verbal test scores	−.0011	.013	.011	.013
Class level:[b]				
Math honors	1.11*	.186	1.12*	.187
Math academic	.478*	.187	.503*	.188
English honors	.627*	.141	.684*	.142
English academic	.370*	.152	.377*	.153
Ethnicity:[c]				
Asian	.701*	.144	.721*	.146
African-American	.930*	.239	.877*	.242
Hispanic	.380	.263	.395	.263
Parent's education (in years)	.037	.023	.047*	.023
Constant	−15.5*	.676	−16.5*	.705
Math self-assessment			.392*	.050
Verbal self-assessment			−.109*	.051

SOURCE.—NELS-88.

NOTE.—Fit statistics: χ^2 = 1,208 (13 *df*) for model 4a and 1,245 (15 *df*) for model 4b; log likelihood = −2,232 for model 4a and −2,183 for model 4b; likelihood ratio χ^2 test of model improvement (model 4a vs. 4b) = 98 (2 *df*).

[a] Estimates are based on 5,876 females and 5,681 males.

[b] Math and English class level variables are a series of dummy variables, with "the general high school track" serving as the reference category.

[c] Ethnicity is measured as a series of dummy variables, with "white" serving as the reference category.

* $P < .05$, one-tailed test.

This suggests that gender differences in the self-assessment of task competence are at least partially responsible for the differential movement of males and females along the path to the quantitative professions.

To further test the path persistence hypothesis, I examine the impact of gender and mathematical self-assessments on selecting a quantitative college major (see table 5).[27] In model 5a, converting the male dummy

[27] The sample analyzed in model 5 is limited to those who attended college, thereby introducing the possibility of sample selection bias. To test for this potential bias, I estimated a Heckman probit model using version 6 of the Stata statistical software package. This model estimates maximum-likelihood probit models with sample selection (see Van de Ven and Van Pragg [1981] for more on this model). No significant difference was found between the model with sample selection and that without, thereby indicating that the selection mechanism does not introduce bias into the estimates produced (ρ = .180; P = .737). This model is presented in the appendix. Comparing the probit coefficients for the model estimated with and without selection,

TABLE 5
MAXIMUM-LIKELIHOOD ESTIMATES OF THE EFFECTS OF GENDER AND OTHER VARIABLES IN A LOGISTIC REGRESSION MODEL OF CHOICE OF QUANTITATIVE MAJOR[a]

	MODEL 5A		MODEL 5B	
INDEPENDENT VARIABLES	Coefficient	SE	Coefficient	SE
Male	1.35*	.129	1.26*	.128
Math grades	.578*	.097	.318*	.109
English grades	−.222*	.109	−.071	.120
Math test scores	.062*	.010	.047*	.010
Verbal test scores	−.018*	.094	−.0096	.0099
Class level:[b]				
Math honors	.367*	.186	.363*	.184
Math academic	.138	.151	.140	.152
English honors	.038	.167	.080	.167
English academic	−.057	.142	−.043	.142
Ethnicity:[c]				
Asian	.229	.213	.228	.220
African-American	1.08*	.205	1.02*	.208
Hispanic	.040	.267	.056	.264
Parent's education (in years)	−.071*	.025	−.063*	.025
Constant	−5.86*	.536	−6.22*	.596
Math self-assessment			.274*	.057
Verbal self-assessment			−.093*	.052

SOURCE.—NELS-88.
NOTE.—Fit statistics: $\chi^2 = 289$ (13 *df*) for model 5a and 294 (15 *df*) for model 5b; log likelihood = −1,599 for model 5a and −1,580 for model 5b; likelihood ratio χ^2 test of model improvement (model 5a vs. 5b) = 38 (2 *df*).
[a] Estimates are based on 3,539 females and 3,085 males.
[b] Math and English class level variables are a series of dummy variables, with "the general high school track" serving as the reference category.
[c] Ethnicity is measured as a series of dummy variables, with "white" serving as the reference category.
* $P < .05$, one-tailed test.

variable coefficient to an odds ratio, we see that males are 3.86 times more likely to choose a quantitative major than are their otherwise equal female counterparts.

In model 5b, I add the self-assessment variables as independent variables. As predicted in hypothesis 3, higher levels of mathematical self-assessment increase the odds of choosing a quantitative major. For every additional point of mathematical self-assessment, the log odds increases by 0.27. This suggests that all students need to develop a personal conception of themselves as skilled at mathematics if they are to move toward a career in a quantitative profession. As with the calculus model, higher verbal self-assessments decrease the odds of choosing a quantitative major,

we can see that while some estimates change, the estimates for the variables of primary theoretical importance to the current study (the male dummy variable and the assessment variables) differ only slightly.

indicating that students use relative understandings of their competencies when making career-relevant decisions. Further, the magnitude of the gender coefficient does decrease with the inclusion of the mathematical assessment variable, although the difference is small. This small effect, combined with the larger effect of mathematical self-assessment on calculus enrollment, suggests that gender differences in mathematical self-assessment contribute to the gender disparity in the decision to pursue a quantitative career.[28]

In fact, others have argued that calculus enrollment might be especially important for females in choosing a quantitative major (Seymour and

[28] The regression coefficients for the African-American dummy variable may seem to contradict established findings about ethnicity and educational attainment. For example, model 4 indicates that African-Americans are more likely than whites to enroll in high school calculus. However, this effect is largely the result of the controls in the model. If math grades and test scores are removed from the model, African-Americans are less likely than whites to enroll in calculus (odd ratios of 0.67). This suggests that the factors that continue to contribute to the lower grades and test scores African-American students receive are probably also behind their lower enrollment in advanced math classes. By contrast, when grades and test scores are removed from the model, males continue to be more likely than females to enroll in calculus (odds ratio of 1.16). Likewise, in model 5, African-Americans who attend college were found to be more likely than whites to choose a quantitative major. When all variables except for the race and gender dummy variables are removed from the model, the coefficient for the African-American dummy variable remains positive and significant, although its magnitude is decreased to 0.47. Model 5 was estimated for students enrolled in two- and four-year colleges. When the model was estimated only for those students who were attending a four-year college, the African-American coefficient was no longer found to be significant. However, the lack of significance still means that African-Americans are just as likely as whites to select a quantitative major. Others have found that, while in the past minority students were less likely to major in engineering or the sciences, this gap has closed in recent years (Brown 1994). Astin (1993) found that approximately equal proportions of black, white, and Hispanic students chose a science, math, or engineering major upon entering college, and the proportion of Asian students was significantly higher. In an extensive ethnographic study of students who were either majoring in science, math, and engineering or had switched out of one of these majors, Seymour and Hewitt (1997) found that children from working-class or minority backgrounds reported being encouraged to select careers that would provide them with a secure future. Engineering was seen as "synonymous with success" (p. 325). This study showed that the extra encouragement that minority children received to enter these fields from their families and teachers did contribute to their decisions to chose a quantitative major. However, African-Americans and Hispanic students dropped out of quantitative majors at a significantly higher rate than whites or Asians, citing as a main reason that they had chosen a major "inappropriate" for them (p. 324). Race often becomes more salient for African-Americans and Hispanics in college than it was in high school since their racial or ethnic group is usually more of a numerical minority in college than in high school. That the choice of an engineering major began to seem "inappropriate" only once in college suggests that cultural beliefs about racial or ethnic groups have an impact on career-relevant decisions, but the influence occurs later in the career-choice process when race and ethnicity are more salient.

TABLE 6
MAXIMUM-LIKELIHOOD ESTIMATES OF THE EFFECTS OF CALCULUS ENROLLMENT IN A LOGISTIC REGRESSION MODEL OF CHOICE OF QUANTITATIVE MAJOR[a]

	MODEL 6	
INDEPENDENT VARIABLES	Coefficient	SE
Male	1.39*	.139
Math grades	.273*	.099
English grades	−.112	.107
Math test scores	.028*	.0095
Verbal test scores	−.011	.0086
Class level:[b]		
Math honors	.138	.161
Math academic	.141	.129
English honors	.104	.142
English academic	−.083	.119
Ethnicity:[c]		
Asian	−.038	.154
African-American	.839*	.165
Hispanic	−.225	.190
Parent's education (in years)	−.072*	.022
Constant	−5.86*	.536
Math self-assessment	.231*	.047
Verbal self-assessment	−.094*	.047
Calculus enrollment	1.17*	.197
Calculus enrollment × male	−.352*	.172

SOURCE.—NELS-88.
NOTE.—Fit statistics: $\chi^2 = 329$ (17 *df*); log likelihood = −1,557; likelihood ratio χ^2 test of model improvement (model 6 vs. 5b) = 46 (2 *df*).
[a] Estimates are based on 3,539 females and 3,085 males.
[b] Math and English class level variables are a series of dummy variables, with "the general high school track" serving as the reference category.
[c] Ethnicity is measured as a series of dummy variables, with "white" serving as the reference category.
* $P < .05$, one-tailed test.

Hewitt 1997; McIlwee and Robinson 1992). If this is true, then gender differences in mathematical self-assessment, which at least partially explained the gender gap in calculus enrollment, become even more consequential. To evaluate this argument with the data used in the current study, I estimated a logistic regression model of the effects of the calculus enrollment variable, the male dummy variable, and the interaction of these two variables on the likelihood of choosing a quantitative major (see model 6, table 6). All other independent variables from models 4 and 5 were also included. The significant negative interaction term indicates that the *effect* of calculus enrollment on choosing a quantitative major is larger for females. Converting the calculus regression coefficient to an odds ratio, we see that females who enrolled in high school calculus are

3.22 times more likely to choose a quantitative major than females who did not take calculus. Males who enrolled in calculus are only 2.27 times more likely than males who did not take calculus to choose a quantitative major.[29] In sum, enrolling in calculus has a significantly larger influence on the decision of females to choose a quantitative major. However, since females make relatively lower self-assessments of their mathematical ability, they are also less likely than their equal ability male counterparts to enroll in calculus. In this way, gender differences in mathematical self-assessment further widen the gender gap in quantitative college majors.

In sum, the results presented provide support for the supply-side model presented. Gender beliefs about task competence bias the assessments individuals make of their own competence at mathematics, and these biased assessments differentially influence the decisions males and females make to persist on the path toward careers in science, math, and engineering. Since males tend to overestimate their mathematical competence relative to females performing at the same ability level, they are more likely to choose careers in the quantitative professions. Importantly, gender differences in the selection of activities leading to these careers are not the result of actual differences in ability or merit, but they are instead the result of biased perceptions of competence.

SUMMARY AND CONCLUSION

The purpose of this study was to develop and test a simple supply-side model about gender differences in early career-relevant decisions. To test the hypotheses generated, I focused on high school students' perceptions of their mathematical competence and how these perceptions, controlling for actual ability, influenced decisions to persist on the path leading to careers in the quantitative professions. Since these professions have remained stubbornly male dominated (Hanson 1996), they represent an important site from which to examine the constraining effects of gender beliefs on career decisions.

The results of this study show that males assess their own mathematical competence higher than their otherwise equal female counterparts. Males are more likely than females with the same math grades and test scores to perceive that they are mathematically competent. Males were *not* found to assess their competence at verbal tasks higher than females, demonstrating that males do not globally assess their competence higher for all tasks, regardless of the task's gender association. Instead, widely shared

[29] The inverse log of $(1.17 - .352)$ is 2.27.

cultural beliefs about gender and task competence bias the perceptions individuals have of their own task ability.

Further, the *effect* of performance feedback on self-assessments was found to differ by gender. Math grades had a significantly larger positive effect on the mathematical self-assessments for females than for males. Proof of their competence could be more important to females because they must contend with lower societal expectations of their mathematical ability. More generally, this suggests that the appraisals individuals make of their own competence at various tasks are more contingent on local evidence when societal expectations for success are lacking.

Importantly, self-assessments of task competence were found to influence career-relevant decisions, even when controlling for commonly accepted measures of ability. For males and females, the higher they rate their mathematical competence, the greater the odds that they will continue on the path leading to careers in the quantitative professions. However, since males tend to overestimate their mathematical competence relative to females, males are also more likely to pursue activities leading down a path toward a career in science, math, and engineering. While standardized test scores and high school grades are certainly imperfect measures of ability, I contend that they are likely more accurate measures of ability than are the self-perceptions of high school students. Therefore, these results suggest that those who persist on a mathematical career path may not even be the best qualified for careers requiring mathematical proficiency. In other words, boys do not pursue mathematical activities at a higher rate than girls do because they are better at mathematics. They do so, at least partially, because they *think* they are better.

This study's major contribution is to highlight one mechanism by which cultural beliefs about gender constrain the early career-relevant choices of men and women. The model presented focuses on how gender beliefs bias self-perceptions of competence. This focus is important since presumptions of competence often legitimate inequality in achievement-oriented societies. The model proposed was evaluated with respect to the quantitative professions. However, my eventual goal is to highlight more generally how gender beliefs associated with various career-relevant tasks bias individuals' perceptions of their competence at those tasks and, consequently, influence their commitment to different career trajectories. Anytime widely shared cultural beliefs about a task advantage males, the self-assessments males make of their competence in regard to the task should be higher, on average, than that of females performing at the same objective level. If the task is also one that is thought to be necessary for movement along a particular career path, then males, acting on upwardly biased appraisals of their task competence, should be more likely than females to continue on the path leading to that career. Conversely, if a task belief advantages females, such as beliefs associated with nurturing skills or abilities, females should assess their task competence higher than males. A gender difference in the self-assessment of nurturing ability, for example, might partially explain the gender gap in professions such as nursing. The model could also be used to explain gender differences in the choice of specialties within a field, assuming that tasks believed to be necessary to pursue various specialties are associated with clear and stable cultural beliefs about gender. For example, if it is widely believed that, to be successful, surgeons have to be able to maintain emotional distance, and men are thought to better than women at maintaining emotional distance, then the model could be employed to understand the continued male dominance of the specialty of surgery within the field of medicine. As these examples suggest, while the quantitative professions have been extreme in their resistance to the entry of women, there is no reason to think that they are the only professions that have skills that are both thought to be necessary and have gender beliefs associated with them. These required skills might either be less "critical" for entrance into a given profession or less stereotyped than mathematical skills are for the quantitative professions. This, however, would only serve to dampen, not eliminate, the effect shown. Career-relevant decisions are made at many points throughout the life cycle. Therefore, even small gender differences occurring at decision-making junctures can serve to carry males and females in substantially different occupational directions.

The cultural belief approach advocated in this article can only explain differences in the supply networks of workers for occupations that have clear and stable gender beliefs in the culture. Since many occupations and specialties within occupations do have stable, widely available cultural beliefs associated with them, the argument presented here is relevant for understanding the continued gender gap in a wide array of occupations. However, newly emerging types of jobs quickly become gender labeled (Game and Pringle 1983), and the gender typing of particular kinds of work changes over time. The processes by which gender beliefs about tasks associated with different kinds of work emerge and change are not fully understood. Given the importance of these processes for reproducing gender inequality, this is fertile ground for future research.

The results of this study demonstrate that widely shared cultural beliefs attached to various tasks affect not only how individuals are channeled into particular activities and subsequent career trajectories by others, but also how individuals "self-select" into occupationally relevant activities. This implies that the gender-segregated labor force will be reproduced partially through the different and seemingly voluntary choices men and women make. Any attempts to counter the effects of gender beliefs on gender segregation and inequality in the labor force, therefore, will require looking beyond how stereotypes are used by gatekeepers, such as teachers and employers, and focusing also on how gender beliefs affect males' and females' perceptions of their own abilities at crucial decision-making junctures.

APPENDIX

TABLE A1
A Comparison of the Estimates of the Effects of Gender and Other Variables in a Probit Regression Model of Choice of Quantitative Major, Estimated with and without Sample Selection[a]

Independent Variables	Model 5b without Selection: Probit Coefficient	SE	Model 5b with Selection: Probit Coefficient	SE
Male	.624*	.053	.615*	.065
Math grades	.158*	.050	.149*	.058
English grades	−.033	.053	.0013	.116
Math test scores	.022*	.0046	.023*	.0050
Verbal test scores	−.0065	.0043	−.0058	.0048
Class level:[b]				
Math honors	.132*	.078	.131*	.080
Math academic	.072	.063	.073	.063
English honors	.085	.072	.084	.072
English academic	−.044	.059	−.043	.059
Ethnicity:[c]				
Asian	.064	.080	.114	.166
African-American	.461*	.085	.484*	.102
Hispanic	−.093	.092	−.069	.118
Parent's education (in years)	−.031*	.011	−.031*	.011
Constant	−2.90*	.218	−3.16*	.745
Math self-assessment	.120*	.022	.119*	.023
Verbal self-assessment	−.050*	.024	−.048*	.025

Source.—NELS-88.
Note.—$\rho = .180$ ($\chi 2 = .113$ [1 *df*]; $P = .737$).
[a] Model 5b "with selection" is a standard Heckman probit model which provides maximum-likelihood estimates with sample selection. Model 5b "without selection" is simply a probit regresssion model. Model 5b without selection is based on 11,557 cases. 4,931 of these cases are censored in the model with selection.
[b] Math and English class level variables are a series of dummy variables, with "the general high school track" serving as the reference category.
[c] Ethnicity is measured as a series of dummy variables, with "white" serving as the reference category.
* $P < .05$, one-tailed test.

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