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THE IMPACT OF ACADEMIC COMPETENCIES ON WAGES, UNEMPLOYMENT AND JOB PERFORMANCE

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THE IMPACT OF ACADEMIC COMPETENCIES ON WAGES, UNEMPLOYMENT AND JOB PERFORMANCE

The scientific and mathematical competence of American high school students is generally recognized to be very low. Of those graduating from high school in 1987, only 45 percent had taken chemistry, only 20 percent had taken physics and only 12 percent had taken pre-calculus and only 6 percent had taken calculus (Educational Testing Service 1990). The National Assessment of Educational Progress (NAEP) reports that only 7.5 percent of 17 year old students can "integrate specialized scientific information" (NAEP 1988a p.51) and 6.4 percent "demonstrated the capacity to apply mathematical operations in a variety of problem settings." (NAEP 1988b p. 42)

Another way of evaluating American performance in math and science is to make comparisons with the upper secondary students of other nations. In the 1960s, the low ranking of American students in such comparisons was defended by citing the fact that higher proportions of American youth took the international test. This is no longer the case. Figures 1 to 4 plot the scores in Algebra, Biology, Chemistry and Physics against proportion of the 18-year old population in the types of courses to which the international test was administered. Where large proportions of the age cohort took the test, lower mean scores tend to result, but this does not explain the poor performance of American high school seniors. In the Second International Math Study, the universe from which the American sample was drawn consisted of high school seniors taking a college preparatory math course. This group represents 13 percent of the age cohort, a proportion that is roughly comparable to the 12 percent of Japanese youth who were in their sample frame and is considerably smaller than the 19 percent of youth in the Canadian province of Ontario and the 50 percent of Hungarians who took the test. In Algebra, the mean score for this very select group of American students was about equal to the mean score of the much larger group of Hungarians and substantially below the Canadian achievement level (McKnight et al 1987). The median score for the Japanese youth was so high it was surpassed by only 2 or 3 percent of the American students taking the test.

THe findings of the Second International Science Study are even more "dismal". Take the comparisons with English-speaking Canada, for example. The 25 % of Canadian 18-year olds taking chemistry know just as much chemistry as the very select 1 % of Americans high school seniors taking their second chemistry course (most of whom are in "Advanced Placement"). The 28 % taking biology know much more than the 6 % of American 17-18 year olds who are taking their second biology course (International Association for the Evaluation of Educational Achievement, 1988).

Clearly, there is a large gap between the science and math competence of

FIGURE 1

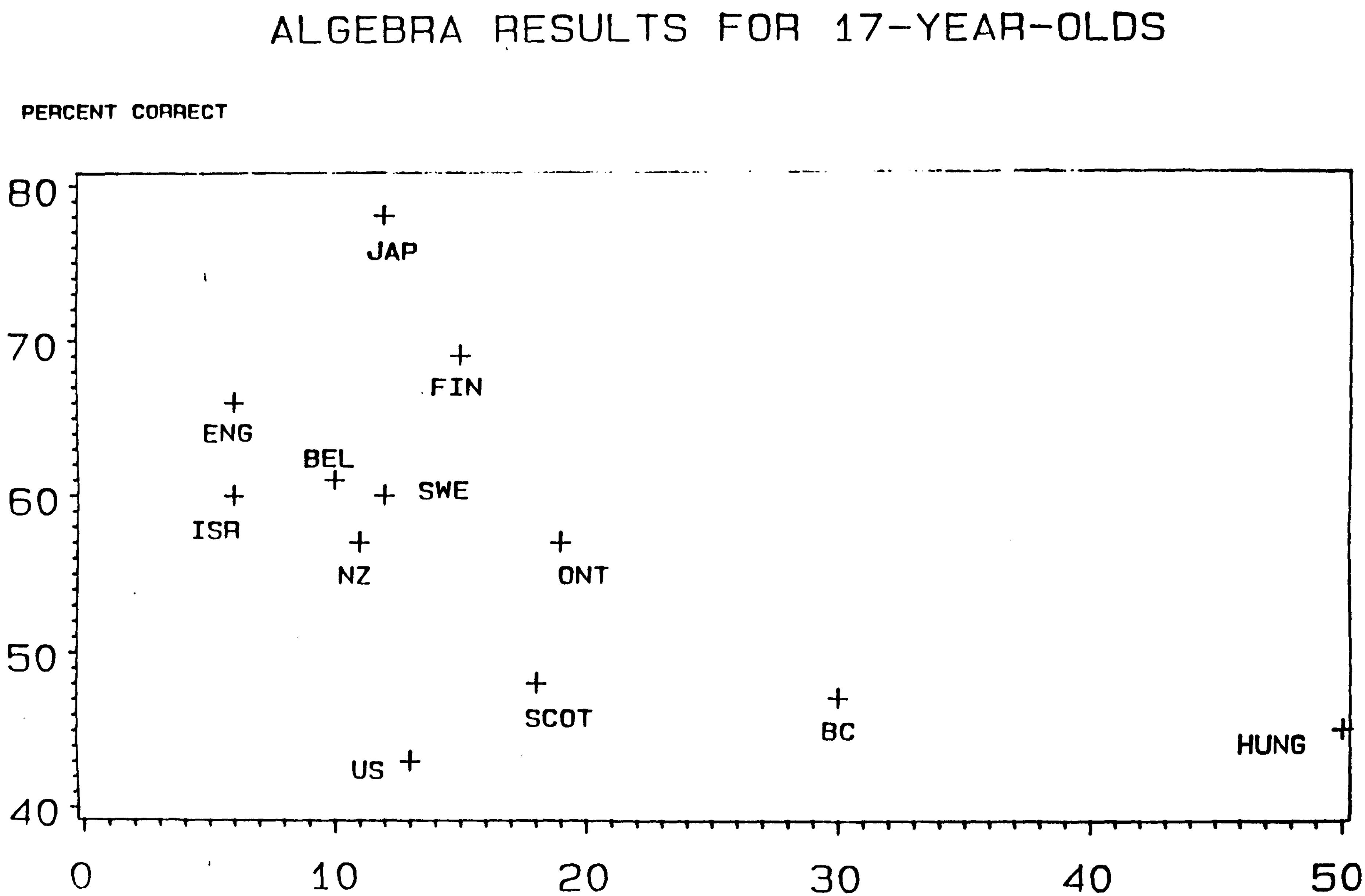

ALGEBRA RESULTS FOR 17-YEAR-OLDS
PERCENT CORRECT
80
70
60
50
40
JAP
FIN
ENG
BEL
SWE
ISR
NZ
ONT
SCOT
BC
HUNG
US
0
10
20
30
40
50

FIGURE 2

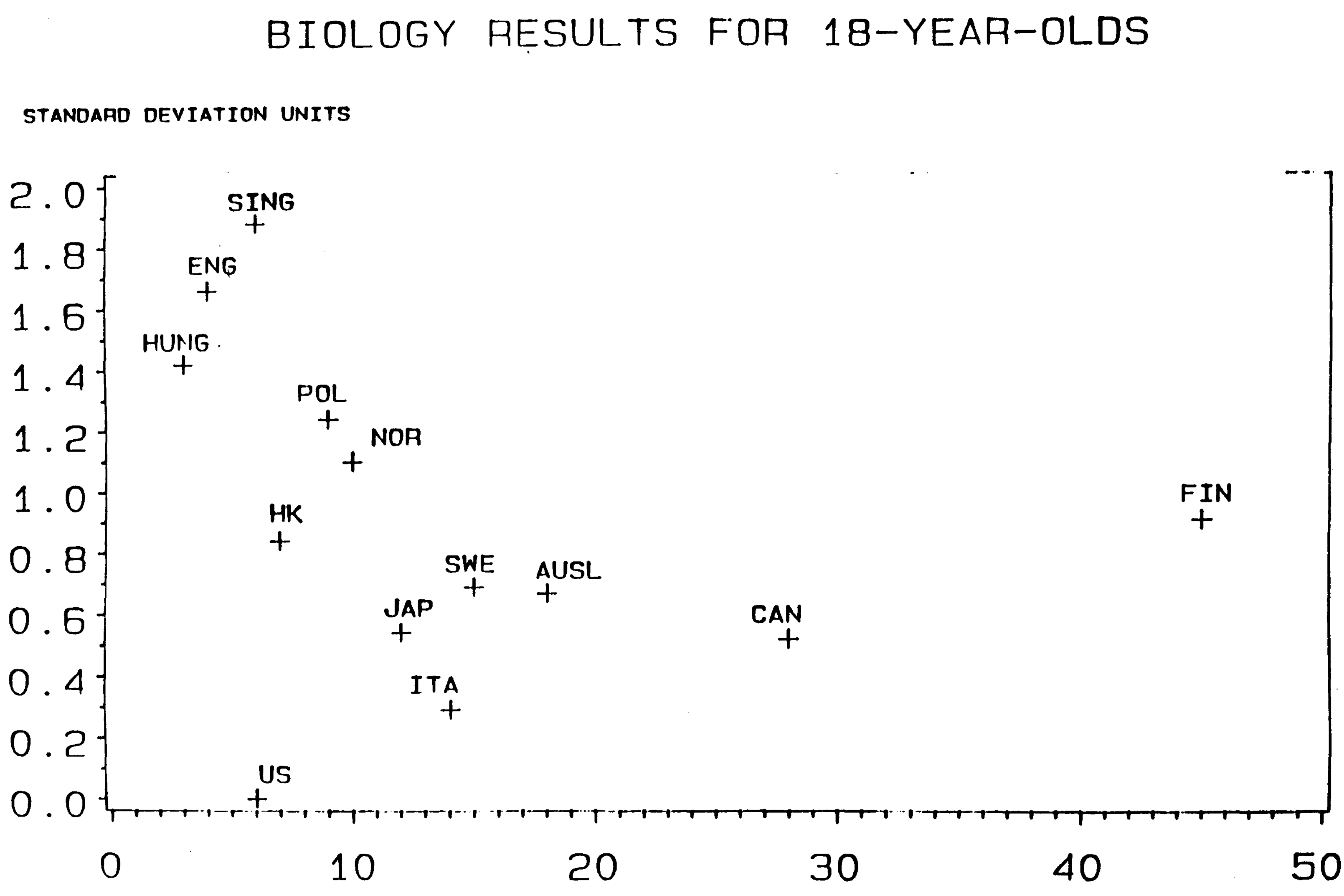

BIOLOGY RESULTS FOR 18-YEAR-OLDS
STANDARD DEVIATION UNITS
2.0
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
SING
ENG
HUNG
POL
NOR
HK
SWE
AUSL
FIN
JAP
CAN
ITA
US
0
10
20
30
40
50

FIGURE 3

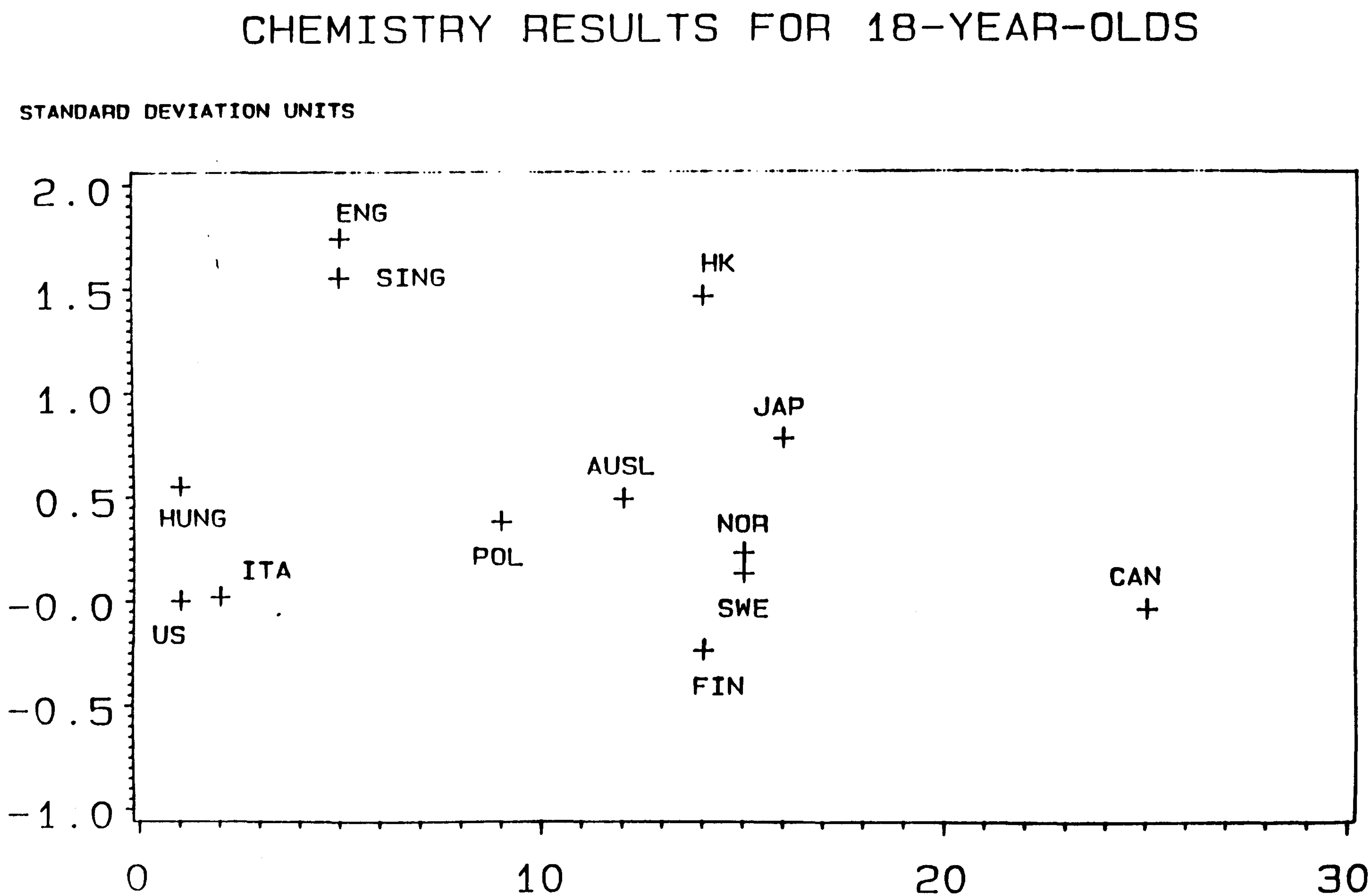
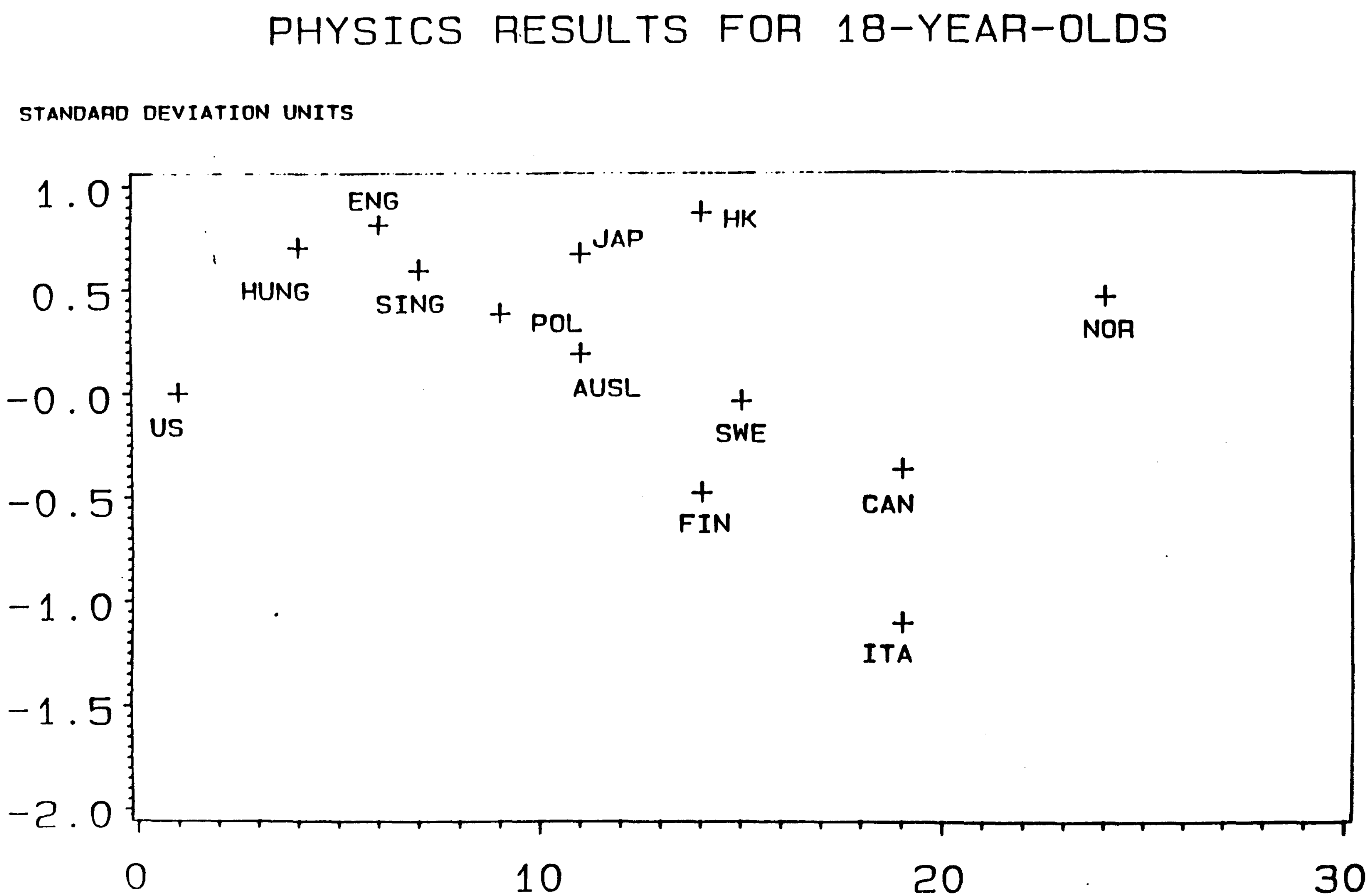

CHEMISTRY RESULTS FOR 18-YEAR-OLDS
STANDARD DEVIATION UNITS
2.0
1.5
1.0
0.5
-0.0
-0.5
-1.0
0
10
20
30
ENG
SING
HK
JAP
AUSL
HUNG
POL
NOR
ITA
CAN
US
SWE
FIN

FIGURE 4


PHYSICS RESULTS FOR 18-YEAR-OLDS
STANDARD DEVIATION UNITS
1.0
0.5
-0.0
-0.5
-1.0
-1.5
-2.0
0
10
20
30
ENG
HK
JAP
HUNG
SING
POL
NOR
AUSL
US
SWE
CAN
FIN
ITA

young Americans and their counterparts overseas. Will this gap have major consequences for the nation's standard of living? In the view of the National Commission on Excellence in Education, it will:

> If only to keep and improve on the slim competitive edge we still retain in world markets, we must dedicate ourselves to the reform of our educational system....Learning is the indispensable investment required for success in the "information age" we are entering. (p. 7).

Behind their call for higher standards and more class time devoted to core academic subjects--math, science, social science and language arts--is an assumption that most jobs require significant competency in these fields. With respect to science, however, there is controversy about these claims. Morris Shamos, an emeritus professor of physics at New York University, argues that "widespread scientific literacy is <u>not</u> essential to... prepare people for an increasingly technological society"(Education Week, Nov. 23 1988. p. 28). The purpose of this paper is to determine whether evidence from the labor market supports these claims?

The first section of the paper addresses the following question: "Are the young workers who have above average competence in these fields receiving higher wage rates?" The findings from this analysis appear on the surface to contradict the recommendations of the Excellence Commission and support Shamos. For young men in the NLS Youth sample, competence in mathematical reasoning, science and language arts does not increase wage rates or earnings in the first 8 years after graduating from high school. The competencies that pay off for young men are speed in doing simple computations (something that calculators do better than people) and technical competence (knowledge of mechanical principles, electronics, automobiles and shop tools), something that has been ignored by the reports recommending educational reform. For young women, the findings are that verbal and mathematical reasoning competence lower unemployment and increase earnings but only mathematical reasoning competence and computational speed increases female wage rates. Competence in science has no effect on earnings or wage rates and verbal ability has no effects on wage rates. While these results provide little support for the Excellence Commission's recommendations, they suggest an immediate explanation for the poor performance of American students in science and higher level mathematics. For the 90 percent of the society who are not going to be scientists, engineers, doctors or technicians, there are no immediate labor market rewards for developing these competencies. For the great bulk of students, therefore, the incentives to devote time and energy to the often difficult task of learning these subjects are very weak.

The Excellence Commission's report, however, makes claims about the **productivity** effects not the **wage rate** effects of science, mathematics and language arts competency. Are these effects necessarily the same? The second section of the paper addresses this question and concludes that, when the specific competencies of students are not signaled to the labor market by a credential (as is the case for math and science achievement in US high schools), there is very little reason to expect the wage rate effects of specific competencies which are highly correlated with each other to be the same as their productivity effects.

The third section of the paper, therefore, tackles the productivity effects question more directly by analyzing data sets in which worker competencies have been correlated with their relative job performance in specific jobs. These analyses provide support for the Excellence Commission's recommendations for better preparation in math and science, but they also reinforce the findings from the analysis of wage rates, earnings and unemployment regarding the important role of technical competence in blue collar, craft and technician jobs.

I. WHICH COMPETENCIES ARE REWARDED BY THE LABOR MARKET ?

The first task of the study is to determine to what degree achievement in the various subjects taught in high school are rewarded by the labor market. This is accomplished by estimating models predicting wage rates, earnings and unemployment as a function of competence in the academic fields of mathematics, science and language arts and in the trade/technical arena while controlling for years of schooling, school attendance, ethnicity, age, work experience, marital status and characteristics of the local labor market.

1.1 DATA

The data set for this analysis is the Youth Cohort of National Longitudinal Survey (NLSY)--all eight waves from 1979 to 1986. The measures of achievement are derived from the Armed Services Vocational Aptitude Battery (ASVAB), a three hour battery of tests used by the armed forces for selecting recruits and assigning them to occupational specialties. The primary purpose of the ASVAB is to predict the success of new recruits in training and their subsequent performance in their occupational specialty. Its ability to accomplish these objectives has been thoroughly researched and the battery has been periodically modified to incorporate the findings of this research. The ASVAB Manual reports:

> Extensive research demonstrates that the ASVAB composites used in military selection and classification predict performance in training for a variety of military occupations. (Booth-Kewley, 1983; Maier & Truss, 1983; Rossmeissl, Martin & Wing, 1983; Wilbourn, Valentine, & Ree, 1984). For example, validity coefficients for electrical & mechanical equipment repair specialties range from .36 to .74; those for communication specialties range from .36 to .52; those for data processing specialties range from .39 to ,77; and those for clerical and supply specialties range from .53 to .73. These coefficients have been corrected for restriction of range. (US Military Entrance Processing Command, 1984, p. 18)

Eighty percent of the jobs held by enlisted personnel in the military have civilian counterparts so the research on the validity of the ASVAB in military settings generalizes quite well to major segments of the civilian economy (US Department of Defense, 1984). The test is highly correlated with the cognitive subtests of the General Aptitude Test Battery, a personnel selection test battery used by the US Employment Service, the validity of which has been established by studies of over 500 occupations. A validity generalization study funded by the armed forces concluded "that ASVAB is a highly valid predictor of performance in civilian occupations" (Hunter Crossen and Friedman, 1985, p. ix).

During the summer of 1980 all members of the NLS Youth sample were asked to take this test and offered a $50 honorarium as an inducement. The tests were successfully administered to 94 percent of the sample. Testing was generally conducted in groups of 5 to 10 persons. The 1980 version of the ASVAB (Form 8A) was administered by staff of the National Opinion Research Corporation according to strict guidelines conforming to standard ASVAB procedures. The Department of Defense which funded this project had Dr. R. D. Bock an authority on educational and psychological testing evaluate the quality of the resulting ASVAB data. He concluded:

> Data from responses of [the NLS Youth Sample] to the ASVAB are free from major defects such as high levels of guessing or carelessness, inappropriate levels of difficulty, cultural test-question bias, and inconsistencies in test administration procedures. (quoted in US Military Entrance Processing Command, 1984, p. 19)

The ASVAB test battery is made up of 10 subtests: Mechanical Comprehension, Auto and Shop Knowledge, Electronics Knowledge, Clerical Checking (Coding Speed), Numerical Operations (a speeded test of simple arithmetic), Arithmetic Reasoning, Mathematics Knowledge (covering the high school math curriculum), General Science, Word Knowledge and Paragraph Comprehension. A fuller description of each of these subtests together with sample questions is given in Appendix B.

Two dimensions of mathematical achievement are measured: the speed of doing simple mathematical computations is measured by a three minute 50 problem arithmetic computation subtest which will be referred to as computational speed. Mathematical reasoning ability is measured by a composite of the mathematics knowledge and arithmetic reasoning subtests. Science achievement is indexed by the ASVAB's General Science subtest. This test focuses on science definitions and has minimal coverage of higher level scientific reasoning. Verbal achievement is measured by a composite made up of the word knowledge and paragraph comprehension subtests.

The universe of skills and knowledge sampled by the mechanical comprehension, auto and shop information and electronics subtests of the ASVAB roughly corresponds to the vocational fields of trades and industry and technical so these subtests are aggregated into a single composite which is interpreted as an indicator of competence in the "technical" arena.[3]

Competencies that are unique to clerical and retail sales jobs do not appear to be measured by the ASVAB. The ASVAB does contain a seven minute 84 item clerical checking subtest which was intended to predict performance in clerical jobs but validity studies of clerical jobs in the military have found that it does not add to the validity of composites based on verbal, arithmetic reasoning and mathematics knowledge subtests (Wise, McHenry, Rossmeissl and Oppler, 1987). The clerical checking subtest is included in the analysis but it should not be viewed as a valid predictor of clerical competency. These six test composites have all been normalized to have zero mean and unit variance. The alternate form reliabilities of these composites are approximately .92-.93 for Technical, .93 for Math, .93-.94 for Verbal, .80 for General Science, .72 for Numerical Operations and .77 for Clerical Checking (US Military Entrance

Processing Command 1984; Palmer et al, 1988). All of these competencies are highly correlated with years of schooling. When these composites are regressed on age, ethnicity, proportion of 1980 spent in school, region, work experience, occupation of parents and schooling, the coefficients on years of high school range between .19 for math and .28 for verbal for males and range from .12 for technical and .24 for verbal and clerical speed for females. Greater work experience significantly increased the clerical speed of women but did not have positive effects on any of the other competencies.

Four measures of labor market success are being studied: the log of the hourly wage rate in the current or most recent job, the log of calender year earnings if they exceed $500, earnings in dollars (with nonworkers over age 16 included in the sample) and the share of labor force time that the individual was unemployed (defined only for people who were in the labor force for at least 8 weeks during the calender year). The sample was limited to those who were not in the military in 1979. At the time of the 1986 interview the NLS Youth ranged from 21 to 28 years of age.

An extensive set of controls are included in the estimating equations. Reports of weeks spent in employment are available all the way back through 1975. For each individual, these weeks worked reports were aggregated across time and an estimate of cumulated work experience (EXP_{it}) was derived for January 1 of each year in the longitudinal file. This variable and its square is included in every model as is age and its square. School attendance is controlled by four separate variables. The first variable indicates whether the youth is in school at the time of the interview. The second is a dummy variable indicating whether the youth has been in school since the last interview. The third is a dummy variable indicating whether the student is attending school part time. A positive coefficient is expected on this variable when the other controls for school attendance are entered in the model. The fourth variable is a measure of the share of the calender year that the youth reported attending school derived from the NLS's monthly time log. Years of schooling is also controlled for by four variables: years of schooling, a dummy for high school graduation, years of college education completed, and years of schooling completed since the ASVAB tests were taken.

The individual's family situation is controlled by dummy variables for being married and for having at least one child. Minority status is controlled by a dummy variable for Hispanic and two dummy variables for race. Characteristics of the local labor market were held constant by entering the following variables: dummy variables for the four Census regions, a dummy variable for rural residence and for residence outside an SMSA and measures of the unemployment rate in the local labor market during that year.

1.2 HYPOTHESES, MODEL SPECIFICATION AND RESULTS

The labor market consequences of the competencies that a young person develops early in life will be examined by testing seven hypotheses relating to the impact of ASVAB subtest scores on wages, earnings and unemployment. These hypotheses are first specified and then the relevant statistical evidence is reviewed.

Main Effects of Test Scores

Hyp. 1: Subtests measuring academic competencies do not have significant positive effects on wage rates and earnings in the years immediately following high school graduation.

The reason for expecting the academic subtests to have no significant positive effects on labor market success is that analyses of other data sets such as High School and Beyond and NLS Class of 1972 have typically found that academic achievement test scores have small effects on early labor market success (Taubman and Wales 1975; Hauser and Daymont 1977; Gardner 1982; Meyer 1982; Kang and Bishop 1986).

Hyp 2: Subtests measuring generic technical knowledge have positive effects on wage rates and earnings and negative effects on unemployment of young men.

The primary reason for expecting tests of generic technical knowledge to have positive effects on labor market success of young men is the demonstrated positive effect of trade and technical course taking on labor market success when the student obtains a job which uses the skills learned in school (Bishop 1988). Since technical skills appear to payoff only when used, the returns to technical skills are likely to be gender specific. Very few young women have jobs for which knowledge of electronics, mechanical principles, auto mechanics and shop tools are essential, so the technical composite is not likely to be good predictor of wages and earnings for women. Very few young men work in clerical jobs, so the clerical checking subtest is not likely to be a useful predictor of wages and earnings for men. These hypotheses are first tested in a model in which the technical and academic competencies are assumed to have linear and additive effects on labor market outcomes:

$$(1)\quad \underline{Y}_t = \underline{a}_t\underline{A} + b_tC + c_tT + e_tS + \underline{g}_t\underline{Z}_t + \underline{u}_t \qquad \text{for } t = 1979\ldots1986$$

where $\underline{Y}_t$ is a vector of labor market outcomes (wage rates, earnings and unemployment) for year t.

$\underline{A}$ is a vector of test scores measuring competence in arithmetic reasoning, algebra, geometry, reading and vocabulary and science knowledge.

C is a measure of speed in simple arithmetic computation.

T is the technical composite measuring mechanical comprehension and electronics, auto and shop knowledge.

S is clerical checking speed.

$\mathbf{Z}_k$ is a vector of control variables such as age, work experience, schooling, school attendance, marital status, parenthood, minority status, region, residence in an SMSA and local unemployment rate.

$\mathbf{u}_t$ is a vector of disturbance terms for each year.

Young men: The results of estimating model 1 are presented in Table 1 through Table 4. Complete results for sample runs are available in Appendix A. The results for young men are as predicted--high level academic competencies do not have positive effects on wage rates and earnings. The mathematics reasoning, verbal and science composites all have negative effects on wage rates and earnings and often positive effects on unemployment. In the wage rate models, 23 of 24 coefficients were negative. F tests on the sum of the coefficients on the three academic composites are presented in columns 9-11 of tables 1 through 4. The sum of the three coefficients in the wage rate models was significantly (at the 5 percent level) negative in 5 of the 8 years. In the log earnings models, 20 of 21 coefficients were negative. In the dollar earnings models, 19 of 21 coefficients were negative. F tests on the sum of the coefficients on academic tests in the dollar earnings models find they are significantly negative in 5 of the 7 years. In the unemployment models, about half of the coefficients were positive and the F test on the sum of the coefficients was never significantly different from zero at even the 10 percent level.

Speed in arithmetic computation has substantial positive effects on labor market success of young men. A one standard deviation increase in computational speed increased wage rates by 5.3 percent and earnings by $837 (10.4 percent) on average. The wage and earnings effects grew over time. The unemployment effects, in contrast, diminished with time. They were significant in 1979-80 but not later. In all eight of the years studied, computational speed had a significantly larger impact on wage rates and earnings than the aggregated academic tests. Computational speed, however, is something that calculators do better than people and is not viewed by most educators as an appropriate goal for a high school mathematics curriculum (National Council of Teachers of Mathematics 198_).

Being able to do clerical checking rapidly significantly lowered unemployment in 4 of the 7 years, significantly increased dollar earnings in 6 of 7 years but had no effect on wage rates.

Technical competence had large and significant positive effects on wage rates and earnings and negative effects on unemployment. The F tests indicate that in all eight years analyzed, it had significantly more positive effects on wage rates and earnings than the aggregated academic tests. A one standard deviation increase in the technical composite increased wage rates by 5.6 percent and yearly earnings by $1065 (12.5 percent) and reduced the rate of unemployment by 1.9 percentage points. This is a very substantial return to technical achievement.

Young women: The competencies that pay off for women are different from the competencies that payoff for men. As with men, scientific competence has no effect on their wage rates, earnings or unemployment. Unlike men, however, technical competence does not pay off. In fact, technical competence had a significant tendency to increase unemployment from 1979 through 1983. As with men, speed of arithmetic computation significantly raised wage rates and earnings. A one SD increase in computational speed increased wage rates by 3.2 percent and earnings by $311 (6.4 percent) on average. Unlike men, mathematical reasoning capability had a significant impact on wage rates, earnings and unemployment. A one SD increase in mathematical reasoning competency raised the wage rates of young women by 2.5 percent and earnings by $407 (4.4 percent) and decreased unemployment by 1.0 percentage point. The wage and earnings effects appear to have grown with time.

Still another contrast with men is the large effects of verbal competence on the unemployment and earnings of young women. A one SD improvement in verbal achievement lowered the risk of unemployment by 2.3 percentage points and raised earnings by $229 (6.2 percent). Wage rate effects were much smaller. Verbal competence had a significant effect on a women's wage rate only in 1985 and 1986.

The overall effect of the three academic competencies on unemployment and earnings was quite substantial. A one SD increase in all three tests lowered the risk of unemployment by 3.6 percentage points and raised earnings by $594 (8.1 percent). The impact of the academic tests on wage rates was much smaller--3.3 percent on average--though it appears to be growing over time.

The clerical checking subtest had weak positive effects on wage rates of young women and large significant effects on their earnings and unemployment.

Interaction Effects

The rest of the hypotheses to be tested relate to how the payoff to academic and technical competencies and speed in arithmetic computation varies with further education, student status and age. To test these hypotheses, a composite of the academic subtests (TA) with unit variance was defined and this composite, the technical composite and the computational speed subtest were then interacted with age deviated from 22, with years of college and with student status. In order to maximize the power of these tests it was assumed that the main effects of the test composites and all interactions with these composites were the same in all years.

$$(2)\quad \underline{Y}_t = \underline{aA} + bC + cT + dTA + e_S + \underline{g}_t\underline{Z}_t + \underline{u}_t \qquad t = 1981,\ldots 1986$$

where $b = b_0 + b_1(\text{Age}_t-22) + b_2(\text{Student}_t)$

$c = c_0 + c_1(\text{Age}_t-22) + c_2(\text{Student}_t)$

$d = d_1(\text{Age}_t-22) + d_2(\text{Student}_t) + d_3(\text{Yrs of College}_t)$

Student_t = proportion of the calender year t attending school

The models were estimated using seemingly unrelated regression. This analysis is conducted on a reduced sample of young people who were valid observations in the model in all of the years between 1981 and 1986. When interactions are defined in this way, the main effects coefficients on the six composites ($\underline{a}$, b_0 and c_0) provide estimates for year t of the effect of the competency on labor market outcomes of 22 year old high school graduates who are not attending school. These subtest main effects coefficients are reported in the top panel of Table 5. The coefficients on the interaction of age and the test composites (b_1, c_1 and d_1) provide estimates of the effect of age on the payoff to academic and technical competencies while controlling on years of college and student status.

Age and the Payoff to Academic Competency

Hyp 3: The return to academic competency grows with the age of the worker. $d_1 > 0$.

A number of studies have found that the return to overall academic achievement increases with the age of the worker (Hauser and Daymont 1977; Taubman and Wales 1975). This would occur if academic achievement improves access to jobs offering considerable training and enables the worker to get more out of the training. A second possible cause of a positive age interaction is that academic achievement is poorly signaled to employers so there are long delays before the labor market identifies and rewards workers who because of their academic achievements are exceptionally productive workers.

The findings regarding the effect of age on the payoff to academic competency are presented in row 8 of Table 5. They do not support hypothesis 3. None of the age/academic composite interaction coefficients in the wage and earnings regressions come even close to being significantly positive and one is significantly negative. The statistically significant interaction coefficient in the male unemployment regression suggests that academic competency has its most favorable effect on unemployment immeadiately after graduating from high school.

The competency that interacts positively with age is computational speed. Interactions of age and computational speed are statistically significant in the male wage rate and dollar earnings regressions and both of the female earnings equation. Ceteris paribus, a one standard deviation differential in computational speed raises the wage rates of male high school graduates not in school by 4.5 percent at age 19, 6.2 percent at age 22 and 7.9 percent at age 25. The impact of one SD of computational speed on the earnings of young men was $623 at age 19, $1088 at age 22 and $1553 at age 25. In the female earnings models, one SD of computational speed raises earnings by $157 at age 19, by $442 at age 22 and by $727 at age 25. The interaction coefficients are positive but not statistically significant in the models of female wage rates and male log earnings.[2]

The positive coefficients on the age interaction in the unemployment regressions for both men and women imply that immeadiately after leaving school, the payoff to computational speed arises largely from its impact on unemployment. This effect diminishes over time but the wage rate and earnings effects (which were initially rather small) become larger and larger.

Age and the Payoff to Technical Competence

Hyp 4: Holding calender year constant, the effect of technical competency test scores on labor market success should be smaller for older workers. $c_1 < 0$.

The reason for expecting the effect of technical competency tests to diminish as a worker ages is that previous studies have found that the large initial effects of trade and technical courses on wages and earnings diminish as the worker gets older (Meyer 1982; Kang and Bishop 1986). This is what one would expect if vocational courses serve as a signal of occupational competency but the signal has diminishing value as the individual gains post-school work experience. Meyer proposes an alternative explanation. He suggests that new hires who already have training in the occupation have less to learn so their performance and wages improve at a slower rate than the new hires who had no previous relevant training or experience. When, however, skill is defined by a technical competency test rather than by vocational courses taken, these explanations may not hold. When filling jobs that involve a great deal of on-the-job training, employers may give preference to job seekers who are already partially trained and who have demonstrated their ability to learn the skills required. If this is the way employers behave, initial skill advantages may be magnified by a positive correlation with opportunities for further training on-the-job and initial rewards for technical competency might grow with age.

None of the coefficients on interactions of technical competence with age have the significantly negative sign predicted by hypothesis 4, so the hypothesis is rejected. In fact in the wage rate model for young men, the interaction between age and technical competence is significantly positive. The interpretation we give these results is that even though the value of the "vocational graduate" signal may diminish with time, the value of technical knowledge does not diminish in value with time out of high school. In fact, for men the value grows either because a wider circle of employers become aware of it or because the individual is able to get jobs which offer more intensive training.

Effect of School Attendance on the Payoff to Academic and Technical Competencies

Hyp 5: The wage rate effects of academic, technical and computational speed competencies are less positive for students than for those who have completed their schooling. $b_2 < 0$, $c_2 < 0$ and $d_2 < 0$ in the wage regression.

Students working during the summer or part time during the school year generally have a narrower choice of occupations than young people who have completed their schooling. The high turnover rates and the necessity of scheduling work around school pushes students into occupations which may not give scope to the academic and technical competencies measured by the ASVAB.

Hyp 6: Among students, high academic competencies are associated with lower earnings. $d_2 < 0$ in the earnings regressions.

Young people with strong academic competency are typically faster learners than their peers and are consequently more likely to devote 100 percent of their time to study (eg. attend a selective college where students do a great deal of home work). Studies analyzing which students tend to devote the most time to jobs for pay have found that students with low grades and academic test scores tend to work more than their peers who are doing better in school (Hotchkiss, Bishop and Gardner 1982).

The findings are presented in rows 10-12 of Table 5. In the wage rate regression, 5 of the 6 coefficients on interactions between student status and test composites had negative coefficients but none of these coefficints were statistically significant. This result suggests that while the opportunities for employment open to students are generally less attractive, we cannot reject the hypothesis that wage rates and unemployment are just as contingent on the competencies of students as they are for nonstudents. On the other hand, being a student has strong negative effects on the earnings payoff to academic competency. Holding the other test composites constant, a one standard deviation increase in math, verbal and science competencies lowered the earnings of 22 year old male <u>nonstudents</u> by $590 and lowered the earnings of 22 year old male <u>students</u> by $1686. For females the effect of a one SD increase in these competencies was an earnings increase of $967 for nonstudents and a $1289 decrease in earnings for students. Students with high academic test scores appear to choose to spend less time working in the labor market than students with low academic test scores.

The Effect of College Education on the Payoff to Academic Competencies

Academic skills appear to be more critical to job performance in professional and managerial occupations than in blue collar and clerical occupations. This suggests the following hypothesis:

Hyp 7: The return to academic competency is larger for college graduates than for high school graduates in the log wage rate and log earnings models. $d_3 > 0$.

Analyses of the NBER/Thorndike data on men who were in the Air Force during World War II, supports this hypothesis but analyses of other data sets have been more equivocal (Taubman and Wales 1975; Hause 1975; Willis and Rosen 1979).

For young women, the hypothesis that the payoff to academic competency is greater for college graduates appears to be supported by the data. Academic competency has a bigger effect on the wage rates and earnings of young women with a college education than it has on the wages and earnings of women with a high school education. On the other hand, high test scores appear to have a smaller impact on the unemployment of college graduates than on the unemployment of high school graduates. This result appears to be caused by ceiling effects in the linear specification of the unemployment risk model for the main effects of test scores and schooling appear to be quite substantial.

The results are more mixed for males. The dollar earnings payoff to higher academic test scores was significantly lower for college graduates than for high school graduates. The wage rate payoff for academic competency was higher for college graduates but not significantly so.

The Effect of Dropping the Years of Schooling Signal from the Model

Since schooling and academic competencies are highly correlated and academic competencies are difficult to measure, employers often use years of schooling as a signal for academic competencies. This suggests that academic competency will have larger effects on wages and earnings when years of schooling are not included in the model. To test this signaling hypothesis, model 2 was reestimated with the same cross equation constraints as before but without the three measures of schooling at the time the ASVAB test was taken--years of schooling, years of college and a high school graduate dummy. The only education variable that remained in the model was years of schooling completed after 1981 which was designed to capture the effects of changes in school generated competencies after taking the ASVAB test. The results of this estimation are presented in Table 6. The effect of dropping the education variables from the model can be determined by comparing these results to those presented in Table 5. The coefficients on technical competency do not become more positive, so it appears that years of schooling is not serving as a signal for technical competency. The coefficients on clerical speed and computational speed rise modestly. The coefficients on the academic composites become substantially more positive. For women, the wage rate effect of a one SD increase in math reasoning, verbal and science competencies increases from 1.9 percent in Table 5 to 5.4 percent in Table 6. Effects on log earnings increase from 8.8 percent to 14.2 percent. For men, the wage rate effect of a one SD increase in the three high school academic competencies changes from -2.4 percent in Table 5 to -0.4 percent in Table 6 and the response of earnings changes from -3.9 percent to 0.8 percent. For males these improvements in the effect of academic competencies only turn negative effects into zero effects. It would appear that the Exellence Commission is recommending that young males pursue a line of study that does not in fact raise their wages and earnings in the short and intermediate term.

II. DOES THEORY IMPLY THAT THE WAGE EFFECTS OF SPECIFIC COMPETENCIES ARE GOOD ESTIMATES OF THE PRODUCTIVITY EFFECTS OF THESE COMPETENCIES ?

Achievement in science has no effects on wage rates, earnings or unemployment of young men and women. Achievement in mathematical reasoning has no effect on the wage rates and earnings of young men. Verbal competency has no effect on the wage rates on young men and women and no effect on the earnings of young men. The finding of small or negative effects of academic competencies for young adults is not unique to this data set. Similar results were obtained in Willis and Rosen's (1979) analysis of the earnings of those who chose not to attend college in the NBER-Thorndike data, Kang and Bishop's (1986) analysis of High School and Beyond seniors and Bishop, Blakemore and Low's (1985) analysis of both Class of 1972 and High School and Beyond data.[3] These results suggest an immediate explanation for the poor performance of American students in science and higher level mathematics. For the 90 percent of the society who are not planning to pursue a career in medicine, science or engineering, there are no immediate labor market rewards for developing these competencies. For the great bulk of students, therefore, the incentives to devote time and energy to the often difficult task of learning these subjects are very weak.

Do these findings also imply that if a way could be found to recruit a high quality engineering and scientific elite (possibly by recruiting talented scientists and engineers from abroad or early identification of scientifically talented youth), there would be little need to worry about the poor math and science preparation of most American youth. In other words, are the productivity effects of these achievements essentially zero in the types of jobs occupied by most young workers? Speed in simple arithmetic computations has large effects on the wage rates of both sexes. Technical competence has large effects on wage rates of young men. Do these skills have comparable effects on productivity? It will be demonstrated shortly that the answer to these questions is **NOT NECESSARILY**.

In the United States academic achievements in high school-- particularly the fine details of achievement in a particular domain like science, mathematical reasoning or reading ability--are not well signaled to the labor market. In a world in which academic abilities are poorly signaled, productivity is hard to measure, specific human capital is important, employers need to promote cooperation among their employees and workers are risk averse, the wage rate effects of tests measuring various dimensions of academic achievement are not reliable indicators of productivity effects of these achievements. When competencies which are highly correlated with each other are poorly signaled to the labor market, employers have a difficult time figuring out which competencies they need and a even more difficult time finding high school graduates with the particular constellations of academic abilities they may believe they need. A conditional expectation function predicting productivity on the basis of the very imperfect signals available to American employers is unlikely to replicate the conditional expectation of true productivity as a function of the true values of the competencies.

The Signaling Failure

In Canada, Australia, Japan, and Europe, the educational system administers achievement exams which are closely tied to the secondary school curriculum. Students generally take between 3 and 9 different examinations. These are not pass/fail minimum competency exams. On the Baccalaureat, for example, there are four different levels of pass: Tre's Bien, Bien, Assez Bien and a regular pass. Failure rates are often quite high (Noah and Eckstein 1988). Not only is university admission based on these tests but job applications, at all levels, require information about exam grades as well (see Exhibits 1 and 2). Good grades on the toughest exams--physics, chemistry, advanced mathematics--carry particular weight with employers.

In Japan, clerical, service and blue collar jobs at the best firms are available only to those who are recommended by their high school. The most prestigious firms have long term arrangements with particular high schools to which they delegate the responsibility of selecting the new hire(s) for the firm. The criteria by which the high school is to make its selection is, by mutual agreement, grades and exam results. In addition, most employers administer their own battery of selection tests prior to hiring. The number of graduates that a high school is able to place in this way depends on its reputation and the company's past experience with graduates from the school. Schools know that they must be forthright in their recommendations because if they fail just once to make an honest recommendation, the relationship will be lost and their students will no longer be able to get jobs at that firm (Rosenbaum and Kariya 1987).

The hiring environment for clerical, service and blue collar jobs is very different in the US. American employers generally lack objective information on applicant accomplishments, skills, and productivity. Tests are available for

NAME:

ADDRESS:

Exhibit 1
Resume of Irish
Secondary School Graduate

DATE OF BIRTH: AGE:

NATIONALITY:

TELEPHONE NO:

EDUCATIONAL DETAILS

Primary School

Post Primary

Secretarial Course

Office Procedures Course

EXAMINATIONS

Intermediate Certificate

SUBJECTS

English	B - L.C.
Irish	C - L.C.
Maths	B - L.C.
Science	C
Geography	C
History	C
Home Economics	D

Leaving Certificate

SUBJECTS

English	D - L.C.
Irish	C - L.C.
Maths	C - L.C.
Biology	C - H.C.
Geography	C - L.C.
French	D - L.C.
Home Economics	B - L.C.

Exhibit ~~5~~

APPLICATION FOR AN APPOINTMENT HANDLED BY MVP

MVP

16, Highfield Road, Edgbaston, Birmingham, B15 3DU Tel: 021 455 9765/0559

United Kingdom

Appointment applied for DISTRIBUTION PROJECTS MANAGER (BXQ) Ref.No.

PERSONAL DETAILS: (block capitals)

Surname [illegible] Title MR Forenames MERVYN JOHN

Address 7 CAERNARVON GARDENS [illegible]

Postal Code [illegible] Tel.No.Home [illegible] W

Marital Status M Children/Dependants (with ages) 1 x 4 YRS 1 x

Age 33 Date of Birth 5.8.55 Nationality BRITISH Place of Birth ILFRACO

State of health OK Height 6' Weight

Any disabilities/recurrent medical problems? — Regd.disabled

Driving Licences CAR Car Owner ✓ Compar

Endorsements, convictions, accidents, etc NONE

Leisure activities and offices held in clubs and societies CYCLING/WALKING

EDUCATION:

Secondary Education

From	To	School	Exams Taken (inc. grades)	O
1966	1972	BARNSTAPLE GRAMMAR	'O' LEVEL:- ENG. LANG. (2), MATHS (1), FRENCH (1), GEOGRAPHY (1), STATISTICS (3), CHEMISTRY (3), ADD. MATHS (6), HISTORY (6), PHYSICS (6) 'A' LEVEL:- CHEMISTRY (C), PHYSICS (E), MATHS (O)	MIDDLE CAPTAIN

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Further Education

From	To	College/University	Course & results (inc.class/grades)	O
1972	1973	UNIVERSITY of BRADFORD	APPLIED CHEMISTRY - LEFT AFTER 1 YEAR - DOMESTIC REASONS	

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Other training and qualifications (inc. in-company and external courses, etc.)

From	To	Establishment	Training/Qualifications
1979		FARNLEY COLLEGE, LEEDS	CERTIFICATE OF PROFESSIONAL COMPETENCE (TRANSPO
1983	1984	CRAVEN COLLEGE	INSTITUTE OF INDUSTRIAL MANAGEMENT CERT.
1986	1989	IN-COMPANY	NUMEROUS MANAGEMENT COURSES.

measuring competency in reading, writing, mathematics, science, and problem solving, but EEOC guidelines resulted in a drastic reduction in their use after 1971. These guidelines prohibit the use of a test on which minorities or women score below white males unless the employer can prove that the test is a valid predictor of performance on jobs at that firm. Each firm proposing to use a test had to do its own validity study separately on blacks and whites (29C.F.R.S607.5(b); Wigdor, 1982). Small firms found the costs prohibitive and did not have enough employees to do such a study. The firm also had to be able to prove that no other test or selection method was available that was equally valid but had less adverse impact. Since there are hundreds of potential selection methods with less adverse impact, the firm was potentially obligated to prove that all of these alternatives were less valid predictors of job performance than the one selected. Litigation costs and the potential liability are substantial. Using an event study methodology, Joni Hersch (1991) found that corporations that were the target of a class action discrimination suit that was important enough to appear in the Wall Street Journal experienced a 15 percent decline in their market value during the 61 day period surrounding the announcement of the suit. Not surprisingly companies are extremely cautious about using tests. The threat of EEO suit caused many firms to drop tests altogether, while other firms used the test only to screen out the bottom 10 or 20 percent of job applicants, rather than to select those with the highest scores (Friedman and Williams, 1982). A 1987 survey of a stratified random sample of small-and medium-sized employers who were members of the National Federation of Independent Business found that aptitude test scores had been obtained in only 3.15 % of the hiring decisions studied (Bishop and Griffin, forthcoming).

Other potential sources of information on effort and achievement in high school are transcripts and referrals from teachers who know the applicant. Both are under-used. In the NFIB survey, transcripts had been obtained prior to the selection decision for only 13.7 % of the hires of people with 12 or fewer years of schooling. If a student or graduate has given written permission for a transcript to be sent to an employer, the Buckley amendment obligates the school to respond. Many high schools are not, however, responding to such requests. The experience of Nationwide Insurance, headquartered in Columbus Ohio, is probably representative. The company obtains permission to get high school records from all young people who interview for a job. It sent over 1,200 signed requests to high schools in 1982 and received only 92 responses. The company reported that colleges were more responsive. Most high schools have apparently designed their systems for responding to requests for transcripts around the needs of college-bound students rather than the students who seek jobs immediately after graduating.

There is an additional barrier to the use of high school transcripts in selecting new employees--when high schools do respond, it takes a great deal of time. For Nationwide Insurance the response almost invariably took more than 2 weeks. Given this time lag, if employers required transcripts prior to making hiring selections, a job offer could not be made for at least a month. Most jobs are filled much more rapidly than that.

Only 16 percent of the NFIB employers asked the applicants with 12 or fewer years of schooling to report their grade point average. The lack of application questions about school performance does not reflect an employer belief that school performance is a poor predicator of job performance. When employers have information on grade point averages, it has a major effect on the ratings employers assign to job applicants in policy capturing experiments (Hollenbeck and Smith, 1984). The absence of questions about grades from most job applications probably reflects the low reliability of self reported data, the difficulties of verifying it, and the fear of EEO challenges to such questions. Hiring on the basis of recommendations by high school teachers is also uncommon. In the NFIB survey, when someone with 12 or fewer years of schooling was hired, the new hire had been referred or recommended by vocational teachers only in 5.5 % of the cases and referred by someone else in the high school in only 3.1 %.

The only information about school experiences requested by most employers is years of schooling, diplomas and certificates obtained, and area of specialization. Hiring decisions are based on easily observable characteristics which are imperfect signals of the competencies the employer cannot observe directly. As a result, hiring selections and starting wage rates are often not influenced by even very gross indicators of academic achievement such as GPA, AFQT or SAT scores (Bishop 1987b). Given the limited information available to employers prior to hiring, it is not realistic to expect their decisions to reflect in a refined manner the specific combinations of academic competencies that students bring to the market.

Implicit Contracts and Performance Rewards

After a worker has been at a firm a while, the employer presumably learns more about the individual's capabilities and is able to observe performance on the job. Workers assigned to the same job often produce very different levels of output (Hunter, Schmidt and Judiesch 1988). Why, one might ask, are the most productive workers (those with just the right mix of specific competencies) not given large wage increases reflecting their higher productivity? The reason appears to be that workers and employers prefer employment contracts which offer only modest adjustments of relative wages in response to perceived differences in relative productivity. There are a number of good reasons for this preference: the unreliability of the feasible measures of individual productivity (Hashimoto and Yu, 1980), risk aversion on the part of workers (Stiglitz, 1974), productivity differentials that are specific to the firm (Bishop, 1987a), the desire to encourage cooperation among coworkers (Lazear 1986) and union preferences for pay structures which limit the power of supervisors. In addition, compensation for differences in job performance may be non-pecuniary -- praise from one's supervisor, more relaxed supervision, or a high rank in the firm's social hierarchy (R. Frank, 1984).

A study of how individual wage rates varied with initial job performance found that when people hired for the same or very similar jobs are compared, someone who is 20 % more productive than average is typically paid only 1.6 % more. After a year at a firm, better producers received only a 4% higher wage at nonunion firms with about 20 employees, and they had no wage advantage at unionized establishments with more than 100 employees or at nonunion establishments with more than 400 employees (Bishop, 1987a).

If relative wage rates only partially compensate the most capable workers in a job for their greater productivity, why don't they obtain promotions or switch to better paying firms? To some degree they do, particularly in managerial and professional occupations. This explains why workers who score high on tests and/or get good grades are less likely to be unemployed and more likely to be promoted, and why, many years after graduation, they eventually obtain higher wage rates (Wise 1975; Bishop 1988b). Since, however, worker productivity cannot be measured accurately and cannot be signaled reliably to other employers, this sorting process is slow and only partially effective. Consequently, when men and women under the age of 30 are studied, the wage rate effects of specific competencies may not correspond to their true effects on productivity and, therefore, direct evidence on productivity effects of specific competencies is required before conclusions may be drawn. We turn now to an examination of direct evidence on the effects of academic and technical competencies on the job performance of young men.

III. THE IMPACT OF ACADEMIC AND TECHNICAL COMPETENCIES ON THE JOB PERFORMANCE OF YOUNG MEN

This section of the paper puts the theoretical arguments of the previous section to an empirical test. A direct estimate of the relative importance of different competencies is undertaken by estimating models in which measures of job performance are regressed on all 9 subtest scores of the ASVAB battery. These direct measures of the productivity effects of the competencies measured by the ASVAB, will then be compared to the wage and earnings regressions of section 1. Is technical competence an important determinant of job performance as well as wages? Do verbal skills and scientific competencies which have no effects on wage rates, nevertheless, have significant positive effects on job performance? The wages and earnings of young men were influenced by computational speed not mathematical reasoning ability. Is this the case for job performance as well?

The ASVAB is one of the most thoroughly researched selection and classification batteries in existence, so there is a wealth of evidence on how its subtests effect job performance in a great variety of jobs. The test battery was developed by the armed forces for use within the military, so military recruits have been the subject of almost all of this research. Eighty percent of the jobs held by enlisted personnel in the military have civilian counterparts, so the research on the validity of the ASVAB in military settings generalizes quite well to large portions of the civilian sector (US Department of Defense, 1984). The civilian occupations that are not represented in the ASVAB research are professional, manager, farmer, sales representative, and sales clerk. Since most of the soldiers studied were young and male, generalizing to other populations must be done with care. This is not a problem in this study, however, for the desired comparisons are with other young males, those in the NLS.

Studies of Training Success

Most of the validity research has involved correlating scores on ASVAB tests taken prior to induction with final grades in MOS specific training courses (generally measured at least 4 months after induction). Since recruits are selected into the army and into the various specialties by a nonrandom process, mechanisms have been developed to correct for selection effects--what I/O psychologists call restriction of range (Thorndike 1949; Lord and Novick 1968; Dunbar and Linn 1986). These selection models assume that selection into a particular MOS is based on ASVAB subtest scores (and in some cases measures of the recruit's occupational interests). For the military environment, this appears to be a reasonable specification of the selection process for attrition is low and selection is indeed explicitly on observable test scores. This ability to model the selection process is an advantage that validity research in the military has over research in the civilian sector.[4]

A reanalysis was conducted of data from two large scale studies of Marine recruits (Sims and Hiatt 1981 reprinted in Hunter, Crossen and Friedman 1985; Maier and Truss 1985). These studies were selected because they used versions of the ASVAB that were quite similar to the one administered to the NLS Youth Cohort. Correlation matrices which had been corrected (for restriction of range and selection effects) were obtained from the appendices of these studies and LISREL was employed to estimate models in which training grades were regressed on the full set of ASVAB subtests. The standardized regression coefficients from this analysis are reported in table 7.

The estimation results are similar to the wage and earnings regressions in only one respect: technical competency as indexed by the mechanical, auto-shop and electronics subtests have major effects on success in training for occupations involving the maintenance or use of complicated equipment. In all other respects, however, the results contrast sharply with the wage rate regressions for young males. The math knowledge and arithmetic reasoning subtests have much larger effects on training success than the computational speed test. Both the science and verbal subtests have strong positive impacts on success in training. It appears that the higher level academic competencies measured by the ASVAB have much larger positive effects on success in training programs than on wage rates of young men in the civilian sector.

Reanalysis of Maier and Grafton's Data on Job Performance

Since, however, both the criterion--training success--and the predictors--competence in particular areas--are measured by paper and pencil tests, there is a danger that results may be biased by common methods bias. Therefore, it would be desireable to check these findings in a data set in which ASVAB subtest scores predict a hands-on measure of job performance. Maier and Grafton's (1981) study of ASVAB 6/7's ability to predict the hands-on Skill Qualification Test (SQTs) provides such a data set. Maier and Grafton described the hands-on SQTs they used in their study as follows:

> SQTs are designed to assess performance of critical job tasks. They are criterion referenced in the sense that test content is based explicitly on job requirements and the meaning of the test scores is established by expert judgment prior to administration of the test rather than on the basis of score distributions obtained from administration. The content of SQTs is a carefully selected sample from the domain of critical tasks in a specialty. Tasks are selected because they are especially critical, such as a particular weapon system, or because there is a known training deficiency. The focus on training deficiencies means that relatively few on the job can perform the tasks, and the pass rate for these tasks therefore is expected to be low. Since only critical tasks in a specialty are included in SQTs, and then only the more difficult tasks tend to be selected for testing, a reasonable inference is that performance on the SQTs should be a useful indicator of proficiency on the entire domain of

> critical tasks in the specialty; that is, workers who are proficient on tasks included in an SQT are also proficient on other tasks in the specialty. The list of tasks in the SQT and the measure themselves are carefully reviewed by job experts and tried out on samples of representative job incumbents prior to operational administration. The process of developing SQTs may be characterized as follows:
>
> 1. Identify tasks for testing.
> 2. Identify behaviors or steps essential for performing each task.
> 3. Develop measures to cover essential behaviors, and have these measures reviewed by job experts.
> 4. Tryout the measures on representative workers to verify accuracy of measurement; i.e., make sure that measures discriminate between task performers and nonperformers.
>
> After each step, the products are reviewed for content validity. The test content cannot be changed after step 3, when the measures are approved by experts. The tryout of step 4 can be used only to improve the measures, and not to change content. When the development process is followed, the validity of the SQTs as measures of job proficiency is assured by job experts and representative workers.(pp. 4-5)

A more extensive discussion of the procedures for developing SQTs is available in a handbook (Osborn et al, 1977). A thorough discussion of their rationale is provided in Maier and Hirshfeld (1978).

Correlation matrices relating the ASVAB subtests and SQTs were taken from Appendices A and B in Maier and Grafton (1981). The correlation matrices were corrected for selection effects and restriction of range by Maier and Grafton using procedures described in Dunbar and Linn (1986). Regressions were estimated using LISREL for eight major categories of Military Occupational Specialties (MOS): Skilled Technical, Skilled Electronic, General Maintenance, Mechanical Maintenance, Clerical, Operators (of Missile Batteries) and Food, Combat and Field Artillery. Except for combat and field artillery, these MOSs have close counterparts in the civilian sector. The independent variables were the 10 ASVAB 6/7 subtest scores which had counterparts in the ASVAB 8A battery used in the analysis of NLS Youth. The standardized regression coefficients from this analysis are reported in Table 8. These coefficients are an estimate of the effect of a one population standard deviation improvement in a test score on the hands-on job performance criterion measured in standard deviation units. Since the ASVAB subtests measure competencies with error and this error has not been corrected for, these results provide lower bound estimates of the effects of the true competencies on true job performance.

The effects of the four "technical" subtests--mechanical comprehension, auto information, shop information and electronics information--are presented in the first four columns of the table. The effects of these subtests on job performance are substantial in all of the nonclerical occupations. The impact of a one standard deviation increase in all four of these subtests is an increase in the SQT of .415 SD in skilled technical jobs, of .475 SD in skilled electronics jobs, of .316 SD in general maintenance jobs, .473 SD in mechanical maintenance jobs, of .450 SD for missile battery operators and food service workers, of .345 SD in combat occupations and .270 SD in field artillery. Note further that, in standard deviation units, the job performance effects of the technical subtests are much larger than their effects on training grades. Methods bias does seem to be at work. Clearly the technical competencies being measured by the four ASVAB technical subtests are important determinants of worker productivity in these jobs. This is consistent with the wage rate regression results.

The results for the academic subtests, however, contrast starkly with the wage rate regressions for young males. Science and word knowledge have substantial effects on job performance in skilled technical, general maintenance, clerical, operator/food and combat arms MOSs. With the sole exception of the mechanical maintenance MOS cluster, the two mathematical reasoning subtests have much larger effects on SQTs than the computational speed subtest. A one standard deviation increase in both of the mathematical reasoning subtests raises predicted job performance by .183 SD in skilled technical jobs, .24 SD in skilled electronic jobs, .34 SD in general maintenance jobs, .447 SD in clerical jobs, .22 SD for missile battery operators and food service jobs, .209 SD in combat arms and .416 SD in field artillery. **The Math Knowledge subtest assessing algebra and geometry is responsible for most of the effect.** The effects of the two tests of mathematical reasoning on job performance are substantial and unlike the wage rate findings much larger than the effects of computational speed. Nevertheless, the effects are somewhat smaller than those obtained in the models of success in training suggesting again the possibility of methods bias.

The attention to detail subtest (which is similar to the clerical checking subtest in ASVAB 8A) has no effect on performance in clerical jobs and small effects on performance in skilled electronic, general maintenance, combat arms and field artillery.

Science knowledge which had small negative effects on wage rates, now has positive effects on hands-on measures of job performance in eight of the MOS clusters, significantly so in 4 clusters and in pooled data. A one standard deviation (SD) increase in science knowledge raises job performance by .057 SD in skilled technical jobs, .072 SD in skilled electronics jobs, .134 SD in general maintenance and construction jobs, .096 SD in mechanical maintenance jobs, .064 SD in clerical jobs, .076 SD in missile battery operator and food service jobs and .070 SD in combat arms. Word knowledge has significant effects on job performance in the skilled technical, general maintenance and clerical jobs and in combat arms. While statistically significant, the effects of these two competencies appear to be rather modest.

Differences in science or verbal competency of one population SD are quite large. In these subjects, one population SD is about the magnitude of the difference between young people with 14 years of schooling and those who left school after the 9th grade. The modest size of the productivity impact of a 5 grade level improvement in test scores may be due to the inadequacies of the 11 minute long ASVAB subtests used to assess these competencies. General science had only 24 items and word knowledge only 35. This biases down the estimated effects of science and word knowledge on job performance. Clearly, there is a need for new research to determine whether broader and more reliable measures of verbal capacity, scientific knowledge and understanding and the ability to solve problems have more substantial effects on job performance in non-technical jobs than these ASVAB subtests.

Marine Rifleman Data

The possibility of differences in validity patterns between hands-on tests and job knowledge tests can be explored further in data that Milton Maier has kindly made available on the correlations between ASVAB subtests and both types of performance measures for the same group of Marine Corps rifleman. This time the raw correlation matrix uncorrected for restriction of range and selection was available. It was assumed that selection into the sample was based on ASVAB test scores and unobservable factors that are uncorrelated with equation error, so regressions that include test scores as regressors should yield unbiased estimates of population parameters. The two dependent variables were normalized by dividing them by their standard deviation. For the ASVAB subtests the metric selected was the standard deviation of 18 to 23 year old men and women in the NLS Youth Cohort. The unstandardized regression coefficients from simple linear regressions are reported in Table 9.

The findings are quite consistent with the results of the reanalysis of Maier and Grafton's data. Technical competencies have much larger effects on hands-on work sample measures of performance than on paper and pencil job knowledge tests. For the rifleman job, technical competencies are clearly more powerful predictors of hands-on performance measures than academic competencies. Coefficients on the computational speed and word knowledge subtests are negative when hands-on performance is the criterion but positive when job knowledge is the criterion. Science and arithmetic reasoning have statistically significant effects on hands-on performance measures but the academic subtests have as a whole smaller impacts on work sample tests than on job knowledge tests. Here again, there is evidence of a paper-and-pencil methods bias. This implies that validity studies based solely on job knowledge tests may not result in a correct selection of subtests for the aptitude composites that are used for selection and classification of recruits.

Project A Data: Core Technical Proficiency

Still more evidence on what truly determines job performance comes from Project A, a massive study (total costs of more than $100,000,000) that is developing improved methods for selecting and classifying army personnel. Wise, McHenry, Rossmeissl and Oppler (1987) have estimated ASVAB validities for 19 very diverse jobs using Core Technical Proficiency, a MOS specific job performance measures, as the criterion. These ratings are about 50 percent based on hands-on work sample tests (the hands-on SQT) and 50 percent based on paper and pencil job knowledge exams. The ratings were obtained after the recruit had been in the army for 2 to 3 years. The study was designed to select the three or four ASVAB subtests which could be used as the aptitude composite for that MOS cluster.

Table 10 reports the names of the three or four subtests which in combination did the best job of predicting Core Technical Proficiency. As before, the technical subtests are important predictors of Core Technical Proficiency in all the nonclerical occupations. For the academic subtests the results are very different from the wage rate regressions but similar to the results of the reanalysis of Maier and Grafton's validity data for hands-on work samples. Computational speed is only a weak determinant of job performance. Competence in science, language arts and mathematical reasoning has very large effects on job performance.

Project A Data: Other Performance Measures

Most of the ASVAB validity studies have studied MOS specific measures of performance which reflect the soldier's ability to do the job not their willingness to do it on a regular basis or under adverse conditions. Do the results change when other dimensions of job performance are studied? The Project A data set again provides an opportunity to address this issue. Besides the Core Technical Proficiency construct already analyzed, Project A offers three other performance constructs which have some applicability to civilian jobs: General Soldiering Proficiency, Effort and Leadership and Maintaining Personal Discipline. General Soldiering Proficiency assesses skills that all soldiers must have (eg. use of basic weapons, first aid, map reading, use of a gas mask) and is measured much the same way as Core Technical Proficiency by a combination of job knowledge tests and hands-on performance tests. These two constructs are designed to measure the can do element of job performance.

The other two constructs attempt to measure the will do element of job performance. John P. Campbell (1986) described the constructs and their measurement as follows:

> Peer Leadership, Effort, and Self Development: Reflects the degree to which the individual exerts effort over the full range of job tasks, perseveres under adverse or dangerous conditions, and demonstrates leadership and support of peers. That is, can the individual be counted on to carry out assigned tasks, even under adverse conditions, to exercise good judgement, and to be generally dependable and proficient? Five scales from the Army-wide BARS rating form (Technical Knowledge/Skill, Leadership, Effort, Self-development, and Maintaining Assigned Equipment), the expected combat performance rating, and the total number of commendations and awards received by the individual were summed for this factor.

> Maintaining Personal Discipline: Reflects the degree to which the individual adheres to Army regulations and traditions, exercises personal self-control, demonstrates responsibility in day-to-day behavior, and does not create disciplinary problems. Scores on this factor are composed of three Army-wide Bars scales (Following regulations, Self-Control, and Integrity) and two indices from the administrative records (number of disciplinary actions and promotion rate). (p. 150)

It had been planned to obtain information on commendations, awards, promotions, and disciplinary actions from administrative records. However, the cost of this approach was extremely high so "everyone crossed their fingers and we collected eight archival performance indicators via a self report questionnaire....Field tests on a sample of 500 people showed considerable agreement between self-report and archival records"(Campbell, 1986, p 144).

These two constructs are related to each other (they correlate .59) but are clearly quite distinct from the two "can do" constructs. Correlations with Core Technical Proficiency are only .28 for Effort and Leadership and .19 for Personal Discipline. The "can do" constructs are based on ratings made by the same person, so they share some common measurement error. Campbell, consequently, constructs residualized "can do" performance constructs by subtracting a ratings method factor from the raw score. With the ratings methods effect removed, Core Technical Proficiency (raw) has a correlation of .465 with Effort and Leadership (residual) and .225 with Personal Discipline (residual). In the view of the Project A team, soldiers must have both qualities--the technical competence to do their job and the willingness to do it under stressful circumstances.

Table 11 presents the results of using ASVAB test scores to predict General Soldiering Proficiency (raw), Effort and Leadership (both raw and residualized) and Personal Discipline (raw) (Campbell, 1986, Table 10). The correlation matrices were corrected for range restriction as described by Dunbar and Linn (1986). In this analysis the 9 ASVAB subtests have been reduced to four composites: Technical, Speed (Numerical Operations and Clerical Checking), Quantitative (Arithmetic Reasoning and Mathematics Knowledge) and Verbal/Science.

For General Soldiering Proficiency, the results are quite similar to the results obtained predicting Hands-on SQTs and Core Technical Proficiency. The technical and quantitative composites have the largest effects, and the verbal/science composite has a substantial effect. Speed has almost no effect. As before, the pattern of coefficients is very different from the wage regression for young men.

The pattern is different for the "will do" performance constructs. The technical composite had large positive effects on both measures of Effort and Leadership. The quantitative composite had a modest positive effect on Maintaining Personal Discipline and the residualized Effort and Leadership. Speed had a modest positive effect on Effort and Leadership. The verbal/science composite had no effect on the residualized Effort and Leadership and a small negative effect on raw score measures of both constructs.

The inclusion of controls for temperament, occupational interests and cognitive constructs not found in the ASVAB such as spatial relations and perceptual speed change leaves these results essentially unchanged. The control variables were all measured concurrently and consisted of 5 interest variables (combat, food service, audio/visual arts, protective service and structural/machines) 4 computer administered perceptual speed test composites, 3 measures of temperament (dependability, physical condition and surgency), a paper and pencil spatial relations test and an index of the need for job autonomy.[5] A fuller description of these control variables is available in Campbell (1986) and McHenry et al. (1986).

For the two "can do" performance constructs, adding the new concurrently measured cognitive and non-cognitive predictors to the model does not appreciably increase the explanatory power of the model above that obtainable with ASVAB test scores alone. R squares rise from .397 to .449 for Core Technical Proficiency and from .4225 to .49 for General Soldiering Proficiency (McHenry et al 1986). The coefficients on the ASVAB composites shrink somewhat but the pattern across composites appears to be quite similar to the analyses presented in tables 7-10. The verbal/science and quantitative composites have effects that are each roughly equivalent to the effect of the technical composite. As before, the pattern of coefficients is very different from the wage regression for young men.

The pattern is quite different for the "will do" performance constructs. The new cognitive and non-cognitive predictors contributed significantly to the explanation of the "will do" performance constructs. Adding all the new concurrently measured predictors to a model based solely on ASVAB test scores raised the R^2 for Effort and Leadership from .096 to .194 and raised R^2 for Maintains Personal Discipline from .026 to .137. The technical composite had large positive effects on both of these performance constructs. The quantitative composite had a modest positive effect on Maintaining Personal Discipline. Speed had a modest positive effect on Effort and Leadership. The verbal/science composite had a negative effects on both of these constructs.

The coefficient pattern for the raw score "will do" performance constructs looks rather similar to the male wage and earnings regressions. This is an interesting result that needs to be investigated in other data sets. It should be treated with caution, however, for four reasons: the information on commendations, awards, promotions and disciplinary actions was self reported, a ratings method effect was clearly visible in the data, other researchers have expressed skepticism about the validity of military ratings (Vineberg and Joyner 1982), and there appears to be major differences between the civilian and military sectors in the effect of academic achievement tests on supervisory ratings (with the effects much larger in the civilian sector)[6](Hunter 1986).

In any case, even if one adopts the Project A position that ratings are a valid measure of the "will do" component of job performance, this in no way implies that the "can do" elements are subsidiary or unimportant. Consequently, the findings reviewed above that science, verbal and mathematical reasoning capability predict hands-on SQTs, Core Technical Proficiency and General Soldiering Proficiency in the military imply that academic competencies of the type stressed by the Excellence Commission are probably important determinants of overall job performance in similar civilian jobs (eg. those involving the use, maintenance and repair of complicated machinery).

IV. SUMMARY AND CONCLUSIONS

The high school graduating class of 1982 took on average only .43 credits of Algebra II, .31 credits of more advanced mathematics courses, .40 credits of chemistry and .19 credits of physics (Meyer 1988 Table A.2). The apparent cause of these low enrollment figures is the perception of most high school students that there is little connection between how much they learn in math and science courses and their future success in the labor market. Less than a quarter of 10th graders believe that geometry, trigonometry, biology, chemistry and physics are needed to qualify for their first choice occupation (Longitudinal Survey of American Youth 1988). The analysis of NLS data undertaken in this study demonstrates that this perception is generally correct. During the first 8 years after leaving high school, young men who do not go to college receive no rewards from the labor market for developing competence in science, language arts and mathematical reasoning. For young males, the only academic competency that appears to be rewarded by the labor market is speed in doing simple computations (something that calculators do better than people). The other competency that has major effects on the wages of young men is technical competence (knowledge of mechanical principles, electronics, automobiles and shop tools), something that has been ignored by the reports recommending educational reform.

For the non-college bound female, computational speed and competence in mathematical reasoning increase wage rates but competence in science, language arts and the technical arena does not. The tendency of so many American high school students to avoid tough math and science courses and their poor performance on international science and mathematics exams, therefore, appears to be a rational response to market incentives.

Educational reformers are claiming that improved math and science education for the great mass of high school students (not just the 15 percent who choose a career in natural science or engineering) is essential if the workforce is to become more productive. But, if people who are competent in math and science are more productive workers, why aren't employers paying them commensurately more? Employers fail to reward high school graduates who are competent in math and science because (1) they do not know which of the job applicants who approach them have these competencies and because (2) workers and employers prefer employment contracts in which wage rates adjust only partially to reflect outstanding performance. Consequently, when the specific competencies of students are not signaled to the labor market by a credential, there is little reason to expect the wage rate effects of specific competencies to be the same as their productivity effects.

Consequently, the productivity effects of competence in math and science must be measured more directly. This is done by analyzing a series of military data sets in which worker competencies have been correlated with hands-on measures of job performance. This analysis demonstrates that greater competence in science, language arts and higher level math is indeed associated with greater success in training and better performance on the job. These results provide support for the Excellence Commission's claim that major improvements in science and math education for the great mass of high school students will improve the productivity of the work force. The results also reinforce the findings regarding the important role of technical competence in blue collar, craft and technician jobs. This is an area of study that needs much more attention than it has been getting.

FOOTNOTES

1. These subtests have some similarities with the occupational competency examinations developed to assess high school vocational students. However, the ASVAB technical subtests assess knowledge in a much broader domain and the individual items are, consequently, more generic and less detailed. The ASVAB technical composite is interpreted as a measure of knowledge and trainability for a large family of jobs involving the operation, maintenance and repair of complicated machinery and other technically oriented jobs.

2. Models were also estimated which did not constrain the main effects coefficients to be the same in all years and much the same results were obtained--eg positive interaction coefficients for computational speed but not for the academic composite. The ability measure in Hauser and Daymont's work was the Henmon-Nelson IQ test. A similar measure of ability can be constructed for NLS data by adding computational speed to the previously defined academic composite. When this composite is used to define the age-academic-competency interaction, the NLS data set yields findings that are similar to those obtained by Hauser and Daymont. Positive coefficients (many of which are significant) are obtained on this interaction variable. What this paper demonstrates is that when computational speed is allowed to have its own separate effects on labor market success, it is computational speed not other academic competencies which has growing effects on wages and earnings as the individual ages. Why this occurs is a puzzle. The issue clearly needs further research.

3. Bishop, Blakemore and Low's (1985) studied the effect of math, reading and vocabulary test scores on the wage rates and earnings of high school graduates for both 1972 and 1980 in a model that contained controls for grade point average and the number of credit hours of academic and vocational courses. In both these years, none of the variables representing academic performance--the three test scores, GPA and the number of academic courses--had a significant (at the ten percent level) effect on the wage rate of the first post high school job. Only one variable (the vocabulary test for female members of the class of 1972) had a significant effect on the wage 18 months after graduation.

4. If hiring selections were based entirely on X variables included in the model, unstandardized coefficients would be unbiased and simple correction formulas are available for calculating standardized coefficients and validities. Unfortunately, in the civilian sector incidental selection based on unobservables such as interview performance and recommendations is very probable (Thorndike 1949; Olson and Becker 1983; Mueser and Maloney 1987). Consequently, in a sample of accepted applicants for a civilian job, one cannot be confident that these omitted unobservable variables are uncorrelated with the included variables that were used to make initial hiring decisions and, therefore, that coefficients on included variables are unbiased. When someone with 10 years of formal schooling is hired for a job that normally requires an associates degree, there is probably a reason for that decision. The employer saw something positive in that job applicant (maybe the applicant received a particularly strong recommendation from previous employers) that led to the decision to make an exception to the rule that new hires should have an associates degree. The analyst is unaware of the positive recommendations, does not include them in the job performance model and, as a result, the coefficient on schooling is biased toward zero. This phenomenon also causes the estimated effects of other worker traits used to select workers for the job such as previous relevant work experience to be biased toward zero. Variables which were not used to select new hires such as test scores will probably have a positive correlation with the

unobservable. Since the unobservable probably has its own independent effect on job performance (ie. it is not serving solely as a proxy for test scores), test score coefficients are likely to be positively biased. Mueser and Maloney (1987) experimented with some plausible assumptions regarding this selection process and concluded that coefficients on education were severely biased but that test validities were not substantially changed when these incidental selection effects are taken into account.

5. The ASVAB test scores are the only regressors which were measured prior to entry into the military. The responses to the interest and temperment questions and performance on the spatial relations and perceptual speed tests may have been influenced by army training, so their estimated effects on the criterion measures may be biased away from zero and the estimated effects of the ASVAB tests may consequently be biased toward zero. This problem will eventually be remedied, for Project A is collecting data on these predictor constructs from samples of newly recruited soldiers and it is planned to redo these analyses when criterion data on those soldiers becomes available.

6. Bishop (1988c) analysis of the GATB Revalidation Data on 31,000 workers in 247 civilian occupations found that verbal and mathematical reasoning capability and computational speed had very substantial effects on supervisory ratings.

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Table 1
Effect of Competencies on Log Wage Rate

	Technical	Clerical Speed	Computational Speed	Math	Verbal	Science	R^2	N	F Test Academic vs. Zero	F Test Academic vs. Tech	F Test Academic vs. Comp
Male											
1986	.080***	.005	.064***	-.007	-.021	-.008	.264	4272	4.35	17.3	18.4
	(6.10)	(.51)	(5.75)	(.51)	(1.49)	(.60)					
1985	.074***	.004	.064***	.007	-.015	-.006	.270	4206	.66	10.2	11.5
	(5.75)	(.37)	(5.84)	(.57)	(1.08)	(.43)					
1984	.066***	.006	.070***	.005	-.015	-.014	.239	4527	2.05	10.8	17.2
	(5.08)	(.60)	(6.38)	(.42)	(1.07)	(1.04)					
1983	.063***	.004	.068***	-.025**	-.036**	.018	.245	4401	6.55	15.2	24.2
	(4.92)	(.40)	(6.27)	(2.01)	(2.53)	(1.32)					
1982	.051***	.006	.041***	-.014	-.011	-.010	.220	4477	4.6	10.3	11.9
	(3.98)	(.62)	(3.84)	(1.16)	(.78)	(.77)					
1981	.033***	-.001	.050***	-.001	-.009	-.024*	.238	3881	4.4	6.4	14.3
	(2.61)	(.09)	(4.65)	(.10)	(.63)	(1.83)					
1980	.048***	-.011	.039***	-.025**	-.006	-.024*	.225	3552	10.8	14.3	16.9
	(3.72)	(1.00)	(3.48)	(2.01)	(.42)	(1.75)					
1979	.034**	.003	.030**	-.004	-.003	-.027	.248	2249	1.6	3.3	3.9
	(2.20)	(.23)	(2.21)	(.26)	(.14)	(1.61)					
Female											
1986	.006	.028***	.024**	.027*	.027*	.012	.275	4080	12.6	3.3	3.0
	(.31)	(2.60)	(2.04)	(1.94)	(1.75)	(.81)					
1985	-.016	.029***	.021*	.042***	.030*	.005	.256	3965	17.9	8.1	5.4
	(.91)	(2.82)	(1.82)	(3.06)	(1.95)	(.36)					
1984	.008	.008	.037***	.048***	.004	-.001	.231	4159	8.1	1.8	.3
	(.48)	(.78)	(3.26)	(3.56)	(.27)	(.07)					
1983	-.013	.010	.042***	.045***	.009	-.003	.204	4054	8.8	4.3	.2
	(.78)	(.97)	(3.82)	(3.49)	(.63)	(.19)					
1982	.017	.015	.038***	.020	.002	-.017	.184	4037	.1	.1	2.1
	(1.03)	(1.56)	(3.55)	(1.62)	(.17)	(1.30)					
1981	.019	.006	.030***	.001	.018	-.004	.190	3481	.8	.0	.5
	(1.14)	(.57)	(2.82)	(.11)	(1.21)	(.27)					
1980	-.027	.017	.025***	.018	-.013	.030**	.150	3173	3.4	3.4	.1
	(1.51)	(1.60)	(2.05)	(1.28)	(.81)	(1.98)					
1979	.013	.002	.038**	.002	.008	-.023	.237	2075	.3	.4	2.7
	(.60)	(.04)	(2.51)	(.10)	(.41)	(1.23)					

Table 2

Effects of Competencies on Log Earnings

	Technical	Clerical Speed	Computational Speed	Math	Verbal	Science	R^2	N	F Test Academic vs. Zero	F Test - Academic vs. Tech	F Test Academic vs. Comp.
Male											
1985	.133***	.004	.119***	-.037*	.014	-.021	.358	4521	2.4	15.3	18.3
	(6.26)	(.21)	(6.55)	(1.78)	(.61)	(.93)					
1984	.115***	.017	.089***	-.002	.009	-.003	.372	4564	0.0	6.0	5.1
	(5.38)	(.98)	(4.89)	(.09)	(.37)	(.14)					
1983	.018***	.027	.110***	-.014	.028	-.025	.376	5004	.1	7.1	10.9
	(5.08)	(1.52)	(6.21)	(.69)	(1.21)	(1.14)					
1982	.120***	.013	.133***	-.036*	-.007	-.020	.416	4959	5.1	16.2	27.1
	(5.56)	(.72)	(7.32)	(1.77)	(.31)	(.88)					
1981	.131***	.018	.111***	-.054**	-.001	-.032	.400	4574	9.4	22.1	26.7
	(5.96)	(1.01)	(6.00)	(2.55)	(.05)	(1.39)					
1980	.151***	.042**	.087***	-.009	-.052**	-.079***	.392	3955	22.2	36.3	31.9
	(6.66)	(2.26)	(4.49)	(.42)	(2.07)	(3.27)					
1979	.114***	.017	.082***	-.034	-.058**	-.023	.380	3411	14.5	21.4	23.2
	(4.85)	(.86)	(4.11)	(1.57)	(2.20)	(.91)					
Female											
1985	-.020	.022	.053***	.065***	.039	.009	.328	3888	11.8	5.1	1.9
	(.64)	(1.14)	(2.60)	(2.66)	(1.40)	(.34)					
1984	.032	.038**	.057***	.053**	.073***	-.040	.368	3893	7.2	.9	.5
	(1.03)	(2.06)	(2.79)	(2.20)	(2.70)	(1.58)					
1983	.025	.058***	.085***	.052**	.045	-.010	.833	4134	7.3	1.2	0.0
	(.82)	(3.09)	(4.11)	(2.16)	(1.62)	(.37)					
1982	-.020	.035*	.053**	.064***	.105***	-.048*	.344	4101	14.3	2.6	6.1
	(.65)	(1.88)	(2.55)	(2.72)	(3.72)	(1.83)					
1981	-.033	.039**	.021	.059**	.119***	-.039	.332	3843	17.4	8.5	7.2
	(1.07)	(2.05)	(1.01)	(2.47)	(4.21)	(1.51)					
1980	.021	.042**	.084***	.037	.036	-.038	.333	3409	1.1	0.1	1.3
	(.66)	(2.23)	(3.99)	(1.55)	(1.26)	(1.42)					
1979	.019	.049**	.097***	-.022	.017	-.006	.333	2886	.1	0.2	5.4
	(.59)	(2.50)	(4.41)	(.89)	(.58)	(.21)					

Table 3

Effects of Competencies on Earnings ($)

	Technical	Clerical Speed	Computational Speed	Math	Verbal	Science	R^2	N	F Test Academic vs. Zero	F Test Academic vs. Tech	F Test Academic vs. Comp
Male											
1985	1365***	251	1241***	-96	-87	-218	.350	4900	1.5	10.9	13.6
	(5.42)	(1.39)	(5.85)	(.39)	(.32)	(.84)					
1984	1321***	96	1035***	14	-213	-30	.350	5007	0.6	10.9	10.4
	(5.96)	(.53)	(5.54)	(.06)	(.89)	(.13)					
1983	1228***	307**	1053***	-141	-194	-158	.367	5642	4.5	20.9	24.6
	(6.89)	(2.10)	(7.05)	(.82)	(1.00)	(.86)					
1982	1114***	280**	926***	-304*	-314*	-187	.354	5742	14.2	30.2	35.9
	(6.71)	(2.06)	(6.65)	(1.92)	(1.74)	(1.08)					
1981	937***	330***	665***	-360**	-76	-278*	.355	5237	12.9	25.8	26.2
	(6.06)	(2.60)	(5.07)	(2.43)	(.45)	(1.73)					
1980	912***	219*	493***	-207	-109	-428***	.344	4543	17.7	32.8	26.8
	(6.69)	(1.95)	(4.28)	(1.58)	(.73)	(2.99)					
1979	580***	41	457***	-375***	-241*	89	.320	3836	10.0	16.3	19.0
	(4.42)	(.38)	(4.14)	(3.08)	(1.67)	(.65)					
Female											
1985	-171	241*	438***	813***	95	30	.405	5150	17.7	7.6	2.9
	(.78)	(1.90)	(3.22)	(4.82)	(.51)	(.17)					
1984	129	160	441***	655***	199	-152	.441	5254	14.5	2.9	1.1
	(.71)	(1.52)	(3.89)	(4.67)	(1.30)	(1.05)					
1983	292*	275**	541***	541***	178	-137	.371	5112	10.8	.8	.0
	(1.70)	(2.71)	(4.94)	(4.06)	(1.21)	(.97)					
1982	202	159*	306***	447***	333*	-56	.360	5773	20.3	3.2	3.8
	(1.29)	(1.70)	(3.03)	(3.69)	(2.46)	(.43)					
1981	185	325***	180**	324***	409***	-248**	.346	5384	11.0	1.3	2.5
	(1.32)	(3.86)	(1.98)	(2.97)	(3.36)	(2.14)					
1980	158	268***	310***	139	250**	123	.330	4758	4.4	0.2	0.1
	(1.30)	(3.71)	(3.91)	(1.48)	(2.37)	(1.22)					
1979	171	288***	273***	-68	141	-37	.318	4024	.1	.4	2.1
	(1.45)	(4.10)	(3.53)	(.75)	(1.37)	(.37)					

Table 4

Effects of Competencies on Unemployment

	Technical	Clerical Speed	Computational Speed	Math	Verbal	Science	R^2	N	F Test Academic vs. Zero	F Test Academic vs. Tech	F Test Academic vs. Comp
Male											
1985	-2.22***	-.84	.11	.42	-.40	1.24*	.206	4459	2.2	6.5	1.0
	(3.46)	(1.61)	(.21)	(.67)	(.57)	(1.84)					
1984	-2.31***	.16	-.83	.17	-.55	.15	.229	4523	0.1	2.1	.3
	(3.40)	(.29)	(1.45)	(.25)	(.74)	(.22)					
1983	-1.00	-1.25**	-.96	-.89	-.92	.26	.212	4888	2.5	.1	.2
	(1.35)	(2.02)	(1.52)	(1.23)	(1.13)	(.33)					
1982	-2.41***	-2.07***	-.70	-2.08***	.20	1.13	.200	4835	.5	1.0	0.0
	(3.03)	(3.19)	(1.06)	(2.76)	(.23)	(1.38)					
1981	-2.38***	-1.32**	-.96	-1.20	-.25	1.95*	.180	4761	0.0	2.2	.5
	(3.10)	(2.07)	(1.47)	(1.64)	(.29)	(1.82)					
1980	-1.52*	-1.68**	-1.62**	-1.59**	1.69*	.00	.163	4305	0.0	.9	1.4
	(1.84)	(2.43)	(2.31)	(2.00)	(1.86)	(.00)					
1979	-1.77**	-1.08	-2.24***	-.50	2.25**	-.46	.177	3057	8.4	3.0	5.6
	(2.07)	(1.48)	(3.05)	(.62)	(2.36)	(.50)					
Female											
1985	.67	-.65	.48	-.52	-1.74**	-.32	.203	4223	8.0	3.9	6.5
	(.75)	(1.24)	(.84)	(.76)	(2.28)	(.44)					
1984	1.43	-1.74***	.52	-.68	-1.55*	-.71	.216	4285	8.8	5.9	7.0
	(1.46)	(3.06)	(.83)	(.91)	(1.87)	(.91)					
1983	1.61*	-.67	-.79	-.86	-2.67***	-.04	.216	4446	12.7	8.3	4.4
	(1.67)	(1.26)	(1.24)	(1.14)	(3.15)	(.05)					
1982	3.28***	-.23	-1.22*	-1.51*	-2.97***	-.82	.223	4442	25.6	20.6	8.6
	(3.21)	(.38)	(1.82)	(1.92)	(3.31)	(.97)					
1981	3.66***	-1.18*	-1.05	-.99	-3.33***	.13	.209	4380	16.1	17.3	5.1
	(3.58)	(1.93)	(1.59)	(1.27)	(3.72)	(.16)					
1980	2.99***	-1.62**	-.20	-1.74**	-1.90*	-.34	.181	3982	12.7	11.9	6.4
	(2.71)	(2.48)	(.28)	(2.10)	(1.98)	(.38)					
1979	2.74**	-1.43**	-1.94**	-1.53*	-1.88*	.23	.168	2914	6.7	7.0	.6
	(2.26)	(2.04)	(2.44)	(1.68)	(1.75)						

Table 5

The Effect of Competencies on Labor Market Outcomes : 1981-1985

	Males				Females			
	Log Wage Rate	Log Earnings	Earnings	Unemployment	Log Wage Rate	Log Earnings	Earnings	Unemployment
Main Effects								
Technical	.044***	.087***	1333***	-2.17***	.017	-.007	-105	.58
	(3.37)	(4.66)	(7.33)	(3.99)	(1.04)	(.24)	(.69)	(.80)
Clerical Speed	-.004	.017	359***	-1.08***	.010	.030**	183**	-1.07***
	(.36)	(1.26)	(2.63)	(2.86)	(1.20)	(2.04)	(2.28)	(3.06)
Comp. Speed	.062***	.095***	1088***	-.40	.031***	.026	442***	-.93**
	(5.54)	(6.01)	(7.11)	(.89)	(3.01)	(1.42)	(4.72)	(2.08)
Math	-.005	-.015	-86	-1.24**	.025**	.074***	663***	-1.15**
	(.43)	(.88)	(.50)	(2.56)	(2.19)	(3.79)	(5.91)	(2.36)
Verbal	-.016	-.015	-438**	.02	.006	.044*	353***	-2.20***
	(1.21)	(.79)	(2.35)	(.04)	(.45)	(1.92)	(2.97)	(4.07)
Science	-.003	-.009	-66	1.02**	-.012	-.030	-49	-.21
	(.22)	(.51)	(.37)	(2.04)	(1.01)	(1.41)	(.43)	(.41)
Age Times								
Technical	.0067**	.0007	76	-.08	.0031	.0012	-4	.03
	(2.10)	(.13)	(1.40)	(.48)	(.72)	(.14)	(.09)	(.14)
Comp. Speed	.0057**	.0017	155***	.23*	.0026	.0097*	95***	.46***
	(2.30)	(.39)	(3.72)	(1.72)	(1.06)	(1.92)	(3.62)	(3.66)
Academic	-.0020	.0040	-5	.49**	.0064	-.0049	-93**	.18
	(.52)	(.60)	(.08)	(2.42)	(1.56)	(.58)	(2.09)	(.87)
Student Times								
Technical	.012	.141***	-496	.60	-.036	.050	347	3.42**
	(.64)	(3.50)	(1.43)	(.46)	(1.63)	(.88)	(1.13)	(2.02)
Comp. Speed	-.006	.000	-607**	.07	-.005	.014	-183	.36
	(.40)	(.01)	(2.19)	(.07)	(.35)	(.40)	(1.00)	(.37)
Academic	-.026	-.237***	-1096***	.65	-.024	-.236***	-2256***	-.95
	(1.24)	(4.98)	(2.67)	(.43)	(1.11)	(4.19)	(7.89)	(.62)
Years of College								
times Academic	.0069	-.0129	-169**	.17	.0156***	.0144	271***	.69***
	(1.29)	(1.60)	(2.11)	(.73)	(2.93)	(1.59)	(5.13)	(3.03)
R^2	.130	.222	.195	.117	.127	.208	.234	.116
Number of Obs.	2155	3054	4122	3342	1919	2240	4532	2867
F Test								
Acad. = Zero	2.0	2.5	3.0	0.1	1.2	8.6	37.8	23.1
Acad. = Technical	6.1	10.1	20.3	2.9	0.0	3.2	14.4	9.5
Acad. = Compute	13.5	15.8	21.2	0.0	0.3	2.5	6.4	7.1

Table 6

The Effect of Competencies on Labor Market Outcomes
(No Controls for Education)

	Males				Females			
	Log Wage Rate	Log Earnings	Earnings	Unemployment	Log Wage Rate	Log Earnings	Earnings	Unemployment
Main Effects								
Technical	.043***	.080***	1233***	-1.99***	.013	-.016	-248	.88
	(3.33)	(4.24)	(6.79)	(3.66)	(.78)	(.58)	(1.60)	(1.21)
Clerical Speed	-.001	.027**	470***	-1.50***	.015*	.035**	213***	-1.25***
	(.07)	(1.99)	(3.41)	(3.96)	(1.72)	(2.44)	(2.63)	(3.58)
Comp. Speed	.065***	.105***	1249***	.68	.031***	.030	437***	-1.12**
	(5.87)	(6.61)	(8.16)	(1.52)	(3.05)	(1.61)	(4.99)	(2.50)
Math	.006	.003	269	-1.75***	.046***	.103	1210***	-1.20***
	(.48)	(.20)	(1.64)	(3.79)	(4.30)	(5.64)	(11.38)	(2.61)
Verbal	-.013	.000	-174	-.45	.008	.053	404***	-2.88***
	(1.01)	(.03)	(.35)	(.86)	(.66)	(2.33)	(3.42)	(5.41)
Science	.005	.005	75	.60	.000	-.014	178	-.14
	(.40)	(.28)	(.42)	(1.20)	(.03)	(.67)	(1.56)	(.27)
Age Times								
Technical	.0032	-.0056	11	.03	.0017	-.001	-47	.06
	(1.05)	(1.04)	(.20)	(.20)	(.40)	(.10)	(2.18)	(.27)
Comp. Speed	.0055**	.0028	179***	.20	.0033	.0109**	114***	.41***
	(2.24)	(.65)	(4.31)	(1.56)	(1.36)	(2.16)	(4.33)	(3.26)
Academic	.0046	.0135**	112*	.28	.0147***	.0048	89**	.18
	(1.27)	(2.17)	(1.80)	(1.49)	(3.76)	(.61)	(2.08)	(.92)
Student Times								
Technical	.010	.138***	-570	.64	-.036	.056	338	3.14*
	(.57)	(3.40)	(1.64)	(.49)	(1.61)	(.99)	(1.09)	(1.95)
Comp. Speed	-.007	.000	-627**	.10	-.006	.009	-186	.44
	(.48)	(.01)	(2.26)	(.09)	(.43)	(.26)	(1.01)	(.45)
Academic	-.026	-.252***	-1243***	1.00	-.018	-.239	-2011***	.10
	(1.28)	(5.37)	(3.07)	(.66)	(.85)	(4.29)	(7.05)	(.07)
R^2	.125	.215	.187	.110	.120	.204	.221	.110
Number of Obs.	2155	3054	4122	3342	1919	2240	4532	2867
F Test								
Acad. = Zero	0.0	0.1	0.6	5.5	12.1	25.3	143.6	35.6
Acad. = Technical	2.9	3.3	8.0	0.1	1.2	9.3	53.1	14.9
Acad. = Compute	8.9	8.4	11.5	0.9	2.1	8.7	42.2	10.3

Table 7
Cognitive Determinants of Success
in Marine Training Programs

	Mechanical Comprehension	Auto & Shop Knowledge	Electronics	Clerical Speed	Computational Speed	Math Reasoning	Math Knowledge	Verbal	Science	Spatial	R^2
<u>Sims & Hiatt</u> ASVAB 6/7 (23061)											
All Occupations	.043*** (5.20)	.098*** (12.46)	.047*** (5.78)	.013** (2.29)	.060*** (8.96)	.116*** (14.44)	.205*** (25.26)	.086*** (11.68)	.089*** (10.68)	.037 (5.89)	.345
<u>Maier & Truss</u> ASVAB 8/9/10											
Electronics Repair (4103)	.055*** (2.73)	.027 (1.40)	.102*** (4.81)	.009 (.69)	.062*** (3.44)	.151*** (6.41)	.256*** (11.91)	.031 (1.40)	.130*** (5.73)	---	.492
Mechanical Maintenance (5841)	.058*** (3.29)	.253*** (15.02)	.094*** (5.02)	.063*** (4.44)	.014 (.87)	.086*** (4.16)	.135*** (7.14)	.120*** (6.27)	.005 (.27)	---	.444
Operators, Food (1897)	.079*** (2.72)	.063** (2.27)	.018 (.57)	.086*** (3.66)	.022 (.82)	.137*** (4.02)	.199*** (6.41)	.164*** (5.20)	.093*** (2.84)	---	.490
Clerical (5231)	.014 (.74)	-.022 (1.22)	.026 (1.33)	.136*** (9.03)	.037** (2.26)	.125*** (5.70)	.259*** (13.02)	.206*** (10.14)	-.101 (.47)	---	.443
Combat (8191)	.087*** (4.98)	.078*** (4.68)	.020 (1.09)	.027* (1.95)	.056*** (3.62)	.069** (3.40)	.143*** (7.71)	.073*** (3.88)	.061*** (3.12)	---	.251
Field Artillery (1062)	.055 (1.34)	.237*** (6.01)	-.009 (.21)	.178*** (5.36)	.060 (1.64)	.148*** (3.07)	.138*** (3.13)	-.011 (.24)	.065 (1.41)	---	.448

Table 8
Effect of Competencies on
Job Performance (SQT)

	Mechanical Comprehension	Auto Info	Shop Info	Electr. Info	Attention to Detail	Comp. Speed	Word Know	Arith Reasoning	Math Know	Science	R^2
Skilled Technical	.092***	.017	.132***	.174***	.024	.031	.215***	.062**	.121***	.057*	.548
(1324)	(3.07)	(.58)	(4.28)	(5.09)	(1.12)	(1.17)	(6.77)	(1.96)	(3.76)	(1.83)	
Skilled Electronic	.086	.098	.246***	.045	.084	-.013	-.004	-.021	.261***	.072	.426
(349)	(1.30)	(1.49)	(3.64)	(.60)	(1.81)	(.22)	(.06)	(.30)	(3.67)	(1.05)	
General (Const) Maintenance	-.004	.082**	.117***	.121***	.043*	.068***	.066*	-.101***	.441***	.134***	.592
(879)	(.11)	(2.34)	(3.25)	(3.05)	(1.76)	(2.19)	(1.80)	(2.73)	(11.70)	(3.67)	
Mechanical Maintenance	.042	.314***	.206*	-.089	.055	.235**	-.004	-.068	.061	.096	.412
(131)	(.38)	(2.88)	(1.84)	(.71)	(.72)	(2.43)	(.03)	(.59)	(.52)	(.85)	
Clerical	-.068	.087***	-.030	.065	.015	.085**	.118***	.241***	.206***	.064	.425
(830)	(-1.59)	(2.05)	(-.69)	(1.33)	(.50)	(2.24)	(2.61)	(5.33)	(4.46)	(1.44)	
Operators & Food	.109*	.179***	.062	.100**	.050	-.037	.061	.114*	.106**	.076*	.414
(814)	(2.50)	(4.11)	(1.39)	(2.02)	(1.62)	(.96)	(1.33)	(2.47)	(2.25)	(1.66)	
Combat	.147***	.060***	.080***	.058***	.048***	.035**	.069***	.070***	.139***	.070***	.358
(5403)	(8.28)	(3.38)	(4.42)	(2.86)	(3.82)	(2.23)	(3.71)	(3.74)	(7.29)	(3.82)	
Field Artillery	.059	.047	.030	.134**	.088**	-.009	.000	.186***	.230***	.061	.422
(534)	(1.10)	(.89)	(.56)	(2.21)	(2.33)	(.19)	(.01)	(3.28)	(3.99)	(1.10)	

Re-Analysis of Maier & Grafton's (1981) data on the ability of ASVAB 6/7 to predict Skill Qualification Test (SQT) scores. The correlation matrix was corrected for restriction of range by Maier & Grafton.

Table 9
Effect of ASVAB Subtests on Different
Attitudes on work samples and job knowledge tests
for Marine Riflemen

	Mechanical	Auto/Shop	Electronics	Clerical	Computational Speed	Math Reasoning	Math Knowledge	Word Know	Science	R^2
Hands-On	.160***	.295***	.093	.099**	-.024	.200***	.015	-.086	.120**	.280
	(3.26)	(6.78)	(1.92)	(2.18)	(.45)	(3.45)	(.27)	(1.25)	(2.21)	
Job Knowledge	.102**	.141***	.111**	.151***	.115**	.212***	.129	.082	.186***	.319
	(2.14)	(3.33)	(2.36)	(3.42)	(2.20)	(3.76)	(2.40)	(1.23)	(3.53)	

Table 10
ASVAB SUBTESTS WHICH ARE THE BEST PREDICTORS OF CORE TECHNICAL PROFICIENCY
by Military Occupational Specialty Cluster

Subtest	Technical	Speed	Quantitative	Verbal/Science
Electronics Repair (123)	Electronics	Compute-Speed		Science
Skilled Tech. (1329)	Mechanical Comp.		Math Knowledge	Science Verbal
Mechanical Maintenance (716)	Auto-Shop Know. Mechanical Comp. Electronics			Science
General Maintenance (272)	Auto-Shop Know.		Math Knowledge	Science Verbal
Operators/Food (1215)	Auto-Shop Know.		Arith Reasoning Math Knowledge	Verbal
Surveillance & Communication (289)	Auto-Shop Know.	Compute-Speed	Math Knowledge or Arith Reason.	Verbal
Clerical (1210)			Arith Reasoning Math Knowledge	Verbal
Combat (1429)	Auto-Shop Know. Mechanical Comp.		Math Knowledge	Science
Field Artillery (464)	Auto-Shop Know. Mechanical Comp.	Compute-Speed		Science

Source: Summarized from Table 2 of Wise, McHenry, Rossmeissl and Oppler, 1987. Based on an analysis of the ability of ASVAB subtests to predict Core Technical Proficiency ratings after the recruit has been in the US Army for 2 or 3 years. Core Technical Proficiency ratings are about 50 percent based on hands-on work sample tests and 50 percent based on paper and pencil job knowledge exams. The subtests listed in the table are the 3 or 4 subtests which in combination maximized the R^2 of the model predicting Core Technical Proficiency.

Table 11

Effect of ASVAB Composite
on other Dimensions of Job Performance

	Technical	Speed	Quantitative	Verbal	R^2
General Soldering Proficiency	.26	.03	.20	.10	.461
Effort and Leadership (resid)	.21	.07	.08	.03	.280
Effort and Leadership (raw)	.21	.09	.03	-.07	.206
Personal Discipline	.06	.04	.07	-.03	.10

Source from John Campbell, 1986, Table 10. Standardized Coefficients from an Analysis of Project A Data on Performance in the Military.

APPENDIX A

Sample Regression Used in

Tables 2-5

Male Wage

18:49 SUNDAY, JANU

DESCRIPTIVE STATISTICS

NLS

STATISTICS

VARIABLE	SUM	MEAN	STD DEVIATION
LWG86	27688.1	6.47979	0.49840
TMATH	9532.4	2.23086	1.04938
TVERBAL	11780.5	2.75696	1.04198
TSCI	399.2	0.09343	1.06127
VOCT	1442.9	0.33767	1.06450
UNL86	13257.4	3.10260	0.91549
CPT86	211.0	0.04938	0.21669
HSG86	2799.0	0.65504	0.47541
NE86	795.0	0.18605	0.38919
SO86	1607.0	0.37608	0.48446
WS86	854.0	0.19986	0.39994
HISP	598.0	0.13995	0.34697
TCLER	-976.7	-0.22857	0.96176
TCOMPU	-560.8	-0.13124	1.00968
CHILD86	1527.0	0.35736	0.47928
MAR86	1545.0	0.36157	0.48051
RUR82	897.0	0.20992	0.40730
NSMSA86	1290.0	0.30190	0.45913
ED86	53525.0	12.52633	2.49898
CED86	4990.5	1.16791	1.78819
EDX86	3265.5	0.76422	1.32634
RACE1	1054.0	0.24667	0.43112
RACE2	219.0	0.05125	0.22054
AGE79	77630.4	18.16767	2.23636
AGES86	380494.6	89.04625	41.84649
AT86	730.0	0.17084	0.37641
ATT86	456.0	0.10672	0.30879
EXPWK86	1150707.0	269.29722	121.55348
EXPWS86	373002049.0	87292.78001	68578.55629
ASV2S86	340.4	0.07967	0.37330
VOCS86	329.2	0.07704	0.37510
COMPS86	174.8	0.04091	0.29787
ASV2AG86	2170.6	0.50797	4.28168
VOCTAG86	7058.6	1.65190	4.50125
COMPAG86	-344.2	-0.08055	3.98408
ASV2WK86	2393.1	0.56005	2.71458
ASV2ED86	4860.1	1.13740	2.66465
INTERCEP	4273.0	1.00000	0.00000

EP VARIABLE: LWG86

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	28	285.41524	10.19340134	55.767	0.0001
ERROR	4244	775.74026	0.18278517		
C TOTAL	4272	1061.15550			

ROOT MSE	0.4275338	R-SQUARE	0.2690
DEP MEAN	6.479785	ADJ R-SQ	0.2641
C.V.	6.597963		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	PROB > !T!
INTERCEP	1	6.16948794	0.40062599	15.400	0.0001
TMATH	1	-0.006602410	0.01292803	-0.511	0.6096
TVERBAL	1	-0.02125653	0.01430650	-1.486	0.1374
TSCI	1	-0.008168513	0.01364133	-0.599	0.5493
VOCT	1	0.07955380	0.01302474	6.108	0.0001
UNL86	1	-0.04292439	0.007825550	-5.485	0.0001
CPT86	1	0.11612484	0.03598091	3.227	0.0013
HSG86	1	0.02666151	0.02218629	1.202	0.2295
NE86	1	0.12259538	0.02117204	5.790	0.0001
SO86	1	0.02849527	0.01795778	1.587	0.1126
WS86	1	0.10485893	0.02088667	5.020	0.0001
HISP	1	0.03840081	0.02278839	1.685	0.0920
TCLER	1	0.005460782	0.01067684	0.511	0.6091
TCOMPU	1	0.06354636	0.01104821	5.752	0.0001
CHILD86	1	0.01182907	0.01748597	0.676	0.4988
MAR86	1	0.08618607	0.01776652	4.851	0.0001
RUR82	1	-0.04862704	0.01816563	-2.677	0.0075
NSMSA86	1	-0.09220226	0.01623190	-5.680	0.0001
ED86	1	0.01561578	0.008062571	1.937	0.0528
CED86	1	0.03198017	0.01002441	3.190	0.0014
EDX86	1	-0.02548001	0.009126239	-2.792	0.0053
RACE1	1	0.03380906	0.02017612	1.676	0.0939
RACE2	1	-0.05731007	0.03252614	-1.762	0.0781
AGE79	1	-0.002297501	0.02931786	-0.078	0.9375
AGES86	1	-0.000231890	0.001553210	-0.149	0.8813
AT86	1	-0.03216152	0.03305113	-0.973	0.3306
ATT86	1	-0.17325475	0.03298882	-5.252	0.0001
EXPWK86	1	0.001157889	0.000229173	5.052	0.0001
EXPWS86	1	-2.79958E-07	4.11561E-07	-0.680	0.4964

EST:	NUMERATOR:	3.16151	DF: 1	F VALUE:	17.2963
	DENOMINATOR:	0.182785	DF: 4244	PROB >F :	0.0001

EST:	NUMERATOR:	.0899707	DF: 1	F VALUE:	0.4922
	DENOMINATOR:	0.182785	DF: 4244	PROB >F :	0.4830

EP VARIABLE: LEARN85

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	29	1322.22534	45.59397722	88.060	0.0001
ERROR	4492	2325.78181	0.51776087		
C TOTAL	4521	3648.00715			

ROOT MSE	0.719556	R-SQUARE	0.3625
DEP MEAN	9.229141	ADJ R-SQ	0.3583
C.V.	7.796566		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	PROB > !T!
INTERCEP	1	8.28388905	0.61618126	13.444	0.0001
TMATH	1	-0.03727279	0.02096176	-1.778	0.0754
TVERBAL	1	0.01411218	0.02331919	0.605	0.5451
TSCI	1	-0.02085496	0.02242950	-0.930	0.3525
VOCT	1	0.13347029	0.02132688	6.258	0.0001
UNL85	1	-0.003540862	0.000403998	-8.765	0.0001
CPT85	1	0.48135176	0.05659768	8.505	0.0001
HSG85	1	0.09951281	0.03671413	2.710	0.0067
NE85	1	0.14018820	0.03446012	4.068	0.0001
SO85	1	0.05389730	0.02973431	1.813	0.0700
WS85	1	0.10584306	0.03387826	3.124	0.0018
HISP	1	0.05672807	0.03745047	1.515	0.1299
TCLER	1	0.003586204	0.01751068	0.205	0.8377
TCOMPU	1	0.11866953	0.01812447	6.547	0.0001
S85	1	-0.68182220	0.08079514	-8.439	0.0001
CHILD85	1	0.05225652	0.03031277	1.724	0.0848
MAR85	1	0.18463553	0.03094106	5.967	0.0001
RUR82	1	-0.12498705	0.02991784	-4.178	0.0001
NSMSA85	1	0.07652404	0.02519581	3.037	0.0024
ED85	1	0.06627947	0.01368494	4.843	0.0001
CED85	1	0.008123332	0.01694630	0.479	0.6317
EDX85	1	-0.05346193	0.01727591	-3.095	0.0020
RACE1	1	-0.008876566	0.03267021	-0.272	0.7859
RACE2	1	0.04589225	0.05268597	0.871	0.3838
AGE79	1	-0.007113356	0.04326685	-0.164	0.8694
AGES85	1	-0.001721455	0.002554291	-0.674	0.5004
AT85	1	-0.18557653	0.05074532	-3.657	0.0003
ATT85	1	-0.20944943	0.06436513	-3.254	0.0011
EXPWK85	1	0.003265187	0.000363466	8.983	0.0001
EXPWS85	1	-0.005562980	0.002069526	-2.688	0.0072

EST:	NUMERATOR: 7.90379	DF: 1	F VALUE: 15.2653
	DENOMINATOR: 0.517761	DF: 4492	PROB >F : 0.0001

EST:	NUMERATOR: 1.18014	DF: 1	F VALUE: 2.2793
	DENOMINATOR: 0.517761	DF: 4492	PROB >F : 0.1312

DEP VARIABLE: EARN85

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ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	29	206783604819	7130469132	91.794	0.0001
ERROR	4871	378375104506	77679142.79		
C TOTAL	4900	585158709325			

ROOT MSE	8813.577	R-SQUARE	0.3534
DEP MEAN	12878.44	ADJ R-SQ	0.3495
C.V.	68.43669		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	PROB > !T!
INTERCEP	1	13628.10963	7181.61285	1.898	0.0578
TMATH	1	-96.38050842	247.89011	-0.389	0.6974
TVERBAL	1	-87.53461686	272.64002	-0.321	0.7482
TSCI	1	-218.04778	260.83248	-0.836	0.4032
VOCT	1	1364.76443	251.63490	5.424	0.0001
UNL85	1	-38.81934631	4.71382354	-8.235	0.0001
CPT85	1	3879.64912	675.16644	5.746	0.0001
HSG85	1	1422.45819	428.78833	3.317	0.0009
NE85	1	1110.74485	404.00132	2.749	0.0060
S085	1	189.33661	347.84319	0.544	0.5862
WS85	1	1146.79439	397.21834	2.887	0.0039
HISP	1	478.86140	439.35544	1.090	0.2758
TCLER	1	286.56038	206.58960	1.387	0.1655
TCOMPU	1	1240.51980	212.02605	5.851	0.0001
S85	1	-6445.60032	921.77771	-6.993	0.0001
CHILD85	1	-54.77381359	352.36410	-0.155	0.8765
MAR85	1	2771.54118	364.05574	7.613	0.0001
RUR82	1	-981.64678	352.93028	-2.781	0.0054
NSMSA85	1	45.51505359	295.64493	0.154	0.8777
ED85	1	556.33945	153.65179	3.621	0.0003
CED85	1	651.84781	193.59691	3.367	0.0008
EDX85	1	-856.38595	200.72702	-4.266	0.0001
RACE1	1	107.64640	377.78032	0.285	0.7757
RACE2	1	318.47445	614.34307	0.518	0.6042
AGE79	1	-615.69675	504.39673	-1.221	0.2223
AGES85	1	14.73497494	29.91631301	0.493	0.6224
AT85	1	-2051.81816	599.02906	-3.425	0.0006
ATT85	1	-2193.31651	751.22885	-2.920	0.0035
EXPWK85	1	17.94602089	4.00024479	4.486	0.0001
EXPWS85	1	52.80562382	23.45161878	2.252	0.0244

EST:	NUMERATOR:	8.5E+08	DF:	1	F VALUE:	10.8982
	DENOMINATOR:	77679143	DF:	4871	PROB >F :	0.0010

EST:	NUMERATOR:	38077.3	DF:	1	F VALUE:	0.0005
	DENOMINATOR:	77679143	DF:	4871	PROB >F :	0.9823

P VARIABLE: UN85

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	29	54.71739516	1.88680673	40.993	0.0001
ERROR	4430	203.90126	0.04602737		
C TOTAL	4459	258.61865			

ROOT MSE	0.2145399	R-SQUARE	0.2116
DEP MEAN	0.1146414	ADJ R-SQ	0.2064
C.V.	187.1399		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	PROB > !T!
INTERCEP	1	-0.24527073	0.18488554	-1.327	0.1847
TMATH	1	0.004241635	0.006333170	0.670	0.5031
TVERBAL	1	-0.003994465	0.007020255	-0.569	0.5694
TSCI	1	0.01240633	0.006723521	1.845	0.0651
VOCT	1	-0.02215004	0.006394135	-3.464	0.0005
UNL85	1	0.000896990	0.000119601	7.500	0.0001
CPT85	1	-0.02970204	0.01746429	-1.701	0.0891
HSG85	1	-0.02219268	0.01096194	-2.025	0.0430
NE85	1	-0.01246959	0.01031576	-1.209	0.2268
SO85	1	-0.01518432	0.008824592	-1.721	0.0854
WS85	1	-0.000358046	0.01022386	-0.035	0.9721
HISP	1	-0.002964458	0.01116760	-0.265	0.7907
TCLER	1	-0.008455603	0.005263406	-1.606	0.1082
TCOMPU	1	0.001112871	0.005430101	0.205	0.8376
S85	1	-0.03038851	0.02416503	-1.258	0.2086
CHILD85	1	0.008408853	0.008977463	0.937	0.3490
MAR85	1	-0.006910862	0.009326896	-0.741	0.4588
RUR82	1	-0.001720144	0.009038782	-0.190	0.8491
NSMSA85	1	-0.009391366	0.007836695	-1.198	0.2308
ED85	1	-0.008787267	0.003971713	-2.212	0.0270
CED85	1	-0.001033347	0.004973608	-0.208	0.8354
EDX85	1	-0.000332810	0.005151389	-0.065	0.9485
RACE1	1	0.02090456	0.009802766	2.133	0.0330
RACE2	1	-0.02319702	0.01589826	-1.459	0.1446
AGE79	1	0.04578556	0.01302990	3.514	0.0004
AGES85	1	-0.001721183	0.000770475	-2.234	0.0255
AT85	1	-0.000116644	0.01555868	-0.007	0.9940
ATT85	1	0.02919357	0.01952008	1.496	0.1348
EXPWK85	1	-0.001954316	0.000110239	-17.728	0.0001
EXPWS85	1	0.006598602	0.000620844	10.628	0.0001

EST:	NUMERATOR:	0.297698	DF: 1	F VALUE:	6.4678
	DENOMINATOR:	.0460274	DF: 4430	PROB >F :	0.0110

EST:	NUMERATOR:	.0298052	DF: 1	F VALUE:	0.6476
	DENOMINATOR:	.0460274	DF: 4430	PROB >F :	0.4210

E AND TECH,ACAD IS MT,SCI,
19:06 SUNDAY, :

DESCRIPTIVE STATISTICS

STATISTICS

VARIABLE	SUM	MEAN	STD DEVIATION
LWG86	25640.6	6.28291	0.52478
TMATH	8936.2	2.18971	0.95401
TVERBAL	12239.7	2.99918	0.89920
TSCI	-236.9	-0.05805	0.88020
VOCT	-1404.5	-0.34415	0.71772
UNL86	12703.2	3.11276	0.91697
CPT86	305.0	0.07474	0.26300
HSG86	3101.0	0.75986	0.42722
NE86	764.0	0.18721	0.39013
SO86	1639.0	0.40162	0.49029
WS86	742.0	0.18182	0.38574
HISP	522.0	0.12791	0.33403
TCLER	1149.6	0.28169	0.94042
TCOMPU	854.7	0.20944	0.92223
CHILD86	1883.0	0.46141	0.49857
MAR86	1606.0	0.39353	0.48859
RUR82	805.0	0.19726	0.39798
NSMSA86	1186.0	0.29062	0.45410
ED86	53014.0	12.99044	2.30143
CED86	5711.0	1.39941	1.77261
EDX86	3264.0	0.79980	1.30604
RACE1	994.0	0.24357	0.42929
RACE2	197.0	0.04827	0.21437
AGE79	74525.3	18.26154	2.21563
AGES86	370081.2	90.68394	41.63000
AT86	808.0	0.19799	0.39853
ATT86	493.0	0.12080	0.32594
EXPWK86	1031095.0	252.65744	123.13031
EXPWS86	322370995.0	78993.13771	65454.01237
ASV2S86	257.2	0.06301	0.33270
VOCS86	-45.1	-0.01105	0.25843
COMPS86	277.2	0.06792	0.32940
ASV2AG86	1821.5	0.44634	3.61321
VOCTAG86	-3257.9	-0.79831	2.94165
COMPAG86	3383.5	0.82909	3.78165
ASV2WK86	3124.7	0.76567	2.19108
ASV2ED86	3690.5	0.90432	2.23516
INTERCEP	4081.0	1.00000	0.00000

EP VARIABLE: LWG86

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	28	314.60465	11.23588042	56.276	0.0001
ERROR	4052	809.01359	0.19965785		
C TOTAL	4080	1123.61824			

ROOT MSE	0.4468309	R-SQUARE	0.2800
DEP MEAN	6.282911	ADJ R-SQ	0.2750
C.V.	7.111845		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	PROB > !T!
INTERCEP	1	5.80877312	0.44498782	13.054	0.0001
TMATH	1	0.02702377	0.01394099	1.938	0.0526
TVERBAL	1	0.02729542	0.01555970	1.754	0.0795
TSCI	1	0.01184051	0.01466895	0.807	0.4196
VOCT	1	0.005523769	0.01811500	0.305	0.7604
UNL86	1	-0.02852499	0.008250927	-3.457	0.0006
CPT86	1	0.10935670	0.03386561	3.229	0.0013
HSG86	1	0.06194364	0.02644153	2.343	0.0192
NE86	1	0.14027139	0.02275772	6.164	0.0001
SO86	1	0.03699361	0.01908543	1.938	0.0527
WS86	1	0.11638318	0.02294717	5.072	0.0001
HISP	1	0.08981530	0.02503811	3.587	0.0003
TCLER	1	0.02770221	0.01065135	2.601	0.0093
TCOMPU	1	0.02366819	0.01161036	2.039	0.0416
CHILD86	1	-0.02777377	0.01782330	-1.558	0.1192
MAR86	1	-0.01498247	0.01651710	-0.907	0.3644
RUR82	1	-0.07516379	0.01991300	-3.775	0.0002
NSMSA86	1	-0.04868516	0.01742432	-2.794	0.0052
ED86	1	-0.008715299	0.01077314	-0.809	0.4186
CED86	1	0.07346229	0.01246133	5.895	0.0001
EDX86	1	-0.03132578	0.01000409	-3.131	0.0018
RACE1	1	0.04627430	0.02144111	2.158	0.0310
RACE2	1	0.002602845	0.03562722	0.073	0.9418
AGE79	1	0.01360852	0.03175166	0.429	0.6682
AGES86	1	-0.001897914	0.001662109	-1.142	0.2536
AT86	1	-0.02481247	0.03299292	-0.752	0.4521
ATT86	1	-0.12350933	0.03248187	-3.802	0.0001
EXPWK86	1	0.001001729	0.000232344	4.311	0.0001
EXPWS86	1	5.67181E-07	4.34955E-07	1.304	0.1923

EST:	NUMERATOR:	0.653603	DF:	1	F VALUE:	3.2736
	DENOMINATOR:	0.199658	DF:	4052	PROB >F :	0.0705

EST:	NUMERATOR:	2.9E-05	DF:	1	F VALUE:	0.0001
	DENOMINATOR:	0.199658	DF:	4052	PROB >F :	0.9904

FEMALE LOG EARNINGS VOC IS TRADE AND TECH, ACAD IS MT.SCI.ENG

21:25 SUNDAY, JANUARY 1, 1989

EP VARIABLE: LEARN85

NLSReg-C

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	29	1147.29032	39.56173507	66.450	0.0001
ERROR	3859	2297.51397	0.59536511		
C TOTAL	3888	3444.80429			

ROOT MSE	0.7715991	R-SQUARE	0.3330
DEP MEAN	8.846423	ADJ R-SQ	0.3280
C.V.	8.722159		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	PROB > !T!
INTERCEP	1	6.77335340	0.74930725	9.039	0.0001
TMATH	1	0.06478352	0.02434109	2.661	0.0078
TVERBAL	1	0.03866029	0.02759419	1.401	0.1613
TSCI	1	0.008837114	0.02603885	0.339	0.7343
VOCT	1	-0.02033731	0.03169744	-0.642	0.5212
UNL85	1	-0.001600858	0.000457043	-3.503	0.0005
CPT85	1	0.54151536	0.05676236	9.540	0.0001
HSG85	1	0.01107340	0.04774354	0.232	0.8166
NE85	1	0.09558597	0.03996000	2.392	0.0168
SO85	1	0.10152780	0.03433952	2.957	0.0031
WS85	1	-0.03027610	0.04027130	-0.752	0.4522
HISP	1	0.18488413	0.04459821	4.146	0.0001
TCLER	1	0.02153457	0.01889926	1.139	0.2546
TCOMPU	1	0.05336899	0.02056726	2.595	0.0095
S85	1	-0.52280714	0.08589156	-6.087	0.0001
CHILD85	1	-0.21963136	0.03244244	-6.770	0.0001
MAR85	1	-0.07368241	0.03023968	-2.437	0.0149
RUR82	1	-0.09297968	0.03570420	-2.604	0.0092
NSMSA85	1	-0.004511564	0.02998459	-0.150	0.8804
ED85	1	0.04595464	0.01993019	2.306	0.0212
CED85	1	0.04224277	0.02283587	1.850	0.0644
EDX85	1	-0.03223493	0.01988179	-1.621	0.1050
RACE1	1	0.08624517	0.03812160	2.262	0.0237
RACE2	1	-0.005185724	0.06359035	-0.082	0.9350
AGE79	1	0.06432451	0.05124828	1.255	0.2095
AGES85	1	-0.006540288	0.002985473	-2.191	0.0285
AT85	1	-0.18376782	0.05724179	-3.210	0.0013
ATT85	1	-0.18747008	0.07090204	-2.644	0.0082
EXPWK85	1	0.003461555	0.000426091	8.124	0.0001
EXPWS85	1	-0.002275993	0.002436580	-0.934	0.3503

EST:	NUMERATOR:	3.04129	DF: 1	F VALUE:	5.1083
	DENOMINATOR:	0.595365	DF: 3859	PROB >F :	0.0239

EST:	NUMERATOR:	0.256403	DF: 1	F VALUE:	0.4307
	DENOMINATOR:	0.595365	DF: 3859	PROB >F :	0.5117

EP VARIABLE: EARN85

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	29	126591392973	4365220447	121.899	0.0001
ERROR	5121	183383107804	35810019.10		
C TOTAL	5150	309974500777			

ROOT MSE	5984.147	R-SQUARE	0.4084
DEP MEAN	7428.012	ADJ R-SQ	0.4050
C.V.	80.56189		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	PROB > !T!
INTERCEP	1	-4970.35635	4847.70536	-1.025	0.3053
TMATH	1	813.35990	168.61409	4.824	0.0001
TVERBAL	1	94.48922727	183.73117	0.514	0.6071
TSCI	1	29.62771998	175.11014	0.169	0.8657
VOCT	1	-170.90553	218.72808	-0.781	0.4346
UNL85	1	-14.64903278	3.02003808	-4.851	0.0001
CPT85	1	4245.77442	415.88724	10.209	0.0001
HSG85	1	424.17422	293.32122	1.446	0.1482
NE85	1	673.28695	269.87826	2.495	0.0126
SO85	1	633.58696	226.89182	2.792	0.0053
WS85	1	44.56335676	269.27544	0.165	0.8686
HISP	1	769.73236	292.77319	2.629	0.0086
TCLER	1	240.68063	127.00746	1.895	0.0581
TCOMPU	1	438.46415	136.15226	3.220	0.0013
S85	1	-2570.77561	616.00371	-4.173	0.0001
CHILD85	1	-2285.83519	216.63390	-10.552	0.0001
MAR85	1	-595.46410	200.17729	-2.975	0.0029
RUR82	1	-498.72563	238.48162	-2.091	0.0366
NSMSA85	1	-241.99980	202.37198	-1.196	0.2318
ED85	1	7.16323918	103.21858	0.069	0.9447
CED85	1	908.41326	129.44310	7.018	0.0001
EDX85	1	-269.06532	135.88058	-1.980	0.0477
RACE1	1	687.30242	252.00407	2.727	0.0064
RACE2	1	142.26621	404.74414	0.351	0.7252
AGE79	1	636.83706	334.64617	1.903	0.0571
AGES85	1	-53.84070316	19.56549440	-2.752	0.0059
AT85	1	-1369.84295	407.24306	-3.364	0.0008
ATT85	1	-1881.20154	510.95977	-3.682	0.0002
EXPWK85	1	16.08315784	2.50662177	6.416	0.0001
EXPWS85	1	51.81671755	15.31174202	3.384	0.0007

EST:	NUMERATOR:	2.7E+08	DF:	1	F VALUE:	7.6016
	DENOMINATOR:	35810019	DF:	5121	PROB >F :	0.0059
EST:	NUMERATOR:	2.6E+08	DF:	1	F VALUE:	7.1551
	DENOMINATOR:	35810019	DF:	5121	PROB >F :	0.0075

EP VARIABLE: UN85

NLS Reg 9

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	29	55.79809034	1.92407208	38.089	0.0001
ERROR	4194	211.86173	0.05051543		
C TOTAL	4223	267.65982			

ROOT MSE	0.2247564	R-SQUARE	0.2085
DEP MEAN	0.1140849	ADJ R-SQ	0.2030
C.V.	197.0081		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	PROB > !T!
INTERCEP	1	-0.17406613	0.20739210	-0.839	0.4013
TMATH	1	-0.005240943	0.006905117	-0.759	0.4479
TVERBAL	1	-0.01742252	0.007632930	-2.283	0.0225
TSCI	1	-0.003180920	0.007232158	-0.440	0.6601
VOCT	1	0.006717332	0.008978740	0.748	0.4544
UNL85	1	0.000532148	0.000127343	4.179	0.0001
CPT85	1	-0.03598935	0.01634271	-2.202	0.0277
HSG85	1	-0.004561248	0.01304187	-0.350	0.7266
NE85	1	-0.02187181	0.01119556	-1.954	0.0508
SO85	1	-0.01033589	0.009507520	-1.087	0.2770
WS85	1	-0.01199307	0.01132147	-1.059	0.2895
HISP	1	-0.01896562	0.01244751	-1.524	0.1277
TCLER	1	-0.006498853	0.005248137	-1.238	0.2157
TCOMPU	1	0.004799927	0.005701176	0.842	0.3999
S85	1	-0.06982069	0.02437641	-2.864	0.0042
CHILD85	1	0.01263949	0.008987849	1.406	0.1597
MAR85	1	-0.02457885	0.008420201	-2.919	0.0035
RUR82	1	0.009530258	0.009980984	0.955	0.3397
NSMSA85	1	-0.003929729	0.008455239	-0.465	0.6421
ED85	1	-0.01289828	0.005300229	-2.434	0.0150
CED85	1	0.009679104	0.006178310	1.567	0.1173
EDX85	1	-0.009304128	0.005603241	-1.660	0.0969
RACE1	1	0.04606868	0.01056939	4.359	0.0001
RACE2	1	0.04271904	0.01766838	2.418	0.0157
AGE79	1	0.04765853	0.01419780	3.357	0.0008
AGES85	1	-0.002221778	0.000828123	-2.683	0.0073
AT85	1	0.02353787	0.01625178	1.448	0.1476
ATT85	1	0.04738730	0.02010905	2.357	0.0185
EXPWK85	1	-0.001837992	0.000113161	-16.242	0.0001
EXPWS85	1	0.007133589	0.000658752	10.829	0.0001

EST:	NUMERATOR:	0.195663	DF: 1	F VALUE:	3.8733
	DENOMINATOR:	.0505154	DF: 4194	PROB >F :	0.0491

EST:	NUMERATOR:	0.060527	DF: 1	F VALUE:	1.1982
	DENOMINATOR:	.0505154	DF: 4194	PROB >F :	0.2737

MALE LOG WAGE RATE
MODELS WITH CROSS EQUATION CONSTRAINTS
NO WORK EXPER INTERACTIONS AND TECH VOC AND HS ACAD & SCH ATT
23:44 SUNDAY, JANUARY 8, 1989

DINT GENERALIZED LEAST SQUARES

ODEL: E1 JGLS
EP VARIABLE: LWG86

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	PROB > !T!
INTERCEP	1	5.70283896	0.57634418	9.895	0.0001
TSCI	1	-0.002861527	0.01285523	-0.223	0.8239
TMATH	1	-0.005303968	0.01229865	-0.431	0.6663
TVERBAL	1	-0.01620374	0.01337480	-1.212	0.2258
VOCT	1	0.04352065	0.01289718	3.374	0.0008
ASV2AG86	1	-0.002016640	0.003869981	-0.521	0.6024
ASV2ED86	1	0.006932437	0.005395494	1.285	0.1990
UNL86	1	-0.03640345	0.009278103	-3.924	0.0001
CPT86	1	0.08935393	0.04121523	2.168	0.0303
HSG86	1	-0.01316534	0.02937111	-0.448	0.6540
NE86	1	0.08966390	0.02740784	3.271	0.0011
SO86	1	0.01824856	0.02289530	0.797	0.4255
WS86	1	0.09063210	0.02654872	3.414	0.0007
HISP	1	0.05969784	0.03034802	1.967	0.0493
TCLER	1	-0.003573519	0.009812371	-0.364	0.7158
TCOMPU	1	0.06179075	0.01114846	5.543	0.0001
CHILD86	1	-0.007862752	0.02065286	-0.381	0.7035
MAR86	1	0.07680855	0.02031719	3.780	0.0002
RUR82	1	-0.04302263	0.02370117	-1.815	0.0696
NSMSA86	1	-0.08246078	0.01992431	-4.139	0.0001
S85	1	-0.11336857	0.07154521	-1.585	0.1132
ASV2S86	1	-0.02553527	0.02060333	-1.239	0.2153
COMPS86	1	-0.005835270	0.01471543	-0.397	0.6917
VOCS86	1	0.01167160	0.01830280	0.638	0.5237
COMPAG86	1	0.005725466	0.002490305	2.299	0.0216
VOCTAG86	1	0.006677902	0.003173920	2.104	0.0355
ED86	1	0.02755818	0.01148826	2.399	0.0165
CED86	1	0.002896352	0.01520462	0.190	0.8489
EDX86	1	-0.01764958	0.01277824	-1.381	0.1674
RACE1	1	0.03051627	0.02805784	1.088	0.2769
RACE2	1	-0.009054418	0.04760470	-0.190	0.8492
AGE79	1	0.02591664	0.04321489	0.600	0.5488
AGES86	1	-0.001091081	0.002226428	-0.490	0.6241
AT86	1	0.08820811	0.05026902	1.755	0.0795
ATT86	1	-0.15447328	0.04122734	-3.747	0.0002
EXPWK86	1	0.000823742	0.000512308	1.608	0.1080
EXPWS86	1	-7.95860E-08	7.50035E-07	-0.106	0.9155

EST:

NUMERATOR:	6.05379	DF:	1	F VALUE:	6.0917
DENOMINATOR:	0.993772	DF:	12780	PROB >F :	0.0136

EST:

NUMERATOR:	0.306183	DF:	1	F VALUE:	0.3081
DENOMINATOR:	0.993772	DF:	12780	PROB >F :	0.5789

MALE LOG EARN
MODELS WITH CROSS EQUATION CONSTRAINTS
NO WORK EXPER INTERACTIONS AND TECH VOC AND HS ACAD & SCH ATT
CONSTRAINTS ON ALL TESTS

20:24 SUNDAY, JANUARY 8, 1989

INT GENERALIZED LEAST SQUARES

DEL: E2 JGLS
VARIABLE: LEARN85

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > !T!
INTERCEP	1	7.75548367	0.79138316	9.800	0.0001
TSCI	1	-0.009227768	0.01821032	-0.507	0.6124
TMATH	1	-0.01521455	0.01729625	-0.880	0.3791
TVERBAL	1	-0.01495466	0.01896477	-0.789	0.4304
VOCT	1	0.08742264	0.01874571	4.664	0.0001
ASV2AG85	1	0.003963008	0.006631239	0.598	0.5501
ASV2ED85	1	-0.01291844	0.008061220	-1.603	0.1091
UNL85	1	-0.002400825	0.000412575	-5.819	0.0001
CPT85	1	0.20014773	0.05208693	3.843	0.0001
HSG85	1	0.02862823	0.03896461	0.735	0.4626
NE85	1	0.11817005	0.03610236	3.273	0.0011
SO85	1	-0.01017905	0.03131534	-0.325	0.7452
WS85	1	0.05461287	0.03483479	1.568	0.1170
HISP	1	-0.01799718	0.03986741	-0.451	0.6517
TCLER	1	0.01707900	0.01357622	1.258	0.2085
TCOMPU	1	0.09531613	0.01585485	6.012	0.0001
CHILD85	1	0.05073238	0.02935289	1.728	0.0840
MAR85	1	0.08956626	0.02876692	3.114	0.0019
RUR82	1	-0.05976132	0.03179125	-1.880	0.0602
NSMSA85	1	-0.005888160	0.02590199	-0.227	0.8202
S85	1	-0.72402440	0.08014343	-9.034	0.0001
ASV2S85	1	-0.23672406	0.04749581	-4.984	0.0001
COMPS85	1	0.000268026	0.03279502	0.008	0.9935
VOCS85	1	0.14138707	0.04041948	3.498	0.0005
COMPAG85	1	0.001684462	0.004278135	0.394	0.6938
VOCTAG85	1	-0.000682258	0.005454428	-0.125	0.9005
ED85	1	0.04094066	0.01513072	2.706	0.0069
CED85	1	0.05026349	0.02080706	2.416	0.0158
EDX85	1	-0.05237297	0.01904028	-2.751	0.0060
RACE1	1	-0.07024504	0.03545818	-1.981	0.0477
RACE2	1	0.03356020	0.05809073	0.578	0.5635
AGE79	1	0.08321575	0.05521983	1.507	0.1319
AGES85	1	-0.004016427	0.003156860	-1.272	0.2034
AT85	1	-0.10497770	0.05138120	-2.043	0.0411
ATT85	1	-0.07300787	0.06126134	-1.192	0.2335
EXPWK85	1	0.000128220	0.000429188	0.299	0.7652
EXPWS85	1	0.004381317	0.002281171	1.921	0.0549

ST: NUMERATOR: 9.99361 DF: 1 F VALUE: 10.1133
DENOMINATOR: 0.988161 DF:15143 PROB >F : 0.0015

ST: NUMERATOR: 8.9E-05 DF: 1 F VALUE: 0.0001
DENOMINATOR: 0.988161 DF:15143 PROB >F : 0.9924

MALE EARNINGS
MODELS WITH CROSS EQUATION CONSTRAINTS
NO WORK EXPER INTERACTIONS AND TECH VOC AND HS ACAD & SCH ATT
CONSTRAINTS ON ALL TESTS

20:59 SUNDAY, JANUARY 8, 1989

OINT GENERALIZED LEAST SQUARES

:ODEL: E2 JGLS
)EP VARIABLE: EARN85

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	PROB > !T!
INTERCEP	1	0.10167441	0.93702289	0.109	0.9136
TSCI	1	-0.006607194	0.01783830	-0.370	0.7111
TMATH	1	0.008557542	0.01727857	0.495	0.6204
TVERBAL	1	-0.04383964	0.01862457	-2.354	0.0186
VOCT	1	0.13330809	0.01817911	7.333	0.0001
ASV2AG85	1	-0.000532372	0.006641986	-0.080	0.9361
ASV2ED85	1	-0.01687833	0.007992357	-2.112	0.0348
UNL85	1	-0.003161606	0.000472414	-6.692	0.0001
CPT85	1	0.14050602	0.06000743	2.341	0.0193
HSG85	1	0.07790490	0.04532946	1.719	0.0858
NE85	1	0.12674510	0.04241354	2.988	0.0028
SO85	1	0.02033390	0.03629804	0.560	0.5754
WS85	1	0.09225884	0.04128938	2.234	0.0255
HISP	1	0.06982571	0.04843606	1.442	0.1495
TCLER	1	0.03591198	0.01366944	2.627	0.0086
TCOMPU	1	0.10875499	0.01529030	7.113	0.0001
CHILD85	1	0.03739709	0.03403551	1.099	0.2719
MAR85	1	0.13627287	0.03425021	3.979	0.0001
RUR82	1	-0.07524851	0.03839898	-1.960	0.0501
NSMSA85	1	-0.02793299	0.02998132	-0.932	0.3516
S85	1	-0.51431789	0.08312323	-6.187	0.0001
ASV2S85	1	-0.10962079	0.04094282	-2.677	0.0074
COMPS85	1	-0.06072772	0.02768483	-2.194	0.0283
VOCS85	1	-0.04963914	0.03479288	-1.427	0.1537
COMPAG85	1	0.01554175	0.004174240	3.723	0.0002
VOCTAG85	1	0.007579674	0.005427247	1.397	0.1626
ED85	1	0.06081492	0.01671769	3.638	0.0003
CED85	1	0.07222084	0.02275356	3.174	0.0015
EDX85	1	-0.09438636	0.02142926	-4.405	0.0001
RACE1	1	-0.05137973	0.04014248	-1.280	0.2006
RACE2	1	-0.02048484	0.06991393	-0.293	0.7695
AGE79	1	0.02632028	0.06560144	0.401	0.6883
AGES85	1	-0.001259738	0.003791497	-0.332	0.7397
AT85	1	-0.09647023	0.05618091	-1.717	0.0860
ATT85	1	-0.18242732	0.06635518	-2.749	0.0060
EXPWK85	1	0.001356388	0.000430231	3.153	0.0016
EXPWS85	1	0.003270863	0.002503406	1.307	0.1914

TEST:	NUMERATOR:	20.0429	DF:	1	F VALUE:	20.2972
	DENOMINATOR:	0.987471	DF:	20483	PROB >F :	0.0001

TEST:	NUMERATOR:	3.67555	DF:	1	F VALUE:	3.7222
	DENOMINATOR:	0.987471	DF:	20483	PROB >F :	0.0537

MODELS WITH CROSS EQUATION CONSTRAINTS
NO WORK EXPER INTERACTIONS AND TECH VOC AND HS ACAD & SCH ATT
CONSTRAINTS ON ALL TESTS

21:06 SUNDAY, JANUARY 8, 1989

JOINT GENERALIZED LEAST SQUARES

MODEL: E2 JGLS
DEP VARIABLE: UN85

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	PROB > |T|
INTERCEP	1	-0.47148516	0.19682476	-2.395	0.0167
TSCI	1	0.01024567	0.005014504	2.043	0.0411
TMATH	1	-0.01242453	0.004861979	-2.555	0.0106
TVERBAL	1	0.000200126	0.005269774	0.038	0.9697
VOCT	1	-0.02169517	0.005438138	-3.989	0.0001
ASV2AG85	1	0.004856227	0.002010370	2.416	0.0158
ASV2ED85	1	0.001724387	0.002373922	0.726	0.4677
UNL85	1	0.000735390	0.000119948	6.131	0.0001
CPT85	1	-0.02910173	0.01699331	-1.713	0.0869
HSG85	1	-0.02187577	0.01137344	-1.923	0.0545
NE85	1	-0.02580211	0.01052965	-2.450	0.0143
SO85	1	-0.01774488	0.009097660	-1.950	0.0512
WS85	1	-0.007252651	0.01046394	-0.693	0.4883
HISP	1	-0.000087137	0.01130023	-0.008	0.9938
TCLER	1	-0.01083796	0.003790230	-2.859	0.0043
TCOMPU	1	-0.004006007	0.004512896	-0.888	0.3748
CHILD85	1	0.008180820	0.008964285	0.913	0.3615
MAR85	1	-0.01272778	0.009173601	-1.387	0.1654
RUR82	1	-0.007146060	0.009232150	-0.774	0.4390
NSMSA85	1	0.001731569	0.008220816	0.211	0.8332
S85	1	-0.02978878	0.02531812	-1.177	0.2394
ASV2S85	1	0.006545683	0.01536318	0.426	0.6701
COMPS85	1	0.000739042	0.01067901	0.069	0.9448
VOCS85	1	0.006029545	0.01323630	0.456	0.6488
COMPAG85	1	0.002259627	0.001300653	1.737	0.0824
VOCTAG85	1	-0.000799649	0.001652682	-0.484	0.6285
ED85	1	-0.009592551	0.004118775	-2.329	0.0199
CED85	1	-0.005880140	0.005765265	-1.020	0.3078
EDX85	1	0.005383539	0.005422462	0.993	0.3209
RACE1	1	0.02112854	0.009911632	2.132	0.0331
RACE2	1	-0.01062853	0.01724651	-0.616	0.5378
AGE79	1	0.06179086	0.01403630	4.402	0.0001
AGES85	1	-0.002683587	0.000818116	-3.280	0.0010
AT85	1	0.005556554	0.01573440	0.353	0.7240
ATT85	1	0.04642814	0.01969364	2.358	0.0185
EXPWK85	1	-0.001525409	0.000141308	-10.795	0.0001
EXPWS85	1	0.004819165	0.000717755	6.714	0.0001

TEST:	NUMERATOR:	2.89391	DF: 1	F VALUE:	2.9169
	DENOMINATOR:	0.99211	DF:16583	PROB >F :	0.0877
TEST:	NUMERATOR:	2.69521	DF: 1	F VALUE:	2.7166
	DENOMINATOR:	0.99211	DF:16583	PROB >F :	0.0993

FEMALE LOG WAGE RATE
MODELS WITH CROSS EQUATION CONSTRAINTS
NO WORK EXPER INTERACTIONS AND TECH VOC AND HS ACAD & SCH ATT
23:37 SUNDAY, JANUARY 8, 1989

NT GENERALIZED LEAST SQUARES

)EL: E1 JGLS
› VARIABLE: LWG86

PARAMETER ESTIMATES

/ARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	PROB > !T!
INTERCEP	1	4.79123542	0.65415910	7.324	0.0001
rSCI	1	-0.01238248	0.01226654	-1.009	0.3129
TMATH	1	0.02474817	0.01131569	2.187	0.0289
TVERBAL	1	0.005822615	0.01292739	0.450	0.6525
VOCT	1	0.01669180	0.01603308	1.041	0.2980
ASV2AG86	1	0.006425048	0.004130590	1.555	0.1200
ASV2ED86	1	0.01558608	0.005314722	2.933	0.0034
UNL86	1	-0.03500083	0.01004791	-3.483	0.0005
CPT86	1	-0.01801786	0.03918521	-0.460	0.6457
HSG86	1	0.01936413	0.03677045	0.527	0.5985
NE86	1	0.13832507	0.02865655	4.827	0.0001
SO86	1	0.01255432	0.02516389	0.499	0.6179
WS86	1	0.11062881	0.02959293	3.738	0.0002
HISP	1	0.07388695	0.03412659	2.165	0.0305
TCLER	1	0.01025341	0.008531233	1.202	0.2296
TCOMPU	1	0.03111019	0.01033676	3.010	0.0027
CHILD86	1	-0.006817776	0.02121838	-0.321	0.7480
MAR86	1	0.005379823	0.01959656	0.275	0.7837
RUR82	1	-0.08235249	0.02659375	-3.097	0.0020
NSMSA86	1	-0.05005692	0.02166747	-2.310	0.0210
S85	1	-0.12698822	0.06453721	-1.968	0.0493
ASV2S86	1	-0.02393739	0.02150341	-1.113	0.2658
COMPS86	1	-0.004910785	0.01392862	-0.353	0.7245
VOCS86	1	-0.03641350	0.02234720	-1.629	0.1034
COMPAG86	1	0.002646382	0.002489345	1.063	0.2879
VOCTAG86	1	0.003080287	0.004306730	0.715	0.4746
ED86	1	0.02982033	0.01722868	1.731	0.0836
CED86	1	0.01148730	0.01952675	0.588	0.5564
EDX86	1	-0.01531532	0.01379460	-1.110	0.2670
RACE1	1	0.02397541	0.02852645	0.840	0.4008
RACE2	1	0.04751052	0.04940447	0.962	0.3363
AGE79	1	0.07702944	0.04781596	1.611	0.1074
AGES86	1	-0.005180066	0.002450526	-2.114	0.0347
AT86	1	0.06566093	0.05032143	1.305	0.1921
ATT86	1	-0.06916363	0.03964920	-1.744	0.0813
EXPWK86	1	0.000085928	0.000602436	0.143	0.8866
EXPWS86	1	.00000185705	8.95948E-07	2.073	0.0383

ΞST:	NUMERATOR: .0025289	DF: 1	F VALUE:	0.0025
	DENOMINATOR: 0.995939	DF:11364	PROB >F :	0.9598

ΞST:	NUMERATOR: 1.03655	DF: 1	F VALUE:	1.0408
	DENOMINATOR: 0.995939	DF:11364	PROB >F :	0.3077

FEMALE LOG EARN
MODELS WITH CROSS EQUATION CONSTRAINTS
NO WORK EXPER INTERACTIONS AND TECH VOC AND HS ACAD & SCH ATT
CONSTRAINTS ON ALL TESTS

20:38 SUNDAY, JANUARY 8, 1989

JOINT GENERALIZED LEAST SQUARES

MODEL: E2 JGLS
DEP VARIABLE: LEARN85

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	PROB > !T!
INTERCEP	1	4.38664808	1.08061209	4.059	0.0001
TSCI	1	-0.02987648	0.02126954	-1.405	0.1603
TMATH	1	0.07352108	0.01940237	3.789	0.0002
TVERBAL	1	0.04373173	0.02274799	1.922	0.0547
VOCT	1	-0.006792861	0.02816599	-0.241	0.8094
ASV2AG85	1	-0.004866432	0.008332802	-0.584	0.5593
ASV2ED85	1	0.01437185	0.009044664	1.589	0.1122
UNL85	1	-0.001725299	0.000503903	-3.424	0.0006
CPT85	1	0.25781054	0.05296497	4.868	0.0001
HSG85	1	-0.03775495	0.05980631	-0.631	0.5279
NE85	1	0.04582477	0.04535125	1.010	0.3124
SO85	1	0.04983460	0.04014084	1.241	0.2146
WS85	1	-0.03254156	0.04611360	-0.706	0.4805
HISP	1	0.14442254	0.05193733	2.781	0.0055
TCLER	1	0.02951816	0.01450278	2.035	0.0419
TCOMPU	1	0.02600916	0.01832107	1.420	0.1559
CHILD85	1	-0.18625205	0.03472632	-5.363	0.0001
MAR85	1	-0.04617236	0.03046047	-1.516	0.1297
RUR82	1	-0.07527531	0.04191723	-1.796	0.0727
NSMSA85	1	-0.07327859	0.03331845	-2.199	0.0280
S85	1	-0.33317831	0.08915218	-3.737	0.0002
ASV2S85	1	-0.23641100	0.05644060	-4.189	0.0001
COMPS85	1	0.01455140	0.03603043	0.404	0.6864
VOCS85	1	0.04950414	0.05652531	0.876	0.3812
COMPAG85	1	0.009712222	0.005048121	1.924	0.0545
VOCTAG85	1	0.001151720	0.008505082	0.135	0.8923
ED85	1	0.07081496	0.03021784	2.343	0.0192
CED85	1	-0.02339780	0.03369347	-0.694	0.4875
EDX85	1	-0.007640665	0.02276923	-0.336	0.7372
RACE1	1	0.04847939	0.04402295	1.101	0.2709
RACE2	1	-0.04286519	0.07631771	-0.562	0.5744
AGE79	1	0.26810415	0.07311590	3.667	0.0003
AGES85	1	-0.01469995	0.004115561	-3.572	0.0004
AT85	1	-0.16104068	0.05923095	-2.719	0.0066
ATT85	1	-0.06495052	0.06777860	-0.958	0.3380
EXPWK85	1	-0.001537592	0.000816520	-1.883	0.0598
EXPWS85	1	0.01272012	0.003868916	3.288	0.0010

TEST: NUMERATOR: 3.14293 DF: 1 F VALUE: 3.1832
DENOMINATOR: 0.987359 DF:11073 PROB >F : 0.0744

TEST: NUMERATOR: 0.854378 DF: 1 F VALUE: 0.8653
DENOMINATOR: 0.987359 DF:11073 PROB >F : 0.3523

FEMALE EARNINGS
MODELS WITH CROSS EQUATION CONSTRAINTS
NO WORK EXPER INTERACTIONS AND TECH VOC AND HS ACAD & SCH ATT
CONSTRAINTS ON ALL TESTS

20:49 SUNDAY, JANUARY 8, 1989

JINT GENERALIZED LEAST SQUARES

JDEL: E2 JGLS
EP VARIABLE: EARN85

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	PROB > |T|
INTERCEP	1	-1.88252902	0.59576733	-3.160	0.0016
TSCI	1	-0.004888816	0.01139886	-0.429	0.6680
TMATH	1	0.06634731	0.01122436	5.911	0.0001
TVERBAL	1	0.03528569	0.01186436	2.974	0.0030
VOCT	1	-0.01054046	0.01534949	-0.687	0.4923
ASV2AG85	1	-0.009309643	0.004442047	-2.096	0.0362
ASV2ED85	1	0.02713336	0.005287174	5.132	0.0001
UNL85	1	-0.001351359	0.000296175	-4.563	0.0001
CPT85	1	0.14468088	0.03607555	4.010	0.0001
HSG85	1	0.03384152	0.03062880	1.105	0.2693
NE85	1	0.08423602	0.02822301	2.985	0.0029
SO85	1	0.07229697	0.02362034	3.061	0.0022
WS85	1	0.02055736	0.02801014	0.734	0.4630
HISP	1	0.07327317	0.03142453	2.332	0.0198
TCLER	1	0.01830580	0.008023530	2.282	0.0226
TCOMPU	1	0.04424786	0.009376567	4.719	0.0001
CHILD85	1	-0.16220008	0.02132066	-7.608	0.0001
MAR85	1	-0.02911251	0.01841903	-1.581	0.1140
RUR82	1	-0.05522279	0.02549541	-2.166	0.0304
NSMSA85	1	-0.02183783	0.02026412	-1.078	0.2812
S85	1	-0.14361700	0.05618210	-2.556	0.0106
ASV2S85	1	-0.22556050	0.02860452	-7.885	0.0001
COMPS85	1	-0.01831126	0.01830115	-1.001	0.3171
VOCS85	1	0.03470989	0.03078816	1.127	0.2596
COMPAG85	1	0.009496122	0.002621429	3.622	0.0003
VOCTAG85	1	-0.000442058	0.004767095	-0.093	0.9261
ED85	1	0.02609957	0.01085931	2.403	0.0163
CED85	1	0.06615717	0.01408811	4.696	0.0001
EDX85	1	-0.02189070	0.01422687	-1.539	0.1240
RACE1	1	0.02767295	0.02574178	1.075	0.2824
RACE2	1	-0.03679598	0.04549805	-0.809	0.4187
AGE79	1	0.13985104	0.04141889	3.377	0.0007
AGES85	1	-0.009038061	0.002373045	-3.809	0.0001
AT85	1	-0.06464124	0.03738322	-1.729	0.0839
ATT85	1	-0.13862443	0.04475204	-3.098	0.0020
EXPWK85	1	0.000788402	0.000260786	3.023	0.0025
EXPWS85	1	0.005805119	0.001593955	3.642	0.0003

EST:	NUMERATOR: 14.2151	DF: 1	F VALUE:	14.4472
	DENOMINATOR: 0.983935	DF:22533	PROB >F :	0.0001
EST:	NUMERATOR: 3.16426	DF: 1	F VALUE:	3.2159
	DENOMINATOR: 0.983935	DF:22533	PROB >F :	0.0729

NO WORK EXPER INTERACTIONS AND TECH VOC AND HS ACAD & SCH ATT
CONSTRAINTS ON ALL TESTS

22:49 SUNDAY, JANUARY 8, 1989

JOINT GENERALIZED LEAST SQUARES

MODEL: E2 JGLS
DEP VARIABLE: UN85

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	PROB > !T!
INTERCEP	1	-0.003407073	0.21211970	-0.016	0.9872
TSCI	1	-0.002058045	0.005116234	-0.402	0.6875
TMATH	1	-0.01146362	0.004858118	-2.360	0.0184
TVERBAL	1	-0.02198570	0.005408994	-4.065	0.0001
VOCT	1	0.005775485	0.007248321	0.797	0.4256
ASV2AG85	1	0.001802802	0.002085010	0.865	0.3873
ASV2ED85	1	0.006889582	0.002276167	3.027	0.0025
UNL85	1	0.000201571	0.000122948	1.639	0.1012
CPT85	1	-0.02440149	0.01444249	-1.690	0.0912
HSG85	1	0.005667349	0.01320361	0.429	0.6678
NE85	1	-0.03772330	0.01067481	-3.534	0.0004
SO85	1	-0.03264712	0.009318852	-3.503	0.0005
WS85	1	-0.02288823	0.01093869	-2.092	0.0365
HISP	1	0.01024087	0.01260543	0.812	0.4166
TCLER	1	-0.01066781	0.003491689	-3.055	0.0023
TCOMPU	1	-0.009338681	0.004493251	-2.078	0.0378
CHILD85	1	0.001910961	0.008568179	0.223	0.8235
MAR85	1	-0.005289697	0.007875679	-0.672	0.5019
RUR82	1	0.01256503	0.009773890	1.286	0.1987
NSMSA85	1	-0.002865998	0.008176221	-0.351	0.7260
S85	1	-0.007340938	0.02380055	-0.308	0.7578
ASV2S85	1	-0.009536924	0.01544158	-0.618	0.5369
COMPS85	1	0.003650525	0.009881245	0.369	0.7118
VOCS85	1	0.03239495	0.01606047	2.017	0.0438
COMPAG85	1	0.004592860	0.001256208	3.656	0.0003
VOCTAG85	1	0.000315291	0.002199369	0.143	0.8860
ED85	1	-0.01728128	0.005847238	-2.955	0.0031
CED85	1	0.003614726	0.006847483	0.528	0.5976
EDX85	1	0.005140101	0.005528591	0.930	0.3526
RACE1	1	0.03671252	0.01012605	3.626	0.0003
RACE2	1	0.02706217	0.01790564	1.511	0.1308
AGE79	1	0.03842048	0.01458010	2.635	0.0085
AGES85	1	-0.001656688	0.000839744	-1.973	0.0486
AT85	1	0.01270951	0.01496586	0.849	0.3958
ATT85	1	0.03062330	0.01828074	1.675	0.0940
EXPWK85	1	-0.001259603	0.000149477	-8.427	0.0001
EXPWS85	1	0.004230472	0.000769393	5.498	0.0001

TEST:	NUMERATOR:	9.48355	DF: 1		F VALUE:	9.5341
	DENOMINATOR:	0.994694	DF:14208		PROB >F :	0.0020
TEST:	NUMERATOR:	1.83459	DF: 1		F VALUE:	1.8444
	DENOMINATOR:	0.994694	DF:14208		PROB >F :	0.1745

APPENDIX B

The ASVAB

Purposes

The ASVAB is a multiple aptitude battery designed for use with students in Grades 11 and 12 and in postsecondary schools. The test was developed to yield results that are useful to both schools and the military. Schools use ASVAB test results to provide educational and career counseling for students. The military services use the results to identify students who potentially qualify for entry into the military and for assignment to military occupational training programs.

Like other multiple aptitude batteries, the ASVAB measures developed abilities and predicts what a person could accomplish with training or further education. This test is designed especially to measure potential for occupations that require formal courses of instruction or on-the-job training. In addition, it provides measures of general learning ability that are useful for predicting performance in academic areas.

The ASVAB can be used for both military and civilian career counseling. Scores from this test are valid predictors of success in training programs for enlisted military occupations. Through the use of validity generalization techniques, predictions from military validity studies can be generalized to occupations that span most of the civilian occupational spectrum. Although some enlisted occupations are military specific, more than 80% of these occupations have direct civilian occupational counterparts.

Since the ASVAB was first used in high schools in 1968, it has been the subject of extensive research and has been updated periodically. Appendix A contains a brief history of the ASVAB and the various forms that have been used.

Key Features

ASVAB-14, introduced in the 1984-85 school year, contains several key features that were not included in previous forms. These key features include

- **improved usefulness in measuring vocational aptitudes:** In addition to yielding *academic composites* that provide measures of academic potential, ASVAB-14 supplies *occupational composites* that provide measures of potential for successful performance in four general career areas.
- **increased reliability:** Changes in the length and number of subtests have increased the test's reliability without a substantial increase in testing time.
- **nationally representative norms:** ASVAB-14 is normed on a nationally representative sample of 12,000 women and men, ages 16-23, who took the test in 1980.

Content

Subtests

The ASVAB consists of 10 subtests. Eight are power subtests that allow maximum performance with generous time limits. Two subtests are speeded.

Figure 1-1 presents the subtests, the time allowed for the administration of each subtest, the number of items per subtest, and the descriptions of the abilities or knowledge measured. The subtests are designed to measure general cognitive abilities and acquired information in specific areas. Sample questions for each subtest are provided in Appendix B.

Figure 1-1. ASVAB-14 CONTENT.

Testing Time	144 minutes
Administrative Time	36 minutes
Total Testing Time	180 minutes
Total Number of Items	334

GENERAL SCIENCE
11 Minutes
25 Items
Description
Measures knowledge of the physical and biological sciences.

ARITHMETIC REASONING
36 Minutes
30 Items
Description
Measures ability to solve arithmetic word problems.

WORD KNOWLEDGE
11 Minutes
35 Items
Description
Measures ability to select the correct meaning of words presented in context and to identify the best synonym for a given word.

PARAGRAPH COMPREHENSION
13 Minutes
15 Items
Description
Measures ability to obtain information from written passages.

NUMERICAL OPERATIONS
3 Minutes
50 Items
Description
Measures ability to perform arithmetic computations in a speeded context.

CODING SPEED
7 Minutes
84 Items
Description
Measures ability to use a key in assigning code numbers to words in a speeded context.

AUTO & SHOP INFORMATION
11 Minutes
25 Items
Description
Measures knowledge of automobiles, tools, and shop terminology and practices.

MATHEMATICS KNOWLEDGE
24 Minutes
25 Items
Description
Measures knowledge of high school mathematics principles.

MECHANICAL COMPREHENSION
19 Minutes
25 Items
Description
Measures knowledge of mechanical and physical principles and ability to visualize how illustrated objects work.

ELECTRONICS INFORMATION
9 Minutes
20 Items
Description
Measures knowledge of electricity and electronics.

COUNSELOR'S MANUAL FOR THE ARMED SERVICES VOCATIONAL APTITUDE BATTERY FORM 14

JULY 1984

DoD 1304.12X

A. History of the ASVAB

Forerunners of the ASVAB date back to World War II. During World War II, each military service employed its own tests to screen recruits for eligibility and to classify and assign enlisted personnel. These tests included general measures of intellectual ability and specific aptitude measures that reflected the needs of each service.

The need for a common test for all the military began with the passage of the Selective Service Act in 1948, which mandated the development of a standard screening test for enlistment qualification. The *Army General Classification Test*, then the most widely used of the military instruments, was selected as the model for the new joint-service test. The new test, called the *Armed Forces Qualification Test* (AFQT), became operational in 1950.

Each service continued to administer a battery of aptitude tests for the initial assignment of recruits to technical schools or on-the-job training. These aptitude instruments were continuously evaluated and revised as training procedures and equipment changed.

The Air Force was the first service to test students within the high schools with the introduction of the *Airman Qualifying Examination* (AQE) in 1958. The AQE, an abbreviated version of the test then used by the Air Force to classify enlisted personnel, was designed to help recruiting efforts and to aid students in career exploration and decision making. The AQE was administered at no cost to students or schools. Shortly after the Air Force began using the AQE, the Army and Navy produced brief versions of their classification batteries that were used in high schools.

To prevent costly duplication of effort by the military and the schools, and to encourage equitable selection standards across the services, the Department of Defense, in 1966, directed all services to explore the development of a single, multipurpose military test battery for use in high schools. Objectives for this testing program included the following:

- Names and test scores of all 11th and 12th graders who were tested would be provided to military recruiters.
- An AFQT score could be derived from test scores to determine eligibility for entrance into the military.
- Test results would provide aptitude composite scores associated with success in military training programs for jobs in all services.
- Students would receive academic ability and vocational aptitude scores to assist them in career exploration and decision making.
- Schools would receive a multiple aptitude battery and supporting materials at no cost to schools or students.
- Students' interest in military careers would be stimulated through the test and associated materials.

The *Armed Services Vocational Aptitude Battery* (ASVAB) was designed to accomplish these objectives. ASVAB testing, as a joint military effort, began in 1968. Since that time, ASVAB testing has been well received by high schools throughout the United States. Presently, the ASVAB is given in about 14,000 schools. Approximately 1 million students take the ASVAB each year.

Various forms of the ASVAB have been produced. Some forms of the ASVAB have been used exclusively in schools. Other forms have been used for military qualification, placement, and research. The different forms that have been developed are identified in Table A-1.

Table A-1

ASVAB Forms by Dates Used

Years in Use	School Use	Military Use
1968-73	1	None
1973-76	2	3†
	(4 was never used)	
1976-84	5	6, 7 (until 1980)
1980-84		8, 9, 10††
1984-present	14	11, 12, 13

† The Air Force and Marine Corps were the only services to use Form 3. The Marine Corps used it only in 1975

††ASVAB-14 is parallel to Forms 8, 9, and 10 as well as to Forms 11, 12, and 13.