PEER MATH ABILITY, QUANTITATIVE CURRICULUM CONTENT, AND WAGES:
A Story of Gender Differences

A thesis

submitted by

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Abstract

In this thesis, I examine the effects of peer math ability at college, total credits achieved in math, sciences, and engineering (MSE hereafter), and GPA on the earnings of young college graduates. I use the High School and Beyond survey to track students from high school through college into the job market. Using average quantitative SAT score of the school attended, I determine that the ability of a student's peers has a significant effect on how many credits that individual chooses to take. I find some evidence that this effect is larger for women than for men. I also find that high school preparation is a stronger determinant of total MSE credits for men than for women. Additionally, I find that total MSE credits have different effects for men and women in determining earnings in the first two years in the job market following graduation.

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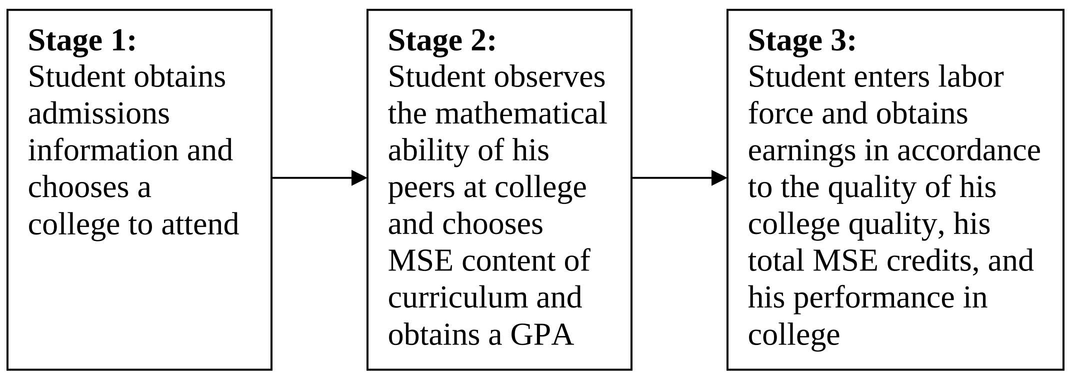
Introduction

In this thesis, I consider the question: How do peer math ability, mathematical content of curriculum, and college GPA influence early career wage outcomes for individuals who have attended an undergraduate institution? The literature examining wage outcomes focuses on student ability, interest, and background in light of only college choice, curriculum choice, or earnings. I feel that a more comprehensive, integrated approach is merited. While each of these factors has a significant effect on earnings, these types of studies do not estimate separate effects for these factors and shed limited light on the complicated optimization process students attending post-secondary education must go through. Specifically, the prevailing literature fails to include the intermediate step of how college environment affects the types of curricula students choose.

At the end of high school, students are forced to make a decision that will have considerable influence on the rest of their lives: whether or not to attend college. Those who choose to attend a four- year college are the focus of this thesis. Potential students follow a multi-stage process in choosing a university and a major. First, a student must make the choice to apply to college or not. Then, he must choose which colleges to target and applies to these. Once he gets his acceptance letters, and potentially, scholarship and financial aid information, he chooses the college which most closely suits his criteria. He then enters college, where he observes his environment and his performance in that environment in order to decide upon a major. Most importantly, he must make his decision having taken into account the aptitude of his peers, as well as his performance in certain classes in relation to his overall performance as a student. He then chooses a major, pursues it, and enters the labor market having either achieved a bachelor's degree or completed some level of education at the four-year college level. In the labor force, he then obtains a wage outcome that is dependent upon his performance in his postsecondary education, the quality of that education, and the curriculum he pursued. (see Chart 1)

Chart 1.



In the model I propose, I begin with the step in which the student chooses to attend a certain school. The application process and choice of college the student is considered exogenous in this model. Of primary concern is the quality of college he attends and how this contributes to his subsequent choice of curriculum. The process of choosing a college, a curriculum, and then receiving a wage occurs in the sequence described above. First he chooses a college, given a set of choices, then he chooses a major field of study, and then he observes his wage in the labor market.[1]

[1] Note that this is a recursive rather than simultaneous model. I assume that students have heterogenous expectations and incomplete information. As Manski (1993) points out, there is no good way for students to inform themselves completely. So simply calculating expectations from theory may not be a good indicator for how they truly behave. Subsequently, I assume that students may have vague ideas about their

While trying to develop a more comprehensive model that includes all of these aspects may be a bit ambitions, my hope is simply to contribute to the prevailing theory by taking a closer look at the decision making process students follow as they proceed with their post-secondary education. In examining these choices, I find evidence that men and women behave differently. Through all three stages, there is evidence that women and men approach college education and curriculum choice in different ways. In the final stage, they also see different rewards in the job market.

In the empirical section, I concentrate primarily on the amount of mathematics, sciences, and engineering credits (MSE credits hereafter) students earn in their time in school and the effects these have on wage outcomes. The rationale for this is that for most students, major field of study matters less than the MSE content of the undergraduate major. For instance, a physics major may well wind up working in finance. The job in finance is available to him because he has taken extensive mathematics, so the importance of mathematics credits is greater than that of the actual major. This measure of an undergraduate program allows for inclusion of students who may not have attained a bachelor's degree since the MSE content of their program can be measured even though they did not complete a major or degree.[2]

It should be noted that because this model focuses on wage outcome immediately following graduation, it does not include those students who enter professional or graduate school right out of college. This means that a portion of high performing students will be omitted from the analysis because they do not immediately enter the

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academic interests and career aspirations, but will be able to act on these only in stages as more information is revealed.

[2] This brings about further questions of signaling models versus human capital models, and will be addressed in section 2.2.

labor force. It does, however, include students who have dropped out of college, but have earned some credits. This raises an important question about whether major choice is a signal to employers or a true human capital builder, which I address in Section 2.2.

Additionally, due to data set limitations, I consider only wages immediately following labor market entry. The empirical work in this paper concentrates purely on the early career effects of peer math ability, field of study, and GPA, and ignores future wage profile.

The HSB Data Set and Empirical Methods

The main focus of this paper is to examine the relative importance and interplay of peer math ability and MSE content of curriculum. In order to assess the quality of academic environment in which the student is immersed, colleges are characterized by their mean mathematical SAT score[3]. Curriculum quality is defined as the mathematical, science, and engineering content in the student's course of study. This data includes all credits received in math, sciences, and engineering at the college level. Since mathematical ability can be considered a scarce input to human productivity, it is highly rewarded in the labor market because it is hard to acquire. (Paglin & Rufolo, 1990) Thus it is not surprising that there is a significant and reliable link between the mathematical and science content of a student's major field of study and his earnings both directly following entrance into the job market, and further in his life as a worker. (Weinberger, 1999; Fiorito & Dauffenbach, 1982) I also choose curriculum content over major field of study because the academic content of the same major can vary from school to school.

[3] As obtained from the College Board 1986 Annual Survey of Colleges.

As a measure of MSE content, I use the sum of these credits obtained at the last institution attended, including any transfer credits allowed by that institution.

The HSB data set consists of two cohorts: sophomores and seniors surveyed first in 1980, with three follow-up surveys through 1986. In order to obtain good wage information, I use only the senior cohort in this analysis.[4] I further restrict the data to students whose last school recorded as attended by the HSB survey was a four year or two year public or private college or university that reported SAT scores to the College Board. Thus students who wind up transferring from four to two year colleges are not excluded, and those who do the opposite also remain in the data. It also includes students who have not yet attained their degrees or dropped out without getting one. In a sense, this includes those students who are described by Adelman (2006) as showing a spiraling effect- moving from school to school without ever attaining a degree. However, since we are using only schools that report SAT scores[5], we are more likely to have higher quality colleges that offer more academically oriented programs.[6]

I use the structural model explained in the following three sections to estimate three equations. The first is a measure of peer math ability at the school a student attends given certain attributes of the student, including measures for ability, interest, and family background. The dependent variable is a measure of mean mathematical SAT score at the college attended.

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[4] Within the time frame of the HSB surveys, the sophomore class was not given enough time to graduate from college in four years and obtain wages.

[5] Of those schools reported in the HSB data set for this subset of the cohort, nearly half of the schools attended did not report SAT scores and were of a religious or vocationally oriented variety. For purposes of pursuing only those students who could legitimately choose a math, science or engineering curriculum, these schools are excluded.

[6] There is significant implication on any type of "signaling" hypothesis, which does require that a degree be finished to signal to the job market.

In the second equation, I regress total college credits achieved in math, science and engineering on a measure of the difference between the student's math SAT score and the college's mean math SAT score. This is intended to endogenize the effect of the peer math ability on curriculum choice. I again include variables to capture student ability, interest, and background.

In the third equation, I measure wage outcome for each student following as of the latest job held in 1986. I include college GPA and independent demographic, background, interest and ability variables. Additionally, I break students into groups according to how many math, science, and engineering credits they obtained and evaluate each group to evaluate differences in earnings levels.

Descriptive Statistics and Overview of the Data

The descriptive statistics and variable list and descriptions for each section are available in the appendix. The data includes include family demographic information, background, interest, and ability variables. There are a few characteristics of this data worth mentioning, particularly with respect to gender.

First, the HSB survey over-sampled schools that were in low income environments. As a result, there is a large proportion (18%) of black students in the data, as race is correlated to income. Hispanic students are included in the variable "other", as this was not coded for in 1980. 52% of the sample is female, as is expected for college data, where women are becoming a larger and larger portion of the population. (Table 1.1)

As will be shown in all three sections, there are differences in gender in all three stages. The mean of the average school quantitative SAT score is 517. This number is slightly lower for women (509), and slightly higher for men (526). (Tables 1.1-1.3) Overall, total credits in MSE average around 32, while again, women have lower and men higher values. (26 and 38 respectively) (Tables 2.1-2.2) After the exclusion of wages below $100 per week due to reporting problems in the survey, average weekly income is $325. Women earn a bit less, and men a bit more ($291 and $365, respectively). (Tables 3.1-3.3)

Section 1: **Stage 1: Choosing a College**

Introduction

In this analysis, I explore what determines the mathematical profile of the college a student attends, given his or her individual characteristics. I consider the peer math ability of the school through mean math SAT score of the school itself. This is particularly important for the overarching theme of wage outcomes because higher mean SAT score is generally positively correlated to such factors as small enrollment numbers, good professorial salaries, private colleges and universities, and PhD granting institutions, all of which hold a positive influence over the future earnings of a student. (Behrman, et al, 1996)[7]

Little has been said about the factors influencing the mathematical abilities of the peers that students choose implicitly when choosing to attend college. The results presented here corroborate the story that prevailing literature tells about how factors such as race, gender, ability, and socioeconomic background influence the type of post-secondary institution a student attends. However, it is focused more closely on how these things affect the "mathematical environment" in which a student is placed. This becomes especially interesting when gender is considered.

[7] We run into a self-selection problem here. An individual's endowments of talent and tolerance for workload present a problem for the further stages of the model: these qualities may determine their selection into, and success in college, and also determine their success in the workplace. Any model estimating both college quality and wage outcome will have to take into account this issue of endogeneity. I will proceed to address this problem further in the next sections.

Literature Review

When examining how students choose a post-secondary institution, several factors must be accounted for in any empirical approach. These include gender, race, socioeconomic status, and for the purposes of this thesis, background, ability, and interest.

The role of gender and race, as in all aspects of college selectivity and earnings, plays a crucial part in the type of college students attend. Davies and Guppy (1998) indicate that, controlling for background factors, men are more likely than women to go to selective colleges. When further controlled for, this disadvantage diminished, but it is true that women tend towards less mathematical majors. Weinberger (1999) shows that when college major is not controlled for, women earn on average 17% less than men. Once major or mathematical content is controlled for, the average fell to 9%. Women may thus face a double disadvantage in the workplace if there is indeed a bias towards males in college selectivity, and women choose less mathematical majors.

Race is also an influential factor in the selectivity of college students attend. Thomas (2004) shows that if nothing else, affirmative action policies pursued by different schools have a strong effect on where black and hispanic students send their SAT scores. When Texas abolished affirmative action in its post-secondary institutions, minority students began to send their scores to less selective Texas schools, but more selective out of state institutions.

Beyond demographic factors lie the influences of high school background and schooling. In a recently published study by the U.S. Department of Education, it is pointed out that the rigor of a student's high school curriculum is the strongest indicator of the success the student will experience in obtaining his bachelor's degree. (Adelman, 2006) This means that the extent to which a student has participated in math and science classes and the grades he gets are crucial for his further development as a college student. However, the study leaves unclear whether the importance from this factor stems from a student's preparation for his college curriculum, or simply reflects innate interests which he will pursue in college as well as in high school. It also ignores the potentially powerful but fairly unobservable phenomenon of determination to succeed. Additionally, students who attend fairly rigorous high school programs may see benefits from them that students who are not of the same ability or interest level do not. In a study of the effects of catholic high school enrollment on attendance at selective colleges, Eide, Goldhaber, and Showalter note that "for those disadvantaged students not likely to attend more selective institutions, attendance at a Catholic high school is unlikely to lead to a higher quality college compared to the type of college the student could have attended if the student had graduated from a public high school." (2003, p.19) Thus I attempt to account for high school performance via individual measures for each student, not for the school itself.

Delving beyond demographic factors, it is important to consider financial factors in the decision to go to college. Savoca's study on the effects of financial aid composition supports the theory that low and high income students have different elasticities for college tuition and thus respond differently to the way that their financial aid is offered or composed. (1991) This may screen out lower income students of very high ability from attending a school that could earn them the highest returns. Thus, assuming there is at least some correlation between cost and quality, it may be the case for poorer students that they are “over matched” to a school which has a lower mean SAT score than the student’s raw score. If this is indeed true of some students, then a model representing utility derived more from ability, interest, and work required might not as accurately reflect college choice as one in which we account for students’ financial constraints. Additionally, it has been shown that socioeconomic status is also an important factor in college choice. Siegfriend and Getz (2003) point out that those students who have parents who are professors behave differently from students who do not. They are better informed of their choices in the “college market”, and tend to choose more selective institutions, and gravitate towards small, liberal arts colleges. Approaching this phenomenon from the other side of the socioeconomic spectrum, Streufert (2000)[8] shows that children of underclass families underestimate the value of education. These potential students gravitate away from college, even more so in situations where the family is on income support. While this is to some extent driven by financial reasons, the undereducation of the parents and their subsequent social isolation from the more educated drives their children away from higher education. Given this evidence, it is not unreasonable to expect students with families of different educational backgrounds to behave differently in the selection process.

Finally, since the ultimate theme of this paper is to estimate the effect of college quality on earnings, it should be noted that there is evidence that college quality may not be a factor in graduates’ earnings at all, but rather, that tuition charged by a school is a much more highly correlated measure. Dale and Krueger (1999) find that when school selection (in the sense that the school chooses the student) is controlled for, earnings

[8] While Streufert does not explicitly treat parental education, but rather concentrates on social class, there is a strong implicit connection between schooling and social standing.

gotten as a result of attending a selective school falls considerably. Conversely, Davies and Guppy (1997) show that while socioeconomic factors have no effect on entrance into lucrative occupational fields when other background variables are controlled for, they do have a strong effect on entrance into selective colleges. The story told by tuition, however, points in a subtly different direction than Dale and Krueger would indicate. Schools that charge a higher tuition tend to produce graduates that earn more on average than their counterparts from less expensive schools. This may be the result of a measurement problem in school quality- this is most certainly a difficult and intangible thing to quantify. Since this stage of the model uses mean math SAT as the dependent variable, this may be of concern.

Theoretical Framework

In developing a structural model for the college choice process, I have adapted the utility maximizing college choice model developed by Manski and Wise in 1983.
In the first stage, a student, denoted with subscript t, wishes to maximize his utility by choosing a school, denoted with subscript i. Note that at this point, he is not yet attending a post-secondary institution, but is merely facing the choice of which to attend:

$$\max U^e = {}^{c}U_{ti}^{e} + {}^{f}U_{ti}^{e}$$

Where utility is decomposed into two components: current utility, ${}^{c}U_{ti}^{e}$, and future utility, ${}^{f}U_{ti}^{e}$. He maximizes his utility by choosing from the list of schools to which he has been accepted the one school which is most likely to maximize this utility. For many students, this is an "opportunistic" process: they apply to only one school which is convenient, and enroll there if admitted.

In this process of enrollment, he must consider the two components of his utility. The first component is the current component:

$$ {}^{c}U_{ti}^{e} = \alpha_{1t}T_i + \alpha_{2t}S_{ti}^{e} + \alpha_{3t}L_i + \alpha_{4t}Y_{ti}^{e} + X_{ti}^{e} + I_{ti} + H_{ti} $$

where T_i is tuition, S_{ti}^{e} is expected scholarship[9], L_i is living expenses, Y_{ti}^{e} is foregone earnings, and X_{ti}^{e} is a consumption term. I_{ti} represents utility gained from pursuit of the student's interest. H_{ti} is a human capital term.[10]

The second component represents future utility derived from attending college:

$$ {}^{f}U_{ti}^{e} = \alpha_{5t}h[g_1(Q_i) + g_2(Q_i - A_t)] + {}^{f}X_{ti}^{e} $$

where A_t is the student's own quantitative SAT score, and Q_i is a measure of the average quantitative SAT score achieved by his potential peers at college. ${}^{f}X_{ti}^{e}$ is a future utility component. It should be noted that $\alpha_{5t} \geq 0$, since h is increasing in g_1 and g_2 (where g_1 is increasing with respect to Q_i and g_2 is decreasing with respect to $(Q_i - A_t)$).

[9] While the student may not be fully informed of his scholarships because schools often assign them following admissions, it is reasonable for him to form expectations about this term.
[10] I assume here that students get utility from gaining human capital in immediate payoff as well as the future. For instance, a student taking large amounts of MSE credits could be doing so for his personal pleasure, and may get a payoff from an interesting internship.

Empirical Results

In order to test this first stage model suggested by Manski and Wise, I estimate the reduced form equation:

$$S = X\beta + Y\delta + Z\varepsilon + D\gamma + u$$

where X is a matrix of variables representing student interests, Y represents student background, Z represents variables or ability, and D represents demographic information. β, δ, ε, and γ are the coefficient vectors. S is a gauge of peer math ability.

Altonji (1993) points out that inherent ability and high school curriculum must be accounted for. In accordance with this assessment, I control for student interests, family background, and human capital in the form of knowledge and skills acquired in high school. Note that the HSB survey does not include any explicit questions about academic interests. I assume interest and ability to be interrelated and highly endogenous. Thus ability and background variables such as math and science courses taken in high school have to do with interest as much as with ability and background. The dependent variable, S, is a gauge of peer math ability, measured by the mean quantitative SAT score of the school a student attends.

In the data, the variables on student interests in high school are primarily amount of math and science taken, labeled math and science respectively. Demographic variables included are geographic location, parental education, gender, and race. The student's ability and interest in MSE, measured by math and science credits taken in high school, and is further augmented by a perceived ability measure, and math and vocabulary scores obtained from tests administered by the HSB surveyors, as well as grades achieved in high school. [11]

Table 1. Results for Regression of Average School Quantitative SAT score on Demographic, Socioeconomic Status, Interest and Ability, and High School Background.

Dependent Variable: Mathsat	**Men and Women** N=1536	Adjusted R^2=0.3238	**Women Only** N=801	Adjusted R^2=0.3283	**Women Only** N=735	Adjusted R^2=0.3147
Independent Variables	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
Race, Gender						
black	-2.88276	4.558701	-10.2859	6.324865	3.727673	6.726209
amind	3.934516	15.60768	5.362008	19.32521	-5.85855	26.62279
apa	20.12522*	7.521622	14.58948	9.909	22.91738***	11.92171
other	9.042898	5.960538	12.10958	8.448437	5.003271	8.653655
mrace	35.9418***	20.57284	-20.2426	60.16841	42.98956***	22.89399
female	-9.69181*	3.324187	-----		-----	
Geographic Region						
ne	12.16206***	6.286877	6.847985	8.390895	17.3656***	9.70562
ma	11.60136**	4.803587	5.436886	6.621552	16.84887**	7.160141
sc	-30.522*	5.806547	-36.8587*	7.918466	-22.9424*	8.789688
nc	16.02968*	4.682771	15.71894**	6.391901	16.14172**	7.028127
mpac	12.4444**	5.698448	16.20061**	8.218889	10.28817	8.213291
High School Grades						
hsmgrade	12.44408*	3.957791	8.914805***	5.363058	17.07828*	6.002202
hsgradea	20.01598*	5.872053	20.95979**	8.243724	18.8994**	8.647687
hsgradeab	6.986507	4.945102	12.20147*	6.967725	0.15323	7.303776
hsgradeb	4.164816	4.982756	7.317503	7.244413	0.722999	7.181219
Parental Education						
fmed	1.748286	5.08059	-3.4323	6.694942	7.128627	7.992225
mmed	13.06304*	4.509858	14.82835**	5.993438	9.12248	7.017046
fhed	18.98708*	4.555834	19.80744*	6.360893	19.07401*	6.740701
mhed	9.508485	5.910506	7.409296	7.742895	11.22911	9.397955
fbg	2.703792	2.842989	-0.54521	3.975863	6.01631	4.184286
High School Courses						
math	2.705552**	1.22418	3.193421**	1.573194	2.774991	1.991333
mmath	42.52265	31.44653	42.84034	60.61075	37.77017	38.50782
science	1.557415	1.023986	1.319859	1.34224	2.145555	1.623417
msci	26.26373**	12.61219	19.14019	16.82539	38.91311**	19.49865
Ability Scores						
pability	-2.03064	2.913966	-2.90655	3.908716	-1.40064	4.469571
mpab	-25.3045	27.78395	-19.9418	43.21621	-33.024	37.18704
vscore	2.475188*	0.347091	2.295603*	0.480265	2.606225*	0.517303
mscore	2.392917*	0.410738	2.599768*	0.548173	2.076637*	0.635826
intercept	369.8513*	13.17783	366.9533*	17.09884	361.7294*	19.78723

*** denotes significance at the 10% level, ** denotes significance at the 5% level, * denotes significance at the 1% level.

[11] For the complete description of the variables, please see Appendix, Table 1.1 through 1.3.

Following the criticism laid out by David and Guppy (1998) and Weinberger (1999), it is important to allow for systematic differences between men and women. While a Chow test indicates that there is no fundamental difference between men and women, I have estimated one regression including men and women, one for women only, and one for men only. As shown by the first regression, being female is highly significant, with women achieving a base score of more than 9 points less in the mean quantitative SAT score in school attended than men.

Prior results from prevailing theories and empirical work on race also tends to hold true in this data. As shown in all regressions, being black has a negative effect on the math SAT score of the school attended, particularly for women. Both Asian and Pacific Islanders and other races, which includes those of hispanic origin, have a positive effect on mean math SAT score, which is in accordance with the pattern of results found by Weinberger. (1998) However, none of these factors prove to be statistically significant.

While the data set includes students who have not finished a degree or have dropped out or transferred multiple times, I control for the amount of science and mathematics courses students take in high school as they do have a strong degree of influence on academic success overall, as indicated by Adelman (2006). I also include controls for grades. The evidence from the regressions points to a significant effect of high school background on the quality of the institution attended. In the general population and for women in particular, math in high school is very significant, while science seems more important for men, but is statistically insignificant. Strong high school grades are also important. However, there are significant gender differences. The effect of A's and B's in high school math courses is nearly twice as strong in men as in women. On the other hand, A's and A's and B's in all courses seem to matter more for the women.

I take into account financial considerations by including a measure that indicates the educational attainment of each student's parents. An F-test for joint significance showed that in this case, income variables are less jointly significant than the educational background of parents. Since education and income are highly correlated, I use parental education as a proxy for income to ensure a better fit. The evidence presented here supports the hypothesis implied by Siegfriend and Getz (2003) and Streufert (2000) that parental education has an effect on the selectivity of the college a student attends. Having a father with at least some college education but no degree showed little significant effect on the mean math SAT score of the school attended when compared with fathers with no college education at all. However, a mother with this background has a positive effect, particularly for women. A father with a college degree or higher has a strong effect on both populations, while having a mother with a college degree or higher has a strong positive, if insignificant, effect in men but not in women.

These effects will correlate to income, as the more educated families tend to earn more than their less educated counterparts. A further aspect is that students from more educated families will be more adept at negotiating the world of higher education than their counterparts who have no experience with these institutions.

It is important to mention a student's perceived ability to finish college. While the sign points to a positive effect[12], it is not statistically significant. Presumably this is because the expectation of finishing college is formed already taking into account the quality of post-secondary education. Thus a high ability student attending a challenging school may be just as secure or insecure in himself than a lower ability student attending a less challenging school. With respect to true ability, both math and verbal HSB test scores are strong predictors of quality of school attended. Notably, this effect is marginally more significant in math score for women than in men, indicating that women may be a bit more sensitive to their actual math ability.

Conclusion and Critique.

The results obtained from the HSB data reaffirm a lot of common knowledge presented in the current literature, but augment it from the mathematical aspect of education. Particularly interesting is the fact that for a woman, the number of courses in mathematics is a statistically important factor in determining the peer math ability at the college she attends. However, this effect is negligible in magnitude. Women also show no statistical significance in their grades in high school math courses, whereas men do. This would indicate that male students are attending schools according to their experience in math, whereas this effect is less pronounced in women. Women seem more prone to match to school according to their overall high school performance, but they do seem a bit more sensitive to their math ability than men, as shown by the marginally larger coefficient for math score.

[12] Highest level of perceived ability is ranked as 0. Thus, the sign on this variable is, not surprisingly, negative.

Section 2.1: Stage 2: Choosing MSE Content of Curriculum

Introduction

Once a student attends a post-secondary institution, he faces the next stage of the decision making process: how to best structure a field of study. In the process he chooses the amount of MSE credits that suits his personal academic interests and career aspirations. He does not make this decision in a vacuum. An early study by Jeffrey Reitz (1975) indicates that students are sensitive to their environment and that those who attend more selective institutions are more likely to switch into majors that are less academically demanding.

In this section, I test the theory that peer math ability has an effect on the MSE content in students' curriculum. In order to do this, I estimate the total credits achieved in MSE by each student, given the relative standing of their own quantitative SAT score compared to the average at the college attended. I find that there is indeed a significant effect, lending support to the theory that students choose curriculum content based upon their evaluation of their ability relative to their peers.

Literature Review

In considering the structure of students' curriculum, several factors pose important considerations. First it is important to consider the implication of human capital vs. signaling on major choice. Further, the effects of mismatching between student and college, as well as the interaction effects between courses may add unobservable effects to a student's curriculum that the job market responds to.

Additionally, personal motives and earnings expectations, as well as gender and race play significant roles on how students choose MSE content.

It is a possibility for a student to observe his surroundings and decide that he is entirely unsuited to any type of major and drop out of college. Factors such as holding a job and financial duress may also contribute in ways that this model does not capture. (Light & Strayer, 2000) It is also a significant possibility that a student who is totally mismatched to his school has a stronger incentive to quit than one who is less mismatched. The result is that we will observe only those who are slightly mismatched to their school actually choosing a field of study- a significant other portion may simply be dropping out or transferring. In the regression analysis, I include those students who attempt to complete a four year degree, but also account for those who transfer into two year colleges, or only complete some credits and never achieve a degree in order to capture this effect.

Curriculum choice is a factor that will later be used by potential employers to gauge an applicant's capabilities. Thus a discussion of curriculum choice invariably leads to a mention of signaling versus human capital building. The signaling theory holds that field of study will not enhance productivity, but rather serves only as a signal for the job market, whereas the human capital theory implies that field of study is a major factor in productivity because students gain the knowledge they need for successful employment. Experience should eventually reveal the true abilities of an individual in the job market, but the last follow–up survey of the HSB senior cohort does not include sufficiently rich data to test this theory. (Núñez & Otero, 2005) However, in a Canadian survey of earnings differences between fields of study, Finnie and Frenette (2001) suggest that not only are there differences between major disciplines, but that these persist two to five years after graduation. Furthermore, these differences persist across demographic control variables.

Prediction of earnings is far easier to achieve reliably for technically oriented fields such as engineering and computer sciences than it is for degrees in humanities and liberal arts, suggesting, if nothing else, that there may be some majors that are truly signals, as proposed by Spence in 1973, such as some disciplines in the liberal arts, and that there are some in which the student truly does accumulate human capital, which is rewarded in the workplace by consistently higher wages. This splitting into two different groups of curricula- one as a signal and one as true building of human capital- complicates estimation when curriculum choice is broken down into majors. This is a good reason to consider curriculum choice in terms of MSE content. While the ensuing empirical work takes no stance on this debate of human capital versus signaling, it is well understood that mathematical content of major is indeed valued in the job market under either theory. This should therefore add some accuracy to further wage estimation by avoiding the problems major groupings have.

A study by Johnes (2005) using neural networks effectively presents evidence that interaction effects of the courses in the curriculum a student are so extensive that simply breaking the curriculum down into major fields of study may not be an effective way of dealing with the impact of studies on wages. However, Dolton and Vignoles (2002) present evidence that that for 16 to 19 year olds in the UK, there does not exist incentive to pursue a broader curriculum, while there is a strong positive return for taking Math A levels. This certainly points in the other direction from Johnes' study, as a narrower curriculum would have less potential for interaction than a broader one. However, due to the fact that the study by Dolton and Vignoles concerns individuals not yet entered into post-secondary education, these results may not be robust in the college setting.

Earnings are a strong motivation for entering into certain types of curricula. Students are influenced to attempt certain types of studies by observing both the starting and lifetime earnings of those who enter the labor market. They are motivated, as presented in the theoretical component above, to achieve as high a level of mathematical content as possible in college in order to gain higher returns later in life. (Flyer, 1997) Thus, as Montmarquette, Cannings, and Mahseredjian (2002) argue, the choice of field of study, and implicitly, MSE content, is driven by the earnings, and the earnings alternative in case of failure that a student can expect. Further, students take into account the probability of success and the amount of effort required to complete the degree. However, it is also significant to the specification of this equation to include variables that span interest, ability, and high school background. The number of math and science courses taken by the student during high school is included and shows a strong positive effect for men and women. The rationale follows Fiorito and Dauffenbach's (1982) point that curriculum choice is strongly determined by mathematical ability and interests. Subsequently, a model that did not include non-labor market factors such as ability would be underspecified.

As in the previous stage, gender and race, and other factors are important here as well. Montmarquette, Cannings, and Mahseredjian (2002) find empirical evidence that men are more motivated by expected earnings than women, and non-whites more than whites. Specifically, gender may play a strong role in the major a student chooses.

Research by Polachek, as well as Gill and Leigh, showed that women tended to evaluate majors differently than men, and that this was possibly the result of the expectation that only certain types of jobs were available for women, or that women have innate differences from men which make them suitable for different types of majors. Regardless of the reasons, the evidence is certainly incontrovertible that women are simply less likely than men to enter into a major with large math content. (Weinberger, 1998, 1999)

Theoretical Framework

After choosing a college to attend, the student must generally declare a major field of study within the first two years. In those first two years, the student generally takes some requirements, including at least a rudimentary exposure to math and science, and also enrolls in courses that may lead to a major. When choosing a major, a student makes an implicit choice about MSE content, given his experience from the courses he has taken. In a process similar to the first stage, he maximizes his immediate and future utility by choosing a field of study subject to his personal constraints. In addition to the fact that he must take into account the same interest, ability, and background variables as in the first stage, he must now also consider the performance of his immediate peers.

It bears repeating that I am not directly estimating field of study, but rather, the total amount of credits a student accrues in mathematics, engineering, and sciences. This is because I believe that students generally approach difficulty of a major by evaluating the amount of math-based courses that must be taken in order to get a degree. Thus, the sum of courses in these fields will be highly correlated with difficulty of major, but adds a degree of comparability across schools.

Thus, the second stage looks similar to the first:

$$\max U^{e} = {}^{c}U_{ti}^{e} + {}^{f}U_{ti}^{e}$$

He maximizes utility generated from studying subject to his interests (I), abilities (A), background (B), and the vector of variables that describe gender, race, etc (C). With respect to his and his peers' performance, he takes into account his abilities to those observed in his peers at his school.

The two components of his utility are as before, divided into current and future utility:

$${}^{c}U_{ti}^{e} = \beta_{1t} D_i + \beta_{2t} \frac{O^e}{P} + \beta_3 I_{ti} + \beta_4 B_{ti} + \beta_5 A_t$$

In this current component, D represents the difficulty of the field of study, P is the performance of his peers, and $\frac{O^e}{P}$ represents the student's expected performance in a major relative to his peers. I_{ti} represents personal interests, B_{ti} represents academic background, and A_t is student t's own quantitative SAT score. This is measured in the same units as D_i, which implicitly requires a certain level of quantitative ability, measurable in "required quantitative SAT score".

$$^{f}U_{ti}^{e} = \beta_{6t} h[g_1(Q_i) + g_2(Q_i - A_t)] + {}^{f}X_{ti}^{e}$$

In the future component, the student essentially makes the same calculation as he made in stage one's maximization process.

Empirical Results

In order to test the second stage of the model that implies that students respond to their relative strengths and abilities, I estimate the equation:

$$C = X\beta + Y\delta + Z\varepsilon + D\gamma + E\phi + u$$

where X is a matrix of variables representing student interests, Y represents student's high school background, Z represents variables of ability, D represents demographic information, and E is a variable representing the ability of the student relative to school quality. β, δ, ε, and γ are the coefficient vectors. C represents total credits accumulated in math, science, and engineering.

In this stage, the dependent variable is the total sum of credits in MSE. These include transfer credits if the school he most recently attended accepted them, and are standardized across schools for uniformity. Student interest and ability are again presented through amount of math and science taken in high school, as well as grades received in that time. Demographic information such as gender, race, and geographic location is included as well. This variable allows the inclusion of students who pursued studies in “signal-type” majors but also took some courses in these subjects, and those who did not, at the end of the last follow-up survey, finish their college education. Evidence presented by Chevalier et al (2004) indicates that even unfinished education causes an increase in human capital, and thus, I do not choose to exclude the portion of the sample that has only partially finished their education.[13]

Table 2. Results for Regression of Total credits achieved in MSE on Demographic, Socioeconomic, Ability/Interest and Background variables.

Dependent Variable: tcred	**Men and Women** N=1577	Adjusted R^2 =0.2097	**Women Only** N=804	Adjusted R^2 = 0.1878	**Men Only** N=738	Adjusted R^2 = 0.1891
Independent Variables	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
Student's relative ability						
diff	0.049979*	0.010848	0.060703*	0.013016	0.038889**	0.017719
Race, Gender						
black	-1.62853	2.271179	1.224032	2.686792	-4.72111	3.747523
amind	5.58061	8.200214	4.417297	8.855655	4.781899	15.27992
apa	12.51913*	3.936506	13.12765*	4.506954	11.84141**	6.863331
other	-4.2747	3.123646	-4.23114	3.806803	-4.68985	5.00791
mrace	-16.6216	10.80806	12.53803	27.62111	-23.6431***	13.13381
female	-10.0042*	1.712784	-----		-----	
Geographic Region						
ne	-8.45002**	3.311811	-6.93268***	3.822869	-9.37313***	5.623418
ma	-12.3487*	2.529072	-11.4405*	3.002848	-14.1999*	4.175081
sc	-6.3783**	3.04124	-7.92431**	3.633384	-6.90435	5.013797
nc	-4.35242***	2.456535	-4.79564***	2.891466	-4.70767	4.09059
mpac	-0.49906	2.988422	3.506622	3.728667	-5.78214	4.739126
High School Grades						
hsmgrade	10.22174*	2.047738	6.414866*	2.403117	14.27851*	3.429811
hsgradea	11.35956*	2.946072	7.830262**	3.589674	13.34665*	4.779856
hsgradeab	7.450788*	2.542235	2.761359	3.08912	10.80029*	4.185718
hsgradeb	3.448289	2.597631	1.150285	3.285065	4.319435	4.104837
High School Courses						
math	3.075095*	0.63249	2.718768*	0.702894	3.559418*	1.136876
mmath	21.84504	16.62874	11.8174	27.81666	29.62561	22.49353
science	3.336652*	0.532301	2.543879*	0.610078	4.194614*	0.919321
msci	22.96816*	6.648205	23.21071*	7.708086	25.1363**	11.32722
Perceived Ability						
pability	1.077376	1.514165	0.060615	1.742649	2.532134	2.580666
mpab	-15.0795	14.57716	-15.3745	19.6987	-13.6042	21.52121
intercept	-6.70206	5.445904	-4.23931	6.056095	-19.035**	9.28716

*** denotes significance at the 10% level, ** denotes significance at the 5% level, * denotes significance at the 1% level.

[13] It should be noted that the argument in this study hinges upon the assumption that marginal utility derived from higher earnings is less than the disutility of an additional year of school. If this assumption does not hold, the hypothesis that an additional year of school is a signal might not have been rejected.

As in section 1, a Chow test finds (narrowly) that I cannot reject the hypothesis that there are no differences between men and women. However, I do estimate separate regressions on the theory that some variables do indeed differ. The results found here agree with prior assessments by Weinberger (1998, 1999), Polachek (1978), Gill and Leigh (2000): a female student on average takes approximately ten credits fewer in math, sciences, and engineering than the average male. Additionally, the effect of having A's and B's in math classes and having A's, or A's and B's is about twice the magnitude in men as it is in women, and statistically significant for both. The effect of taking math and science courses in high school shares this phenomenon. Thus men seem to be more sensitive to their academic abilities when it comes to choosing MSE content than women. Indeed, the mean number of MSE credits taken by women is 25.9, while men take on average of 38.2, despite taking nearly the same amount of math and science courses in high school. This raises the question of why women seem to be less motivated by high school preparation and performance than men.

Race also plays a strong role, as evidenced by the particularly large and statistically significant coefficient for Asian and Pacific Islanders, and that this may carry similar explanations. Thus, the curriculum choice for a white male, a white female, and a black male with similar backgrounds may be totally different. This decomposition into different racial and gender groups may significantly distort choice in a way not directly predicted by the model proposed by Manski and Wise.

Demographic variables also show a strong effect on the amount of MSE content. Compared with students from South Atlantic states, those from Northeastern, Middle Atlantic, Mountain and Pacific, and South Central states choose lower amounts of this content in their curriculum. These geographic effects apply to both men and women. This is likely the effect of regional differences in income. It may be that students from lower income regions take more MSE courses because they are motivated by higher returns.

Lastly, this result suggests a significant role for school quality and environment in a student's curriculum choice. The effect of the difference between a student's math SAT score and the mean math SAT score of the school he or she attends is highly significant, both statistically and economically. The student who beats his or her school math SAT score by 100 points will, on average, take 5 more credits in math, sciences, and engineering than the counterpart who scores exactly at his school's mean. When broken down by men and women, the effect becomes even more interesting: a 100 point difference translates into a 6 credit gain for women, and a 3.8 credit gain for men. This suggests that women are more sensitive to the relative valuation of their abilities in their environment.

Conclusion and Critique

In the previous section, it was shown that women tend towards schools that have marginally lower average quantitative SAT scores than men. This would indicate that women are more likely to outperform their peers, thus they may be more able to take advantage of their math abilities because they are not in as competitive an environment. Men, on the other hand, seem to be less sensitive to their environment and more attuned to their interests and abilities. However, regardless of these factors, women do, on average take fewer MSE credits than men. This implies that they perhaps pursue different optimization behaviors and may expect different things of the job market.

***Section 3.1:* Stage 3: Wage Outcome**

Introduction

In this section I describe the final stage of the student's three stage processes. In the years spent in college, students differentiate themselves for the job market in three ways. They have attended schools of differing peer math ability, they have earned certain GPAs, and they have taken differing levels of MSE content in their curricula. When they enter the job market, potential employers evaluate applicants by these merits. They then offer those they feel most suitable for the job a position at a given wage. This raises the question of the relative importance of the three factors described above. In this stage I attempt to shed some light on this matter, and evaluate differences in returns to education by gender.

Literature Review

A concern here is that those students who start out with a higher earnings capacity are generally taken by more selective schools. Thus there tends to be a correlation between school quality and high wage outcomes simply by a prior selection mechanism, creating a problem of endogeneity. As mentioned before, once school selectivity is accounted for, the financial windfall for those who attended higher selectivity colleges falls drastically.[14] Dale and Krueger (1999) find that, even when controlling for selectivity, schools that charge more in tuition tend to produce students who earn more. One study has shown that men who take on more debt to finance their education are more likely to get jobs that pay more immediately following graduation, but have lower growth

[14] By contrast, a study by Harmon and Walker suggests that most OLS models designed to estimate the rate of return to education hold a negative bias, and that IV estimation is needed for accuracy.

potential. (Minicozzi, 2005) It should be noted however, that SAT of a school is correlated with tuition costs, and thus this data is catching either a tuition effect via this measure or college SAT score does have an influence. Additionally, evidence presented by Behrman, Rosenzweig, and Taubman (1996) suggests that students who attend institutions that grant PhDs, pay higher faculty salaries, and spend more per student fare better in the job market. Thus there is strong evidence that the quality of the post-secondary environment has a significant effect on earnings.

As in the previous sections, it is necessary to address the effects of gender and race. According to previous results presented by Loury and Garman (1995), I expect difficulty of curriculum and GPA to have a significant effect on earnings. It should be noted that in the same paper, the authors point out that the effects of school selectivity can overstate earnings potential for whites and understate it for blacks if these performance factors are not accounted for. Weinberger (1998) presents a study showing that compared to white men of similar characteristics, white, black, and asian women, and black and asian men earn 10-15% less. She points out that white, black, and hispanic women were much more likely to have a degree in a lower paying field than men. Thus, the difference in college majors explained nearly half of the wage disadvantage estimated by the study.

With such evidence in mind, the most robust theories and results are those that account for career expectations and labor markets. Particularly of interest are those which point out that women have lower expectations than men do when it comes to jobs and earnings, and thus pursue less challenging curricula in their college years. For instance, Blau and Ferber (1991) argue that while women expect starting wages comparable to men upon graduating from college, they expect their lifetime earnings to be lower, regardless of what career paths they pursue, than those of men. In a similar vein, they appear to expect to spend less time in the labor market than men. (Daymont & Andrisani, 1984) Whether this is due to expectations of family obligations or discrimination amongst employers is not immediately clear, but most studies find that the gender-wage gap does not disappear even when background and expectations are controlled for. Filer (1983) points out that omission of tastes and preferences may overstate labor discrimination against women, but not for women with a college education. Additionally, he finds evidence that education actually reduces the amount of the gender wage gap. Grogger and Eide (1995) also provide evidence that during the 1980's, returns for mathematical ability for women rose significantly, more so than for men, and that by not controlling for a woman's ability, the wage gap may be overstated by a full factor of two.

However, in another study by Weinberger (1999), she points out that it is precisely the low numbers of women with majors with heavy mathematical content that makes mathematical curricula such a strong explanatory component in understanding the gender wage gap. This may be evidence of affirmative action- employers needing to hire women place a higher premium on those educated in MSE than men because they are harder to find but are needed to round out affirmative action hiring processes. Further evidence presented by Graham and Smith (2005) indicates that more of the gender wage gap can be explained in science and engineering disciplines than other, indicating that education does not necessarily have a uniform effect. This is corroborated by Mitra's

(2002) finding that for women with strong mathematics skills, the gap becomes insignificant.

Finally, students highly value the option to switch their career paths later in life. Thus, while many students may have had some significant mathematical and science content in their college curricula, it may simply be that they chose to augment their studies on the side, and concentrated instead on subject matter that was less technical. This would give them the option of moving between careers later in life, but we cannot observe this for such students. As a matter of fact, in Flyer's (1997) study of the effects of earnings variability on career decisions, he notes that nearly half of the sample studied moved between occupational categories within the first ten years of their entrance into the labor force. Thus, by essentially diversifying their curriculum, students ensure themselves the option of changing career paths later on. Consequently, they do not necessarily see immediate gains from a highly mathematical or scientific education, and in fact may never do so.

Theoretical Framework

When the student graduates from college or finishes some measure of schooling, he directly enters into the job market. Note that this does not take into account the possibility of graduate or professional school. The result is that some observations are lost on the most academically capable students, as the incentive for them to continue in higher education is higher than for their less capable counterparts.

In the prior stages of this paper, I have shown how students optimize their utility by choosing a school and MSE content. This is the final stage, at which they become employees with observable incomes. In order to explain the market forces contributing to this observable income, I use an adapted form of the Mincerian human capital earnings function. (Card, 1999) Employers observe the quality of the college the student attended, difficulty in the major field of study, M, and performance of the individual student, G. They offer him an employment package, observed as weekly income, W, dependent upon the quality of these three factors. The student then obtains a weekly income from working expressed as

$$\log W_i = \beta_{1t} C_{ti} + \beta_{2t} M_{ti} + \beta_{3t} M_{ti}^2 + \beta_{4t} G_i$$

While the original Mincerian form includes a quadratic experience term, little job experience has been obtained by these students. Thus, a potential employer can evaluate their acquired human capital only on the evidence provided by the difficulty of the major studied, the college quality, and GPA. I thus substitute the MSE credits as an observable term for human capital for years of job experience.

Empirical Results

To evaluate the effects of the results discussed above on wages, it is necessary to specify an equation that accounts for school quality, student performance, and the amount of credits taken in math, science, and engineering. This equation is expressed as:

$$\log W = S\alpha + C\beta + C^2\eta + P\delta + D\lambda + u$$

Here, W is the wage outcome for individual i. S, C, and P represent student's demonstrated ability, student's curriculum choice, as measured by MSE credits, and peer math ability at the school attended respectively. D is a set of demographic variables, while u is the error term. The coefficient vectors are α, β, δ, and λ.

Wage is estimated via the log of weekly earnings of each individual. The student's demonstrated ability is reflected in his gpa, gengpa. His curriculum choice is the total number of credits attained in math, science, and engineering, labeled tcred, and a quadratic form of this term, cred2. Mathsat is the mean quantitative SAT score of the school attended. The demographic variables include geographic area of origin, gender, and race.

Table 3. Results of Regression for weekly income

Dependent Variable: lweekly	**Men and Women** N=1095	Adjusted R^2 =0.1051	**Women Only** N=581	Adjusted R^2 =0.0664	**Men Only** N=514	Adjusted R^2 = 0.0456
Independent Variables	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
Total MSE credits, college SAT, GPA						
tcred	0.000579	0.001091	0.002999***	0.00166	-0.00071	0.001501
Cred2	9.10E-06	7.79E-06	-1.1E-05	0.000013	2.01E-05**	1.01E-05
mathsat	0.001036*	0.000198	0.001421*	0.000276	0.000711**	0.000288
gengpa	0.001114	0.012592	0.014368	0.017011	-0.02051	0.018973
Race, Gender						
black	-0.09621**	0.038718	-0.09823***	0.053846	-0.07982	0.055808
amind	-0.02322	0.122231	-0.1154	0.15086	0.133144	0.206819
apa	-0.01174	0.070651	-0.05586	0.092761	0.091382	0.109829
other	-0.03271	0.051949	-0.03829	0.072151	-0.00907	0.074849
mrace	-0.13795	0.225258	0.532469	0.445598	-0.34385	0.265514
female	-0.19729*	0.027784	-----		-----	
Geographic Region						
ne	-0.0152	0.054035	-0.02837	0.071122	0.006559	0.082434
ma	0.035058	0.042279	0.065197	0.056785	0.001334	0.063409
sc	0.042729	0.050726	0.071626	0.068655	0.031544	0.075374
nc	-0.01532	0.040165	-0.0453	0.053313	0.021393	0.06078
mpac	-0.03223	0.051234	-0.09069	0.073475	0.001193	0.072754
intercept	5.21429*	0.11138	4.768165*	0.153277	5.428911*	0.156561

*** denotes significance at the 10% level, ** denotes significance at the 5% level, * denotes significance at the 1% level.

Table 4. Distribution of Weekly income across Quartiles of Total Math, Science, and Engineering Credits.

Quartile	Mean	Standard Deviation
1st, N=292	298.0109	197.3201
2nd, N=276	292.9561	179.4809
3rd, N=306	303.7108	182.9016
4th, N=300	336.3628	170.8643

Again, a Chow test narrowly finds that there is no difference between men and women. Using the same reasoning as before, I nonetheless estimate two different equations for men and women in order to examine differing effects of variables. As expected, being black shows a negative effect on weekly earnings. However, this effect is statistically significant for women but not for men. Asian or a Pacific Island descent has a negative effect for women, and a positive effect for men, but is statistically significant for neither. Women are clearly less rewarded than men in the labor market. Even when controlling for GPA, MSE credits, and peer math ability, the effect of being female translates into nearly a 20% lower weekly earnings profile. This corroborates the evidence given in nearly every piece of literature treating the gender wage gap.

The hypothesis that there is no effect on weekly earnings from mean quantitative SAT score at the school attended can be rejected at the 1% level. For the general population, a 1 point increase in the school's mean math SAT corresponds, on average, to a 1% increase in weekly earnings. This corroborates the theory that the labor market rewards high quality education, and that it makes sense for students to attempt studies at a selective institution. It is notable that this effect is more strongly evident in women than in men by nearly an order of magnitude. This would indicate that the labor market is more sensitive to the quality of school for women than for men.

While the GPA earned at the school last attended had a positive effect in the combined regression, it was significant for neither men nor women. However, it is interesting that men and women show opposite signs in the coefficient, suggesting that the approach for a man and a woman with identical GPAs may be slightly different when they enter the job market.

Finally, the pattern of magnitude and statistical significance for total MSE credits shows differing value to the two different genders. For women, the quadratic term of these credits is statistically unimportant and shows a negative sign. Meanwhile, the linear form of MSE credits proves to be positive and significant, translating an additional credit into a 3% increase in weekly earnings[15]. Men see a nearly opposite effect. The square of total credits achieved in math, science, and engineering during college has a statistically significant effect. Total credits accumulated do not have a significant effect and has a negative sign. This would indicate that men see lesser effects from taking a low number of MSE credits, but increasing returns as they take more and more. Thus a man taking 10 credits actually get on average .5% lower wages, while a man taking 50 credits would see a 1.47% increase, and a man taking 100 even more.[16] Broken up by quartiles of MSE credits, weekly earnings do show an upward trend for more education in this area for both genders. However, the difference between intermediate categories is, as shown by the results in the regression, fairly small.

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[15] There may be an increased number of MSE credits for students majoring in health sciences or nursing, which is popular amongst women. These fields tend to have a lower payoff than pure engineering or other sciences. This would pose a possible explanation for the decreased marginal returns to MSE credits observe in the job market. However, in a specification excluding life science credits for women, I find no evidence to counter the argument that women do indeed see decreasing marginal returns.

[16] The turning point for women is 272.6 credits. The turning point for men is 35.3 credits.

While the effect of MSE credits appears small compared to other effects, such as gender, the difference in patterns by genders holds interesting implications. These results imply that women and men may value their MSE education differently. For women, it makes more sense to take limited numbers of credits, as returns are diminishing, while for men, the effect is the opposite. They are penalized for having too few credits, and do not see the increased dampening effect that women see on returns for more MSE credits. Thus for men, it makes sense to immerse themselves in highly mathematical curricula. For women, this may not hold true. This is inconsistent with the earlier hypothesis that affirmative action policies created a higher demand for women with high math achievement.

This would lend support to Johnes' hypothesis that the way a curriculum is constructed may have a significant effect. There may be gender effects in the construction of curriculum. Thus for a man who has taken extensive coursework, perhaps due to major requirements, the effects on wage are quite large, but this may hold true only for men. Women may see higher returns to majors that integrate more broadly other fields of study.

Critique and Conclusion

The limitations of the wage data makes it impossible to estimate the life-time earnings of any students. The latest wage data that is available following departure from post-secondary school is 1986, a mere two years after the fastest students would have graduated from college. These estimates are thus only for starting wages, and cannot be extrapolated to further life-cycle earnings. Berger (1988) strongly criticizes using only starting wages in college-earnings models, as he provides evidence that students will be more likely to pick on major over another by taking into account the present discounted value of future earnings rather than those earned immediately after college. However, there is a strong correlation between starting wages and life time earnings, so that this type of analysis, which somewhat imprecise, may not be entirely on the wrong path.

The evidence shows that of the effects from GPA, MSE content, and peer math ability, the latter is by far the most economically significant. Thus, when students optimize for future earnings by choosing a college, it may be wiser to aim for a more selective college and forgo the earnings gotten from MSE content. This may be particularly true for women, who are more sensitive to peer math ability, and get higher returns for this factor than men, but lower returns for their MSE credits. This would imply that women and men should optimize earnings differently. It may make more sense for a woman to go to a more selective school and take fewer MSE credits. Men, however, should attempt to maximize their returns on MSE, and would perhaps be better off at schools where they will take more of these credits.

Conclusion

In this paper, I have examined the effects of demographic factors, background, interest, ability and peer math ability on the MSE choices and earnings of individuals attending college. In the first section, I examine what types of schools students chose based on their demographic, interest, ability, and background profiles. In the second section, I examine the effects of these variables and students' own quantitative SAT score in relation to the schools' average quantitative SAT score. In the final section, I examine the relative importance of peer math ability, MSE credits earned, and GPA on weekly earnings.

In examining what types of schools students attend, I find that high school preparation in math and sciences and performance in these subjects has a strong impact. Additionally, race plays a role, but not as strongly as previously expected. Of all effects, gender is one of the most striking- women attend schools which have on average, an average quantitative SAT score of 9 points lower than the average for men. Additionally there are gender differences in the importance of high school preparation. For women, high school math grades less significant than for men. They appear about half as strong as the effects for men. Taking more math classes appeared more important for women than for men, and the opposite was true for science classes, although science classes showed no statistical significance. Men and women saw nearly identical effects of math score on the peer ability at the college attended. While the effects are subtle, this implies that even at the early stages of preparing for the job market, we see differences in the way that men and women behave and are selected for in post-secondary institutions.

In the second section, I again find that math and science preparation is crucial. Students take higher MSE content in their curriculum when they have higher math grades in high school and have taken more math and science courses before college. Again, the effects differ by gender. The effect of A's and B's in math courses in high school has twice the effect on men that it has on women. While the difference is not so large for preparatory math and science courses, the same pattern holds. A woman taking an additional course in math in high school might take 2.7 more MSE credits, whereas a man would take 4.2. A final and important factor is the difference between a student's quantitative SAT score and the average quantitative SAT score at the school attended. For the entire population, a 100 point difference results in a nearly 5 credit increase in MSE credits attained. For women, the same difference results in an approximately 6 credit increase, while for men it is about 4. This would indicate that women are more sensitive to their relative abilities than men, and less sensitive to their preparation in high school.

Finally, I examine the effects of peer math ability, MSE credits, and GPA on the students' weekly earnings. Surprisingly, GPA shows little statistical significance, but there are important effects from the average school quantitative SAT score and the total number of MSE credits taken. An estimation for the general population shows that women earn, on average, nearly 20% less than men. Separate estimations for both populations find that there are significant differences in the effects of average school quantitative SAT score and MSE credits earned. For women, the effects of mathematical peer ability are much larger than for men. A one point increase in the average school quantitative SAT score translates to a 1% increase in earnings. For men, this is a smaller gain of .07%. MSE credits seem to show diminishing marginal returns for women, but increasing returns for men as they earn more credits. This implies that women and men may be valued differently in the job market. Since women do have different expectations than men, it may not be unreasonable for a firm to prefer to hire a man with an MSE education over a woman. There may be more sunk costs in training more highly educated workers because they are taking on more technically complicated and specific jobs. Thus if firms expect family related matters such as maternity leave to affect women's productivity, they may avoid hiring them or offer them lower compensation than men.

The effects of MSE education are generally positive for the whole population. However, the overall pattern indicates that women attend schools with lower average quantitative SAT scores, that they are more sensitive to their performance relative to their college environment, and less to their preparation from high school, and earn less for their MSE credits when they enter the job market. This implies that policymakers attempting to increase MSE education in postsecondary institutions may need to approach the genders differently. If these results do hold true, it may be that women would respond quite differently to certain incentives than men would.

APPENDIX

Variable List

mathsat	average math SAT score at school attended
black	dummy for black.
white	dummy for white.
amind	dummy for american indian.
apa	dummy for asian or pacific islander.
other	dummy for other race.
mrace	dummy for missing or incomplete data on race.
ne	dummy for New England.
ma	dummy for Middle Atlantic.
sa	dummy for South Atlantic.
sc	dummy for South Central.
nc	dummy for North Central.
mpac	dummy for Mountain or Pacific State.
female	dummy for female.
hsmgrade	dummy for A's and B's in high school math courses
hsgradea	dummy for mostly A's in high school
hsgradeab	dummy for mostly A's and B's in high school
fled	dummy for father's education lower than college
mled	dummy for mother's education lower than college
fmed	dummy for father's education some college, but no degree
mmed	dummy for mother's education some college, but no degree
fhed	dummy for father's education college degree or more
mhed	dummy for mother's education college degree or more
math	number of math credits earned in high school
mmath	dummy for missing record on number of math credits earned in high school
science	number of science credits earned in high school
msci	dummy for missing record on number of science credits earned in high school
fbg	parents' goal for student. 2= both parents expect student to go to college, 1= one parent expects student to go to college, 0= neither parent expects student to go to college.
pability	continuous variable for students perceived ability to complete college. 1=highest ranking.
mpab	Dummy for missing pability variable
vscore	total vocabulary questions answered correctly on HSB test
mscore	total math questions answered correctly on HSB test
tcred	sum of all technical, mathematical, science and engineering credits earned at last school attended, including approved transfer credits.
weekly	weekly income
lweekly	log of weekly income
diff	Difference between student quantitative SAT score and school average quantitative SAT score

Table 1.1. Descriptive Statistics for Entire Population (Section 1)

Variable	Obs	Mean	Std. Dev.	Min	Max
mathsat	1536	517.2917	73.78741	275	740
black	1536	0.179037	0.383508	0	1
amind	1536	0.010417	0.101562	0	1
apa	1536	0.051432	0.22095	0	1
other	1536	0.086589	0.281323	0	1
mrace	1536	0.005859	0.076347	0	1
female	1536	0.521484	0.499701	0	1
ne	1536	0.089193	0.285115	0	1
ma	1536	0.204427	0.403414	0	1
sc	1536	0.121094	0.326342	0	1
nc	1536	0.227865	0.419591	0	1
mpac	1536	0.132813	0.339483	0	1
hsmgrade	1536	0.582682	0.493277	0	1
hsgradea	1536	0.261719	0.439714	0	1
hsgradeab	1536	0.30599	0.460975	0	1
hsgradeb	1536	0.205078	0.40389	0	1
fmed	1536	0.11263	0.316243	0	1
mmed	1536	0.147787	0.355004	0	1
fhed	1536	0.166667	0.372799	0	1
mhed	1536	0.087891	0.283228	0	1
math	1536	6.285156	1.505495	0	8
mmath	1536	0.002604	0.050981	0	1
science	1536	5.483073	1.901064	0	8
msci	1536	0.019531	0.138428	0	1
fbg	1536	1.734375	0.568228	0	2
pability	1536	1.30599	0.571976	0	5
mpab	1536	0.003255	0.05698	0	1
vscore	1536	16.16602	5.565404	1	27
mscore	1536	23.45638	5.469077	7	32

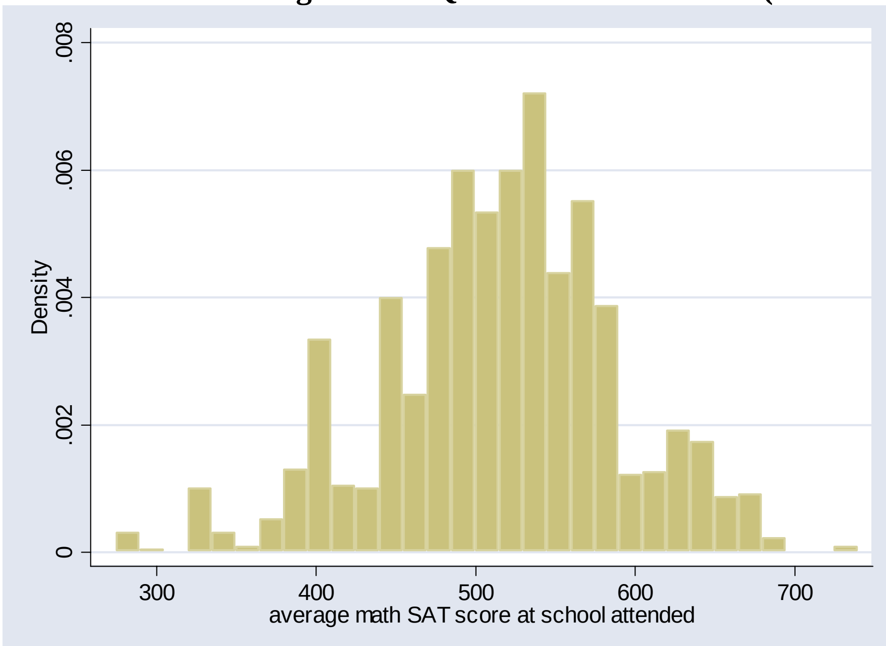
Table 1.2. Descriptive Statistics for Women Only (Section 1)

Variable	Obs	Mean	Std. Dev.	Min	Max
mathsat	801	508.789	72.63888	275	740
black	801	0.178527	0.383195	0	1
amind	801	0.012484	0.111103	0	1
apa	801	0.058677	0.235165	0	1
other	801	0.082397	0.27514	0	1
mrace	801	0.001248	0.035333	0	1
female	801	1	0	1	1
ne	801	0.094881	0.293234	0	1
ma	801	0.203496	0.40285	0	1
sc	801	0.11985	0.324989	0	1
nc	801	0.229713	0.420911	0	1
mpac	801	0.122347	0.327891	0	1
hsmgrade	801	0.593009	0.49158	0	1
hsgradea	801	0.275905	0.447249	0	1
hsgradeab	801	0.350812	0.477522	0	1
hsgradeb	801	0.193508	0.395295	0	1
fmed	801	0.123596	0.329325	0	1
mmed	801	0.157303	0.364314	0	1
fhed	801	0.151061	0.358332	0	1
mhed	801	0.091136	0.287982	0	1
math	801	6.067416	1.566189	0	8
mmath	801	0.001248	0.035333	0	1
science	801	5.213483	1.906074	0	8
msci	801	0.019975	0.140002	0	1
fbg	801	1.735331	0.56335	0	2
pability	801	1.327091	0.583419	0	5
mpab	801	0.002497	0.049938	0	1
vscore	801	15.78901	5.456114	2	27
mscore	801	22.47066	5.472838	7	32

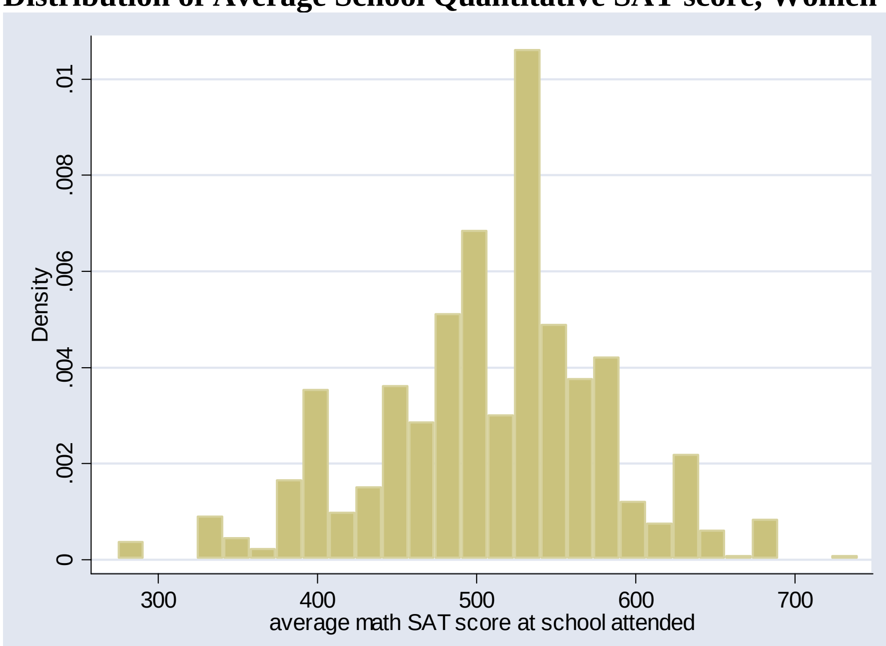
Table 1.3 Descriptive Statistics for Men Only (Section 1)

Variable	Obs	Mean	Std. Dev.	Min	Max
mathsat	735	526.5578	73.96232	275	740
black	735	0.179592	0.384109	0	1
amind	735	0.008163	0.090043	0	1
apa	735	0.043537	0.204203	0	1
other	735	0.091157	0.288028	0	1
mrace	735	0.010884	0.103829	0	1
female	735	0	0	0	0
ne	735	0.082993	0.27606	0	1
ma	735	0.205442	0.4043	0	1
sc	735	0.122449	0.328027	0	1
nc	735	0.22585	0.418426	0	1
mpac	735	0.144218	0.35155	0	1
hsmgrade	735	0.571429	0.495209	0	1
hsgradea	735	0.246259	0.431124	0	1
hsgradeab	735	0.257143	0.437356	0	1
hsgradeb	735	0.217687	0.412955	0	1
fmed	735	0.10068	0.30111	0	1
mmed	735	0.137415	0.344519	0	1
fhed	735	0.183674	0.387481	0	1
mhed	735	0.084354	0.278107	0	1
math	735	6.522449	1.399387	0	8
mmath	735	0.004082	0.063801	0	1
science	735	5.776871	1.852683	0	8
msci	735	0.019048	0.136786	0	1
fbg	735	1.733333	0.573879	0	2
pability	735	1.282993	0.558727	0	4
mpab	735	0.004082	0.063801	0	1
vscore	735	16.57687	5.657264	1	27
mscore	735	24.53061	5.262207	7	32

Graph 1.1.
Distribution of Average School Quantitative SAT score (Section 1)



Graph 1.2
Distribution of Average School Quantitative SAT score, Women Only (Section 1)



Graph 1.3
Distribution of Average School Quantitative SAT score, Men Only (Section 1)

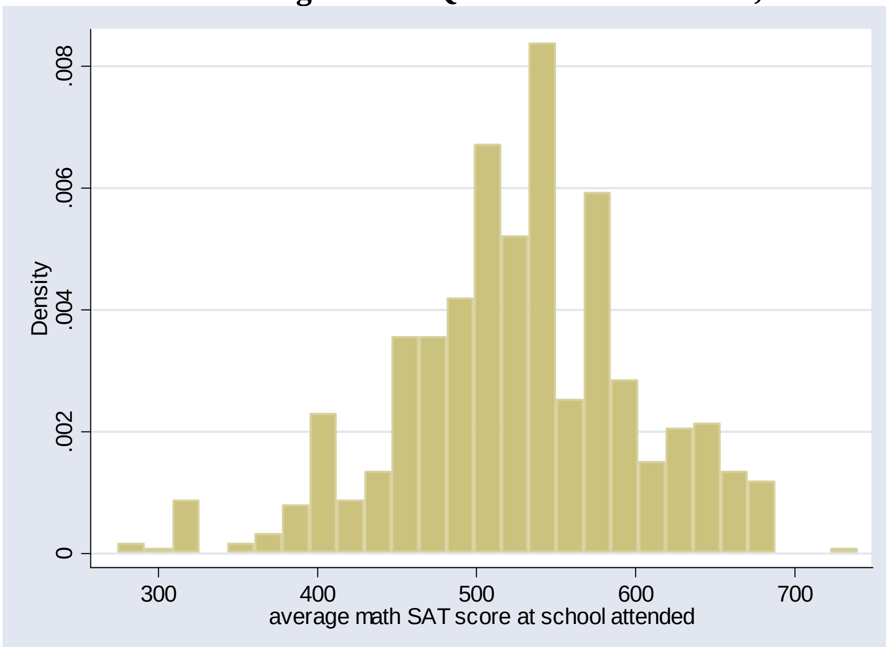


Table 2.1: Descriptive Statistics for Entire Sample (Section 2)

Variable	Obs	Mean	Std. Dev.	Min	Max
tcred	1542	31.79507	36.10811	0	204
diff	1542	-50.3344	78.75342	-309.071	206.4395
black	1542	0.180934	0.385088	0	1
amind	1542	0.010376	0.101366	0	1
apa	1542	0.051232	0.220543	0	1
other	1542	0.086252	0.280826	0	1
mrace	1542	0.005837	0.076199	0	1
female	1542	0.521401	0.499704	0	1
ne	1542	0.088846	0.284613	0	1
ma	1542	0.20428	0.403305	0	1
sc	1542	0.121271	0.326548	0	1
nc	1542	0.227627	0.419436	0	1
mpac	1542	0.132296	0.338922	0	1
hsmgrade	1542	0.583009	0.493221	0	1
hsgradea	1542	0.2607	0.439159	0	1
hsgradeab	1542	0.305448	0.460746	0	1
hsgradeb	1542	0.206226	0.404726	0	1
math	1542	6.287938	1.504515	0	8
mmath	1542	0.002594	0.050882	0	1
science	1542	5.481193	1.900674	0	8
msci	1542	0.019455	0.138163	0	1
pability	1542	1.305447	0.571401	0	5
mpab	1542	0.003243	0.056869	0	1

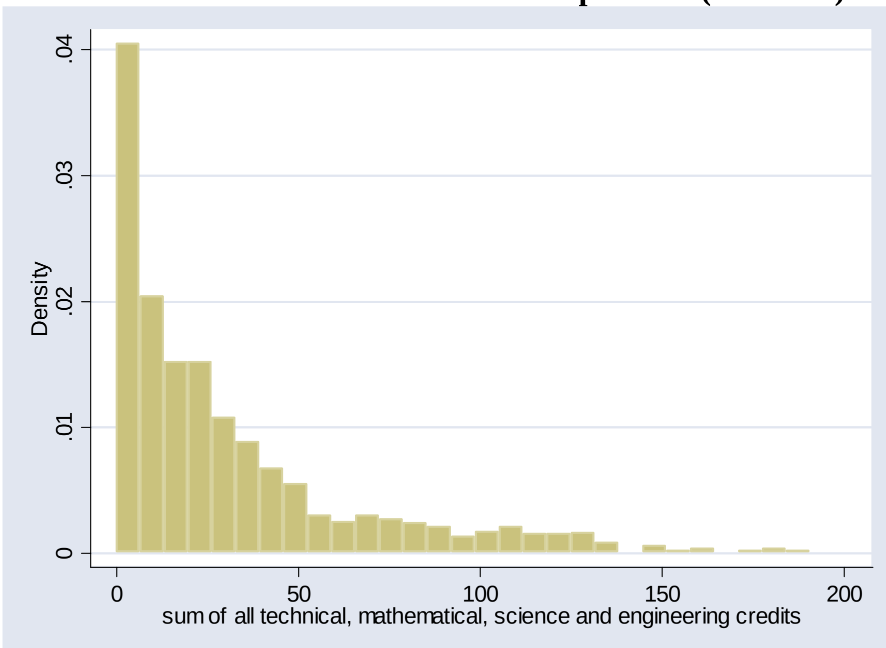
Table 2.2. Descriptive Statistics for Women Only (Section 2)

Variable	Obs	Mean	Std. Dev.	Min	Max
tcred	804	25.93035	30.36359	0	191
diff	804	-55.7718	77.41147	-303.747	183.7774
black	804	0.180348	0.384717	0	1
amind	804	0.012438	0.110898	0	1
apa	804	0.058458	0.234753	0	1
other	804	0.08209	0.274672	0	1
mrace	804	0.001244	0.035267	0	1
female	804	1	0	1	1
mgender	804	0	0	0	0
ne	804	0.094527	0.292743	0	1
ma	804	0.202736	0.402288	0	1
sc	804	0.119403	0.324464	0	1
nc	804	0.2301	0.421158	0	1
mpac	804	0.121891	0.327363	0	1
hsmgrade	804	0.593284	0.491527	0	1
hsgradea	804	0.274876	0.44673	0	1
hsgradeab	804	0.350746	0.477501	0	1
hsgradeb	804	0.19403	0.395698	0	1
math	804	6.070896	1.566683	0	8
mmath	804	0.001244	0.035267	0	1
science	804	5.215174	1.906852	0	8
msci	804	0.019901	0.139745	0	1
pability	804	1.325871	0.58267	0	5
mpab	804	0.002488	0.049844	0	1

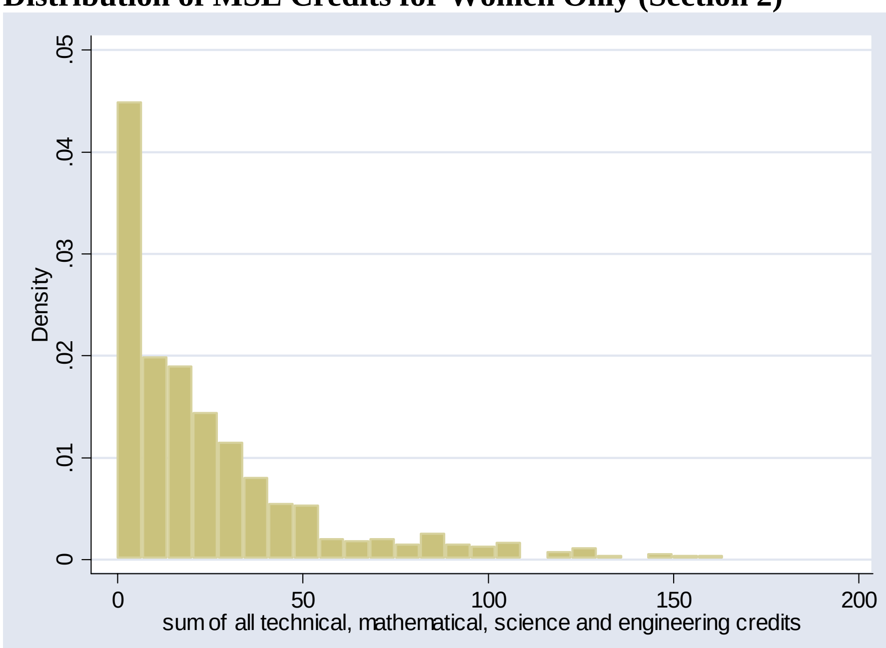
Table 2.3. Descriptive Statistics for Men Only (Section 2)

Variable	Obs	Mean	Std. Dev.	Min	Max
tcred	738	38.18428	40.53651	0	204
diff	738	-44.4109	79.82144	-309.071	206.4395
black	738	0.181572	0.385753	0	1
amind	738	0.00813	0.089861	0	1
apa	738	0.04336	0.203805	0	1
other	738	0.090786	0.287499	0	1
mrace	738	0.01084	0.10362	0	1
female	738	0	0	0	0
mgender	738	0	0	0	0
ne	738	0.082656	0.275548	0	1
ma	738	0.205962	0.404677	0	1
sc	738	0.123306	0.329011	0	1
nc	738	0.224932	0.417821	0	1
mpac	738	0.143631	0.350954	0	1
hsmgrade	738	0.571816	0.495151	0	1
hsgradea	738	0.245258	0.430532	0	1
hsgradeab	738	0.256098	0.436772	0	1
hsgradeb	738	0.219512	0.414197	0	1
math	738	6.52439	1.396867	0	8
mmath	738	0.004065	0.063671	0	1
science	738	5.771003	1.852169	0	8
msci	738	0.01897	0.136512	0	1
pability	738	1.283198	0.558409	0	4
mpab	738	0.004065	0.063671	0	1

Table 2.1
Distribution of MSE Credits for Entire Population (Section 2)



Graph 2.2.
Distribution of MSE Credits for Women Only (Section 2)



Graph 2.3.
Distribution of MSE Credits for Men Only (Section 2)

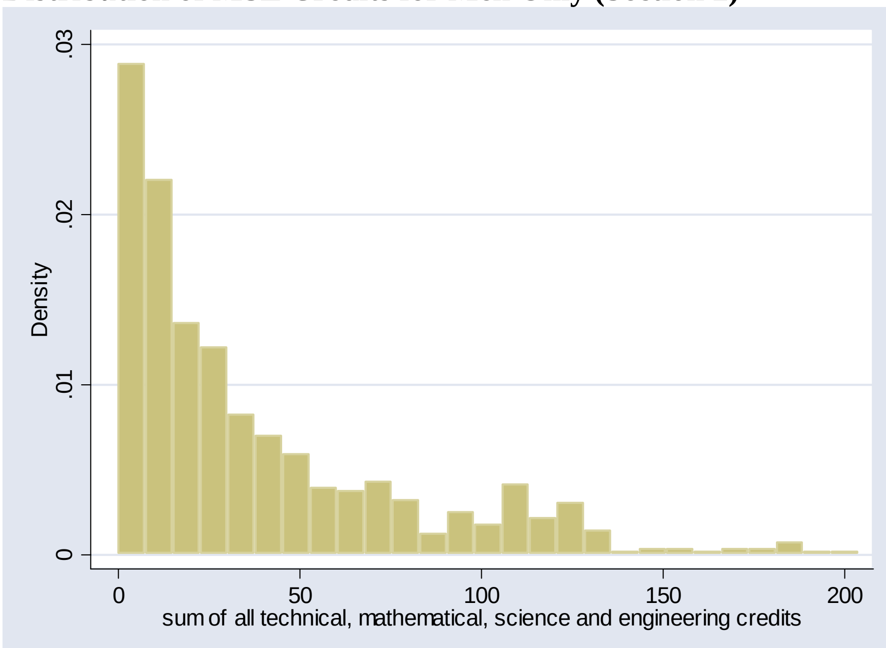


Table 3.1: Descriptive Statistics for Entire Population (Section 3)

Variable	Obs	Mean	Std. Dev.	Min	Max
weekly	1095	325.4786	177.6304	100	1941.25
lweekly	1095	5.670801	0.473097	4.60517	7.571087
tcred	1463	31.52221	36.30865	0	204
cred	1463	2311.067	4929.106	0	41616
mathsat	1463	516.6746	74.02719	275	740
gengpa	1463	2.10912	1.191282	0	4
black	1463	0.178401	0.382981	0	1
amind	1463	0.010936	0.10404	0	1
apa	1463	0.047847	0.213515	0	1
other	1463	0.084757	0.278616	0	1
mrace	1463	0.006152	0.078218	0	1
female	1463	0.51743	0.499867	0	1
ne	1463	0.090226	0.286603	0	1
ma	1463	0.205742	0.404381	0	1
sc	1463	0.119617	0.324624	0	1
nc	1463	0.230349	0.4212	0	1
mpac	1463	0.130554	0.337027	0	1

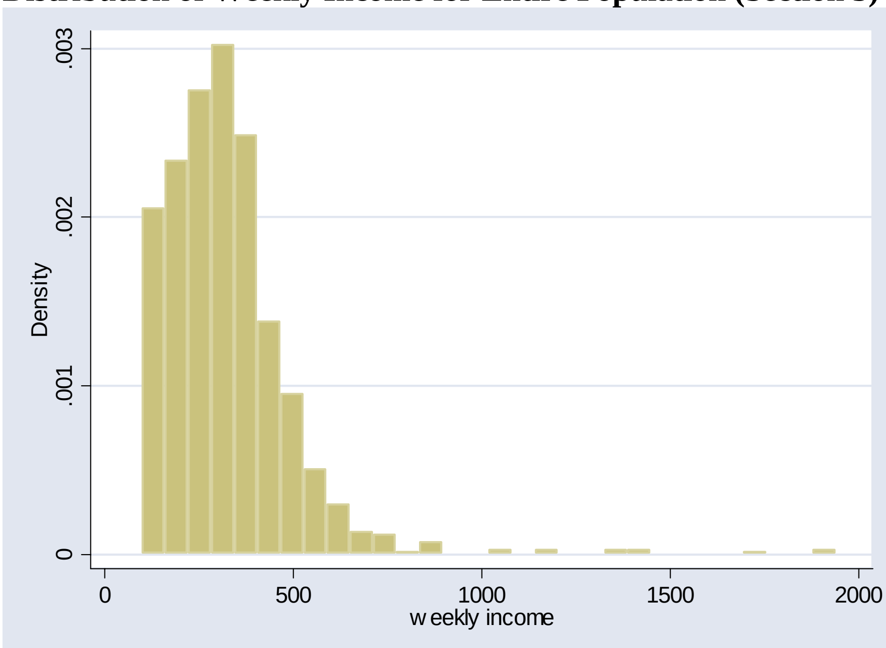
Table 3.2: Descriptive Statistics for Women Only (Section 3)

Variable	Obs	Mean	Std. Dev.	Min	Max
weekly	581	290.9166	164.7452	100	1941.25
lweekly	581	5.563921	0.455406	4.60517	7.571087
tcred	757	25.73712	30.50745	0	191
cred	757	1591.875	3742.009	0	36481
mathsat	757	507.9062	72.28696	275	740
gengpa	757	2.152334	1.205352	0	4
black	757	0.173052	0.378542	0	1
amind	757	0.01321	0.114249	0	1
apa	757	0.054161	0.226485	0	1
other	757	0.077939	0.268253	0	1
mrace	757	0.001321	0.036346	0	1
female	757	1	0	1	1
ne	757	0.095112	0.293564	0	1
ma	757	0.203435	0.402819	0	1
sc	757	0.117569	0.322311	0	1
nc	757	0.233818	0.423537	0	1
mpac	757	0.114927	0.319145	0	1

Table 3.3: Descriptive Statistics for Men Only (Section 3)

Variable	Obs	Mean	Std. Dev.	Min	Max
weekly	514	364.5459	183.6292	100	1903.846
lweekly	514	5.791612	0.463969	4.60517	7.551631
tcred	706	37.72521	40.75996	0	204
cred	706	3082.212	5849.593	0	41616
mathsat	706	526.0765	74.76471	275	740
gengpa	706	2.062785	1.175095	0	4
black	706	0.184136	0.38787	0	1
amind	706	0.008499	0.09186	0	1
apa	706	0.041077	0.198608	0	1
other	706	0.092068	0.289327	0	1
mrace	706	0.011331	0.10592	0	1
female	706	0	0	0	0
ne	706	0.084986	0.279058	0	1
ma	706	0.208215	0.40632	0	1
sc	706	0.121813	0.327302	0	1
nc	706	0.226629	0.418947	0	1
mpac	706	0.147309	0.354665	0	1

Graph 3.1:
Distribution of Weekly Income for Entire Population (Section 3)



Graph 3.2:
Distribution of Weekly Income for Women (Section 3)

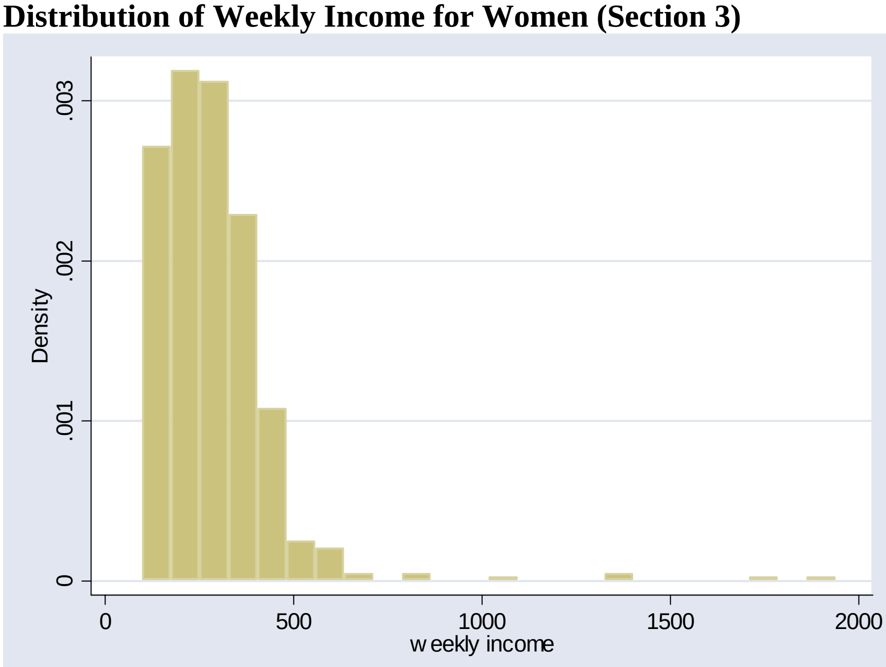
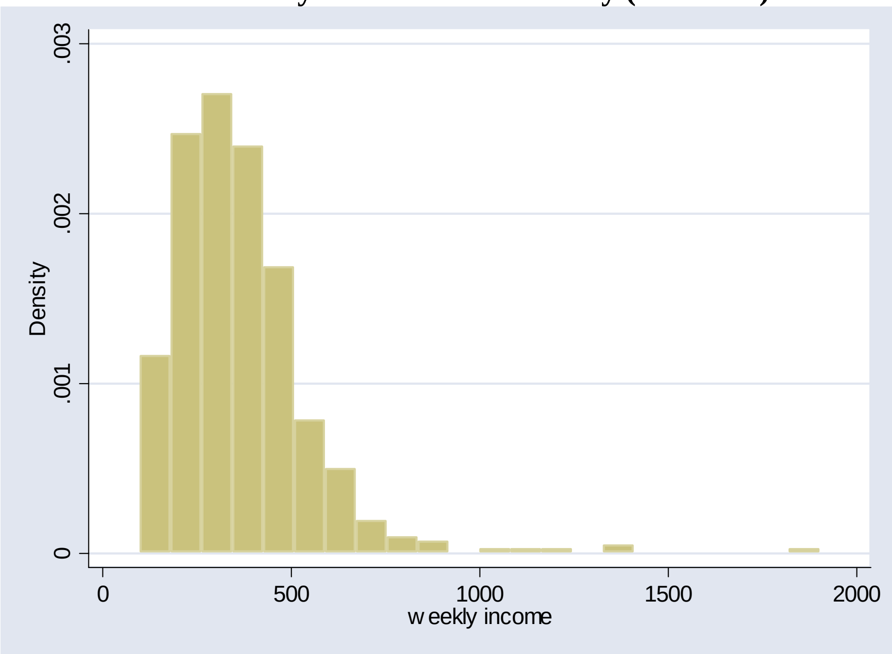


Table 3.3:
Distribution of Weekly Income for Men Only (Section 3)



References:

Adelman, C., (2006, February). The Toolbox Revisited: Paths to Completion from High School through College. *US Department of Education,* retrieved February 26,2006 from http://www.ed.gov/rschstat/research/pubs/toolboxrevisit/toolbox.pdf

Altonji, J. (1993, January) The Demand and Return to Education when Education Outcomes are Uncertain. *The Journal of Labor Economics,* 11 (1) , Part 1, 48-83.

Behrman, J., Rosenzweig, M., & Taubman, P. (1996, November) College Choice and Wages: Estimates Using Data on Female Twins. *The Review of Economics and Statistics*. 78 (4), 672-685.

Berger, M. (1988, April) Predicted Future Earnings and Choice of College Major. *Industrial and Labor Relations.* 41 (3), 418-429.

Blau, F.,& Ferber, M. (1991, Autumn) Career Plans and Expectations of Young Women and Men. *The Journal of Human Resources,* 26 (4), 581-607.

Card, David. (1998). The Causal Effect of Education on Earnings. “Handbook of Labor Economics.” 3(A), 801-63

Chevalier, A., Harmon, C., Walker, I., & Zhu, Y. (2004, November) Does Education Raise Productivity, or Just Reflect It? *The Economic Journal.* 114 (499), F499-F517

Dale, S., & Krueger, A. (2002, November). Estimating the Payoff to Attending a more Selective College. *Quarterly Journal of Economics*. 117 (4), 1491-1527.

Davies, S. & Guppy, N. (1997, June). Fields of Study, College Selectivity, and Student Inequalities in Higher Education. *Social Forces*. 75 (4), 1417-1438.

Daymont, T., & Andrisani, P. (1984). Job Preferences, College Major and the Gender Gap in Earnings. *The Journal of Human Resources.* XIX(3), 408-428.

Dolton, P., & Vignoles, A. (2002). Is a Broader Curriculum Better? *Economics of Education Review*. 21, 415-429.

Eide, E., Goldhaber, D., & Showalter, M. (2003, November). Does Catholic School Attendance Lead to Attendance at a More Selective College? Preliminary Draft, University of Washington. Retrieved February 13, 2006, from https://evans.washington.edu/fac/Goldhaber/pdf/CathCQ_11-18-03.pdf

Filer, R. (1983, Winter). Sexual Differences in Earnings: The Role of Individual Personalities and Tastes. *The Journal of Human Resources.* 18(10), 82-99.

Finnie, R., & Frenette, M. (2003, April). Earning Differences by Major Field of Study: Evidence from Three Cohorts of Recent Canadian Graduates. *Economics of Education Review*. 22 (2), 179-192

Fiorito, J., & Dauffenbach, R. (1982, October). Market and Non-Market Influences on Curriculum Choice by College Students. *Industrial and Labor Relations Review*. 36, (1), 99-101.

Flyer, F. (1997, October). The Influence of Higher Moments of Earnings Distributions on Career Decisions. *Journal of Labor Economics.* 15 (4), 689-713.

Gill, A., & Leigh, D. (2000, October). Community College Enrollment, College Major, and the Gender Wage Gap. *Industrial and Labor Relations Review*. 54 (1), 163-181.

Graham, S., & Smith, S. (2005). Gender Differences in Employment and Earnings in Science and Engineering in the US. *Economics of Education Review*. 24, 341-354.

Grogger, J., & Eide, E. (1995, Spring). Changes in College Skills and the Rise in the College Wage Premium. *The Journal of Human Resources*. 30(2), 280-320.

Harmon, C., & Walker, I. (1995, December). Estimates of the Economic Return to Schooling for the United Kingdom. *The American Economic Review*. 85(5), 1278-1286.

Johnes, G. (2005, July). 'Don't Know Much About History'… Revisiting the Impact of Curriculum on Subsequent Labour Market Outcomes. *Bulletin of Economic Research*. 57(3), July, 249-271

Koch, J. (1972, October). Student Choice of Undergraduate Major Field of Study and Private Internal Rate Of Return. *Industrial and Labor Relations Review*., 26, (1), 680-685.

Light, A., & Strayer, W. (.2003) Determinants of College Completion: School Quality or Student Ability. *The Economics of Higher Education*. 336-369

Loury, L., & Garman, D. (1995). College Selectivity and Earnings. *Journal of Labor Economics*. 13(2), 289-308.

Manski, C., & Wise, D. (1983). *College Choice in America*. USA: Library of Congress.

Manski, C., (1993) Adolescent Econometricians: How Do Youth Infer the Returns to Schooling? *Studies of Supply and Demand in Higher Education.* Chicago and London: The University of Chicago Press.

Minicozzi, A. (2005). The Short Term Effect of Educational Debt on Job Decisions. *Economics of Education Review.* 24, 417-430.

Mitra, A. (2002). Mathematics Skill and Male-Female Wages. *Journal of Socio Economics.* 31, 443-456.

Montmarquette, C., Cannings, K., & Mahseredjian, S. (2002). How Do Young People Choose College Majors? *Economics of Education Review*. 21, 543-556.

Núñez, J., & Otero, A. (2005, June) The Choice of Majors as a Signaling Device. *Revista de Analisis Economico.* 20(1), 23-43.

Paglin, M., & Rufolo, A. (1990, January). Heterogenous Human Capital, Occupational Choice, and Male-Female Earnings Differences. *Journal of Labor Economics*. 8(1), 123-144.

Polachek, S. (1978, July) Sex Differences in College Major. *Industrial and Labor Relations Review.*, 31(4), 498-508.

Reitz, J. (1975, Summer). Undergraduate Aspirations and Career Choice: Effects of College Selectivity. *Sociology of Education*. 48(3), 308-323.

Sautner-Howell, J. (2004, January). A Structural Equilibrium Model of the Market for Higher Education: Assessing the Impact of Eliminating Affirmative Action. Phd Dissertation, Department of Economics, University of Virginia. Retrieved October 2005 from http://www.csus.edu/indiv/h/howellj/Research/Dissertation/howelldissertation.pdf

Savoca, E. (1991, January-March). The Effect of Changes in the Composition of Financial Aid on College Enrollments. *Eastern Economic Journal*. 17(1), 109-21.

Siegfried, J., & Malcolm, G. (2003). Where do the Children of Professors Attend College?
Department of Economics, Vanderbilt University, Working Papers: 0302.
Spence, M. (1973, August). Job Market Signalling. *The Quarterly Journal of Economics.* 87(3), 355-374
Streufert, P. (2000, January). The Effect of Underclass Social Isolation on Schooling Choice. *Journal of Public Economic Theory*. 2(4), 461-482.
Thomas, M. (2004, December). Where College Bound Students Send Their SAT Scores: Does Race Matter? *Social Science Quarterly*. 85(5), 1374-89
Weinberger, C. (1998, January). Race and Gender Gaps in the Market for Recent College Graduates. *Industrial Relations.* 37(1), 67-84.
Weinberger, C. (1999, July) Mathematical College Majors and the Gender Gap in Wages. *Industrial Relations.* 38(3), 407-413.