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Workforce Preparedness

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Abstract

[Excerpt] Concern about slackening productivity growth and deteriorating competitiveness has resulted in a new public focus on the skills and education of frontline workers. The introduction of Lean Production and Total-Quality-Management is apparently raising the cognitive demands placed on blue collar workers (Womack, Jones and Roos, 1990). Increasingly they are working in production cells in which every member of the team is expected to learn every job and to take on responsibilities formerly the sole province of supervisors, specialized technicians and industrial engineers. Higher order thinking and problem solving skills are believed to be in particularly short supply so much attention has been given to mathematics and science education because it is thought that these subjects are particularly relevant to their development.

Keywords
workforce, preparedness, productivity, growth, skill, work, management, job, supervisor, industrialized, human resource, nation, America, high school, student, education

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WORKFORCE PREPAREDNESS
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John Bishop

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WORK FORCE PREPAREDNESS

"Knowledge and Human Power are Synonymous"
--Francis Bacon

Concern about slackening productivity growth and deteriorating competitiveness has resulted in a new public focus on the skills and education of frontline workers. The introduction of Lean Production and Total-Quality-Management is apparently raising the cognitive demands placed on blue collar workers (Womack, Jones and Roos, 1990). Increasingly they are working in production cells in which every member of the team is expected to learn every job and to take on responsibilities formerly the sole province of supervisors, specialized technicians and industrial engineers. Higher order thinking and problem solving skills are believed to be in particularly short supply so much attention has been given to mathematics and science education because it is thought that these subjects are particularly relevant to their development.

The debate has been enlivened by the availability of comparative data on mathematics and science achievement of representative samples of secondary school students for many industrialized nations. American high school students lag far behind their counterparts overseas. In the 1960s, the low ranking of American high school students in such comparisons was attributed to the fact that the test was administered to a larger proportion of American than European and Japanese youth. This excuse is no longer valid. Figures 1 to 4 plot the scores in Algebra, Biology, Chemistry and Physics against the proportion of the 18-year old population in the types of courses to which the international test was administered (IAEEA 1988). 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 which represents only 13 percent of American 17 year olds, is roughly comparable to the 12 percent of Japanese youth who were in the 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 were taking college preparatory mathematics. 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 findings of the Second International Science Study are even more dismal. For example, the 25 % of Canadian 18-year olds taking chemistry know just as much chemistry as the very select 1 % of American 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).

(Figure 1-4 about here)
ALGEBRA RESULTS FOR 17-YEAR-OLDS

PERCENT CORRECT

FIGURE 2

BIOLOGY RESULTS FOR 18-YEAR-OLDS

STANDARD DEVIATION UNITS
Clearly, there is a large gap between the mathematical and scientific competence of young people from different nations. Do such gaps have major consequences for a nation's standard of living? In the view of many, it does:

Learning is the indispensable investment required for success in the "information age" we are entering. (National Commission on Excellence in Education, p. 7).

Morris Shamos, an emeritus professor of physics at New York University, on the other hand, argues that "widespread scientific literacy is not essential to... prepare people for an increasingly technological society" (Education Week, Nov. 23 1988. p. 28). Other commentators have questioned the relevance of algebra and geometry to the great majority of jobs that do not require technical training. It has been argued, for example, that since the great majority of employers do not currently use the new management techniques that are supposed to require a high skill work force, preparing young people for working in high performance work systems will make them unfitted for the boring and repetitive jobs that predominate in the labor market. This article examines whether evidence from labor markets supports the claims that schooling and academic achievement improve worker productivity and that the productivity benefits of quality schooling are increasing?

The paper is divided into two parts. Part 1 examines the productivity effects of academic competencies in representative samples of current jobs--ie. jobs which presumably reflect Taylorist-Fordist work environments rather than the new high performance or lean production paradigm. Part 2 looks at trends in skill demands of jobs, in supplies of highly skilled workers and in the payoff to skill. Recommendations for future research are presented in bold italics throughout the article.

I. THE IMPACT OF ACADEMIC COMPETENCIES ON WORKER PRODUCTIVITY IN CURRENT JOBS

The standard way of assessing the impact of a worker trait on productivity is to infer its effect by studying its effect on wage rates. That is what is attempted in section 1.1. The surprising finding is that competence in mathematical reasoning, science and language arts has almost no effect on wage rates during the first 8 years after graduating from high school. While These results suggest an immediate explanation for the poor performance of American students in science and higher level mathematics--the absence of significant rewards for the competencies. They appear, however, to provide only very weak support for the Excellence Commission's recommendations.

The reports recommending educational reform, however, make claims about the productivity effects not the wage rate effects of science, mathematics and language arts competency and these effects are not necessarily the same when the specific competencies of students are not signalled to the labor market by a
credential (as is the case for math and science achievement in US high schools).

Sections 1.2, 1.3 and 1.4, therefore, tackle 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 recommendations for better preparation in math and science, but they also reinforce the findings from the analysis of wage rates regarding the important role of technical competence in blue collar, craft and technician jobs.

1.1 THE IMPACT OF ACADEMIC COMPETENCIES ON WAGES?

How large are the economic returns to the academic competencies taught in high school? When do these returns appear? The traditional way to address this issue is by estimating models predicting wage rates and earnings of young adults 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.

The Youth Cohort of National Longitudinal Survey (NLS) is a good data for analyzing this issue because it contains subtest scores on 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. Even though the ASVAB was developed as an "aptitude" test, the current view of testing professionals is that:

Achievement and aptitude tests are not fundamentally different....Tests at one end of the aptitude-achievement continuum can be distinguished from tests at the other end primarily in terms of purpose. For example, a test for mechanical aptitude would be included in a battery of tests for selecting among applicants for pilot training since knowledge of mechanical principles has been found to be related to success in flying. A similar test would be given at the end of a course in mechanics as an achievement test intended to measure what was learned in the course (National Academy of Sciences Committee on Ability Testing 1982 p.27)."

The Arithmetic Reasoning and Mathematics Knowledge subtests of the ASVAB were combined into a single mathematical reasoning construct and Word Knowledge and Paragraph Comprehension were combined into a Verbal construct. 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. A population standard deviation on these tests is approximately equal to 4 to 5 grade level equivalents of learning.

Two measures of labor market success were studied: the log of the 1986 hourly wage rate in the current or most recent job and the log of yearly earnings for 1985 when they exceed $500. 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 was included in the estimating equations.

Holding academic competencies in 1980 constant, female high school dropouts with 10 years of schooling earned 10 percent less than high school graduates and college graduates earned 42 percent more. Male high school drop outs earned 21 percent less than high school graduates and college graduates earned 35 percent more. The effects of our measures of academic and technical achievement are summarized in Table 1 (see Bishop 1991 for a more complete description of the results).

The results for young men were as follows—high level academic competencies do not have positive effects on wage rates and earnings. The mathematics reasoning, verbal and science composites all had negative effects on wage rates and earnings. Speed in arithmetic computation had significant positive effects on labor market success of young men. This competency, however, is a lower order skill that is not (and should not be) a focus of high school mathematics (National Council of Teachers of Mathematics 1989). In addition, the technical composite had large and significant positive effects on wage rates and earnings.

For young women, speed in arithmetic computation and mathematical reasoning ability significantly increased wage rates and earnings. Verbal competence had very small effects and science and technical scores had no effects.

This pattern of results 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. Measures of non-cognitive achievement in high school such as rates of attendance, extracurricular activities and an absence of discipline problems also fail to have positive effects on initial success in the labor market for the non-college bound in High School and Beyond data (Hotchkiss 1986, Bishop, Blakemore and Low 1985, Rosenbaum 1989).

Rewards for academic achievement do, however, grow with age. Apparently, certain types of academic achievement improve access to jobs offering considerable training and enable workers to get more out of the training. Furthermore, academic achievement is poorly signalled 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. When age has been interacted with an overall indicator of academic achievement positive interactions was obtained by Hauser and Daymont (1977), Taubman and Wales (1975), and Murnane, Willett and Levy (1991). Bishop's (1991) analysis of NLSY found, however, that it is the reward to technical competence and computational speed which grows with age not the reward to mathematical reasoning, verbal and science
subtests of the ASVAB.

These results suggest an immediate explanation for the poor performance of American students in science and mathematics and possibly even for the absenteeism and discipline problems that plague American high schools. For the 80 percent of youth 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 and significantly delayed.

Do these findings also imply that if a way could be found to recruit a high quality engineering and scientific elite (possibly by recruiting scientists and engineers from abroad or early identification of talented youth), there would be little need to worry about the poor math and science preparation of most American youth. It is to this question I now turn.

### 1.2--IS THERE REASON TO EXPECT WAGE EFFECTS OF SPECIFIC COMPETENCIES TO BE THE SAME AS THEIR PRODUCTIVITY EFFECTS?

Are the productivity effects of achievement in science, mathematical reasoning and English essentially zero in the types of jobs occupied by most young workers? What are the effects of technical competence on productivity?

One approach to these questions is to ask employers directly about the nature of the tasks performed in specific jobs. When the owners of small and medium sized business in the United States were asked how frequently the employee most recently hired by their firm needed to "use knowledge gained of chemistry, physics or biology" in their job, 74 percent reported that such knowledge was never required and only 12 percent reported such knowledge was used at least once a week.¹ Asked how frequently the new employee had to "use algebra, trigonometry or calculus", 68 percent reported that such skills were never required by the job and only 12 percent reported they were used at least once a week.

The skills used by entry level workers at small and medium sized firms, however, are not decisive evidence regarding employer needs for three reasons. First, the low levels of scientific and mathematical competence in the work force available to small and medium sized firms may have forced them to put off technological innovations such as statistical process control that require such skills and to simplify the functions that are performed by workers who lack technical training. If better educated workers were available, entry level workers might be given greater responsibility and become more productive. Second, the study just quoted does not tell us what is happening at large firms or in the jobs occupied by long tenure employees at small firms. The CEOs of many large technologically progressive companies such as Motorola and Xerox are insisting that their factory jobs now require workers who are much better
prepared in math and science than ever before. Third, employers may not realize how the knowledge and skills developed in high school science and mathematics classes contribute to productivity in their jobs. Not knowing which employee possesses which academic skill, they would have no way of learning from experience which scientific and mathematical skills are helpful in doing a particular job. Science and mathematics are thought to teach thinking, reasoning and learning skills applicable outside the classroom and the laboratory. If these skills are indeed successfully developed by these courses, productivity might benefit even when there are no visible connections between job tasks and course content.

A second approach to estimating the effect of a trait on productivity, one favored by economists, has been to infer its effect by studying its effect on wage rates. Such an approach is not justified in this case. 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 signalled to the labor market. When competencies which are highly correlated with each other are poorly signalled to the labor market, American employers have a difficult time figuring out which competencies they need and an even more difficult time finding high school graduates with the particular constellations of academic abilities they may believe they need. As a result, the relationship between their wage offers and the imperfect signals of worker competencies available to them is unlikely to reflect the true relationship between productivity and these competencies.

The Signalling Failure in the United States

In Canada, Australia, Japan, and Europe, educational systems administer 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 Baccalaureate, for example, there are four different levels of pass: *Très Bien*, *Bien*, *Assez Bien* and a regular pass (Noah and Eckstein 1988). Grades on these exams are requested on job applications and typically included on one's resume. While employers report they pay less attention to exam grades when hiring workers who have been out of school many years, it is nevertheless significant that the information remains on one's resume long after graduation from secondary school.

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 (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
measuring basic skills, 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 for the jobs at that firm. During
the 1970s 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. Litigation costs
and the potential liability were 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
became 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 2014
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
2.9% of the hiring decisions studied (Bishop and Griffin, forthcoming).

Other potential sources of information on effort and achievement in
American high school are transcripts and referrals from teachers who know the
applicant. Both are under-used. 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 5.2% of the cases and referred by someone else
in the high school in only 2.7%. Transcripts had been obtained prior to the
selection decision for only 14.2% of the hires of people with 12 or fewer years
of schooling. Transcripts are not obtained because differing grading standards
in different schools and courses make them difficult to interpret, because many
high schools are not responding to requests for the information and because there
are generally long delays before the transcripts arrive.

The only information about school experiences requested by most American
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. 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.

But 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 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), the unwillingness
of workers to risk that their wage may be reduced if their supervisor decides
they are not doing a good job (Stiglitz, 1974), the absence of any real danger
that one's best employees will be raided because the skills of these top
performers can be fully used only within 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
better than average 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 4 % more
after a year at small non-union firms and they had no wage advantage at unionized
plants with 100+ employees and non-union plants with more than 400 employees
(Bishop, 1987a). Over time there is some tendency for those with high test
scores and good grades to be promoted more rapidly and to be employed more
continuously (Wise 1975, Grubb 1990, Bishop 1990). Since, however, worker
productivity cannot be measured accurately and cannot be signalled 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. Research on the determinants of job
performance in the US military is examined in section 1.3. Research on the
determinants of job performance in the civilian sector is examined in section
1.4.
1.3--THE IMPACT OF ACADEMIC AND GENERIC TECHNICAL COMPETENCIES ON THE JOB PERFORMANCE IN THE AMERICAN MILITARY

Direct estimates of the relative importance of different competencies were obtained by estimating models in which measures of job performance in the military are regressed on subtest scores of the ASVAB battery. These results will then be compared to the wage and earnings effects of ASVAB subtests presented in section 1.1. 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?

Most of the military's validity research has involved correlating scores on ASVAB tests taken prior to induction with final grades in occupationally specific training courses (generally measured at least 4 months after induction). When predictor and criterion are both paper and pencil tests, however, relationships may be inflated by common methods bias. This review will, therefore, concentrate on studies which relate ASVAB test scores to a direct hands-on measure of job performance--the Skill Qualification Test (SQT).

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 (Maier and Grafton, 1981, pp. 4-5).

The SQT is about as good a measure of the job performance in a Taylorist work setting as is available.

Maier and Grafton Data on Marine Recruits

A reanalysis of Maier and Grafton's data on the relationship between ASVAB 6/7's ability to predict SQTs was conducted (Bishop 1990). Selection into the military 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.

Regressions were estimated for each of the nine major categories of Military Occupational Specialties. 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 2. 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.

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. As one might anticipate, these subtests had no effect on job performance in clerical jobs. However, they had very substantial effects on job performance in all the other occupations. The impact of a one population 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, of .473 SD in mechanical maintenance jobs, of .450 SD for missile battery operators and food service workers and of .170 SD in unskilled electronics jobs. If we assume the SD of true productivity averages 30 percent of the mean wage in these jobs, the impact of a simultaneous one SD increase in all four technical subtests is 11.5 percent of the wage (or about $2875 per year) averaging across the six non-clerical non-combat occupations. The present discounted value of such a learning gain is about $50,000 (using a 5 percent real rate of discount). This is consistent with the wage rate findings presented earlier. These results imply that broad technical literacy is essential for workers who use and/or maintain equipment that is similar in complexity to that employed in the military.

The results for the academic subtests contrast sharply with the wage rate regressions for young males. With the sole exception of the mechanical maintenance MOS cluster, the two mathematical reasoning subtests have much larger effects on SQTs than on wage rates. The Math Knowledge subtest assessing algebra and geometry is responsible for most of this effect. Assuming that the standard deviation of true productivity is 30 percent of the wage, the impact of a simultaneous one SD increase in both mathematics reasoning subtests is 6.4 percent averaging across all seven non-combat occupations. The effects of
Mathematical reasoning is substantial and unlike the wage rate findings much larger than the effects of computational speed.

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 four clusters and in pooled data. 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. Assuming that the standard deviation of true productivity is 30 percent of the wage, the effect (averaged across the seven noncombat occupations) of a one SD increase in test scores is 2 percent of the wage for science and 1.9 percent for word knowledge when mathematics and technical competence is held constant.

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 or 10th grade. Consequently, a productivity increase of about 2 percent per population SD on the test appears to be only a modest return. This 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. On the other hand, a 2 percent increase in productivity should not be dismissed as unimportant. It is about $500 per worker per year and has a present discounted value of about $8700. (using a 5 percent real rate of interest and a 40 year working life). Studies using other samples of military recruits yield similar findings (John P. Campbell 1986; Wise, McHenry, Rossmeissl and Oppler 1987).

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. The military is currently conducting a massive high quality study of the determinants of job performance in the military called Project A. Eighty percent of the jobs held by enlisted personnel in the military have civilian counterparts, so much of the Project A research has application to the civilian labor market. If the lessons are to be learned, however, research resources will have to be directed at that objective and versions of the ASVAB must be made available to employers.

1.4--The Impact of Academic and Technical Competence on Job Performance in the Civilian Sector

Ghiselli's Review of Validation Research Prior to 1973

Over the last 50 years, industrial psychologists have conducted hundreds of studies, involving many hundreds of thousands of workers, on the relationship
between supervisory assessments of job performance and various predictors of performance. In 1973 Edwin Ghiselli published a compilation of the results of this research organized by type of test and occupation. Table 3 presents a summary of the raw validity coefficients (correlation coefficients uncorrected for measurement error and restriction of range) for six types of tests: mechanical comprehension tests, "intelligence" tests, arithmetic tests, spatial relations tests, perceptual accuracy tests and psychomotor ability tests. As pointed out earlier, mechanical comprehension tests assess material that is covered in physics courses and applied technology courses such as auto mechanics and carpentry. The intelligence tests used in this research were paper and pencil tests assessing verbal and mathematical competency.

Intelligence tests were the best predictors of the performance of foreman. For craft occupations and semi-skilled industrial jobs, the mechanical comprehension tests are more valid predictors of job performance than any other test category. For protective occupations, mechanical comprehension tests and intelligence tests had equal validity. For clerical jobs, the best predictors of job performance were tests of intelligence, arithmetic and perceptual accuracy. These results are consistent with the analysis of job performance in the military data reported in Table 2.

Analysis of GATB Validation Studies

More recent data on what predicts job performance is available from the US Employment Service's program for revalidating the General Aptitude Test Battery (GATB). This data set contains data on job performance, the 9 GATB "aptitudes" and background data on 36,614 individuals in 159 different occupations at 3052 different employers. Professional, managerial and high level sales occupations were not studied but the sample is quite representative of the 71,132,000 workers in the rest of the occupational distribution. It ranges from drafters and laboratory testers to hotel clerks and knitting-machine operators.

Since a major purpose of these validation studies was to examine the effects of race and ethnicity on the validity of the GATB, the firms that were selected tended to have an integrated workforce in that occupation. Firms that used aptitude tests similar to the GATB for selecting new hires for the job being studied were excluded. This last requirement did not result in the exclusion of many firms.

The workers in the study were given the GATB test battery and asked to supply information on their age, education, plant experience and total experience. Plant experience was defined as years working in that occupation for the current employer. Total experience was defined as years working in the occupation for all employers. The dependent variable was an average of two ratings (generally two weeks apart) supplied by the worker's immediate
supervisor. The Standard Descriptive Rating Scale obtains supervisory ratings of 5 aspects of job performance (quantity, quality, accuracy, job knowledge and job versatility) as well as an "all around" performance rating.

The mathematical achievement index was an average of normalized scores on the same arithmetic reasoning test and on a numerical computations test. Verbal ability was assessed by a vocabulary test. Perceptual Speed was a normalized sum of the P and Q aptitudes of the GATB. Psychomotor Ability was a normalized sum of the K, F and M aptitudes of the GATB. The GATB does not contain subtests similar to the technical subtests of the ASVAB.

Because wage rates, average productivity levels and the standards used to rate employees vary from plant to plant, mean differences in ratings across establishments have no real meaning. Therefore, normalized ratings deviations were predicted by deviations from the job/establishment's mean for gender, race, Hispanic, age, age squared, plant experience, plant experience squared, total occupational experience, total occupational experience squared, schooling and test composites.3

The results of estimating the model are presented in Table 4. Mathematical achievement was clearly the most important determinant of job performance for all occupational categories except operatives. Uncorrected for the downward biasing effects of selection on the dependent variable, a one population standard deviation increase in mathematics achievement raise job ratings by .16 to .22 SDs in technical, craft, clerical and service jobs. Verbal ability had no effect on job performance in craft and operative jobs. In clerical and service jobs its impact is roughly 40 percent of mathematical achievement's effect.

Spatial ability had significant positive effects on performance only for craft occupations. Perceptual speed had small effects on job performance, but the coefficients are nevertheless significant in all but technical occupations (where the sample is quite small). Psychomotor skills were significantly related to performance in all occupations but in the better paid and more complex jobs the magnitude of the effect was only about one-third of that of verbal and mathematical achievement together. The effect of psychomotor skills was larger in the two least skilled occupations--operatives and service except police and fire. For operatives the impact of psychomotor skills was roughly comparable to the impacts of mathematical and verbal achievement. These results are consistent with previous studies of these and other data sets (Hunter 1983).

Models were estimated containing squared terms for academic achievement and psychomotor skills but these additions did not produce significant reductions in the residual variance. When test scores are controlled, selection effects result in years of schooling having very low and sometimes negative partial correlations with job performance. On the issue of racial bias when basic skills tests are used in selection, the National Academy of Sciences concluded:

Use of a single prediction equation relating GATB scores to
performance criteria for the total group of applicants would not give predictions that were biased against black applicants.... A total-group equation is somewhat more likely to overpredict than to underpredict the performance of black applicants (Hartigan and Wigdor, 1989, p. 188).

The results presented in Table 4 are consistent with the National Academy of Sciences finding. Holding test scores and work experience constant, blacks in 5 of the 6 occupations are rated significantly less productive by their supervisors than white workers doing the same job.

The effects of occupational experience and tenure are quite substantial for all occupations. The negative coefficients on the square terms for occupational experience and tenure imply they are subject to diminishing returns. For workers who have no previous experience in the field, the expected gain in job performance (i.e. the combined effect of tenure and occupational experience) is about 12-13 percent of a standard deviation in the first year and about 8-9 percent of an SD in the fifth year. The effect of tenure on job performance stops rising and starts to decline somewhere between 16 and 24 years of tenure. Increases in occupational experience lose their positive effect on performance even later--at 37 years for operatives, at over 55 years for craft workers and high skill clerical workers and at 19-31 years for other occupations. Except for technicians, age has large curvilinear effects on job performance as well. Holding tenure and occupational experience constant, age had a significant positive effect on job performance in all except technical occupations. In these occupations, twenty year olds with no experience at all in the field were 7.2 to 10.3 percent of an SD more productive than 18 year olds with no experience in the field. Thirty year olds with no occupational experience were 4.7 to 7.4 percent more of an SD more productive than 28 year olds with no experience in the field.

The substantial effects of age and previous occupational experience on job performance are consistent with current hiring practices which give great weight to these job qualifications. These results suggest that a job applicant who has age and relevant work experience in his favor but low test scores will often be preferable to a young applicant who has high test scores but no relevant work experience. This is particularly likely to be the case if turnover rates are high for the productivity benefits of age and previous relevant work experience are large initially but diminish with time on the job.

Bias Problems in Validity Research: It should be recognized that the validity literature in general and this model in particular do not yield unbiased estimates of the true structural relationships prevailing in the full population (Brown 1978; Mueser and Maloney 1987). Validity studies based on examining which job incumbents are most productive are subject to bias for three reasons: omitted variables, the selection process that determines which new hires were retained by the firm and the selection process by which members of the population were hired for the job.
While the model described above is a more complete specifications of the background determinants of job performance than is typically found in the validity literature, it lacks controls for important characteristics of the worker which effect worker productivity. Examples of things left out of the model are occupationally specific schooling, grades in relevant subjects in school, reputation of the school, the amount and quality of on-the-job training, performance in previous jobs, character traits like reliability and need to achieve, physical strength and a desire to work in the occupation. Exclusion of these variables from the model causes bias in the coefficients of included variables.

The second problem arises from the fact that job performance outcomes have been used to select the sample used in the analyses. Since incompetent workers were fired or induced to quit and high performing workers were probably promoted to jobs of a higher classification, the job incumbents used in this study were a restricted sample of the people originally hired for a job. The systematic nature of attrition from the job substantially reduces the variance of job performance and biases coefficients of estimated job performance models nearly half the way to zero (Bishop 1988).

The third problem is biases introduced by the selection that precedes the hiring decision. If hiring selections were based entirely on X variables included in the model, unstandardized coefficients would be unbiased and correction formulas would be available for calculating standardized coefficients and validities. Unfortunately, however, incidental selection based on unobservables such as interview performance and recommendations is very probable (Thorndike 1949; Olson and Becker 1983; Mueser and Maloney 1987). In a selected sample like accepted job applicants, one cannot argue 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 12 years of schooling, 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 12 years of schooling. 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. Consequently, the results just presented should not be viewed as estimates of the structural effect of schooling and previous work experience on worker productivity (Weiss and Landau 1987).

The test score results are not similarly biased, however, because very few
firms use cognitive tests to select workers and those that do were not included in the sample of firms studied specifically to avoid this source of bias. Mueser and Maloney (1987) experimented with some plausible assumptions regarding the hiring selection process and concluded that coefficients on education were severely biased but that coefficients on test scores were not substantially changed when incidental selection effects were taken into account. There is a need for a great deal more research on the determinants of job performance, turnover and initial hiring selections which makes use of the latest econometric methods. I suspect that in available data sets there is no real solution to the selection problem, but I hope I am wrong. This is a field which could benefit from additional simulation analyses of the effects of various selection processes similar to the Mueser and Maloney paper.

The revision of the GATB and the Employment Service's referral system recommended by the National Academy of Sciences (Hartigan and Wigdor 1989) is going to require a massive expansion of validity research. Hopefully, this research program will add to our understanding the effects of technical competence, higher level mathematical and scientific skills and occupational experience and how these patterns vary across occupations. Criterion data should be expanded to include wage rates, absenteeism, turnover intentions, employee suggestions for increasing sales or improving productivity and ratings of the employee's ability to work effectively as part of a team and the employees success in relating to customers and suppliers.

Prospective validity studies are needed to refine and empirically validate instruments measuring domain specific knowledge (eg. electronics, auto mechanics) and to expand the criterion demand to include turnover and promotions. Such models would allow us to study the effects of the selective nature of turnover on estimates of the relationship between worker competencies at time of hiring and subsequent job performance.

Policy Responses to the Lack of Rewards for Academic Achievement

A number of education and business leaders have pointed out that the absence of labor market rewards for achievement in school is a major contributor to the public, parental, and student apathy about the low levels of achievement in American high schools. Recognizing this problem, the Secretary of Labor's Commission on Workforce Quality and Labor Market Efficiency recommended that "The business community should...show through their hiring and promotion decisions that academic achievements will be rewarded. (1990 p. 3)"

The President's new education initiative has responded to this problem by proposing that "Employers will be urged to pay attention to [the new American Achievement Tests] in their hiring" (U.S. Department of Education 1991). The new American Achievement tests now under development are not conventional multiple choice tests. The assessments would be designed to evaluate the application of
higher order thinking skills to realistic problems. Essays would be written on science, literature and history topics and portfolios of the student's best work might also be evaluated. The assessments would be aligned with course content so that studying and preparing for the assessment would result in the student developing competencies that are the objective of the course. The shift away from multiple choice tests towards what educators call "authentic" assessment appears to be an essential part of the bargain that is being struck between the Department of Education, the 50 Governors and the education community. High stakes assessments inevitably influence teaching and curricula. Most educators feel that many important educational goals (eg. the ability to communicate in writing) cannot be assessed in a multiple choice format. Consequently, new forms of more "authentic" assessment are an essential part of a high stakes assessment system like the one proposed by the President and the National Governors Association or the one being proposed by the SCANS Commission (Secretary's Commission on Necessary Skills 1991).

Will, however, employers play the part that has been assigned to them and base hiring decisions, in part, on the results of these new assessments? Without evidence that these assessments are valid predictors of job performance, substantial use of these assessments by employers is unlikely. There is a great deal of evidence that multiple choice tests of verbal and mathematical competence such as the GATB and the ASVAB predict job performance in Tayloristic work environments. There is, at present, no evidence on whether constructed response tests assessing higher order thinking skills, assessments employing essay answers and the yet to be developed assessments of SCANS competencies have a similar ability to predict job performance. High priority should be given to research which examines these issues which focuses in particular on how validity patterns differ across occupations and between Tayloristic and High Performance work sites.

Assuming that employers can be persuaded to use measures of high school accomplishment in hiring, how are these accomplishments best signalled to the labor market? Probably the primary mechanisms will be direct application at employers (using competency profiles as credentials) and through the computerized job bank similar to the Worklink system being piloted in Tampa, Florida sponsored either by an ETS like organization or by state Departments of Education. Research also needs to be undertaken on how indicators of accomplishment in high school would be incorporated into the Employment Service's system of referring workers to jobs.
II. TRENDS IN PAYOFF TO ACADEMIC COMPETENCE

The evidence just reviewed implies that even in a Tayloristic-Fordist economy, mathematical and scientific competence contributes significantly to productivity. The case for higher standards in education, thus, does not depend on employers immediately switching to lean production and high performance work systems. The pace of this transition and the magnitude of its impact on skill demands cannot be predicted at present. More research is required on this issue.

The second argument for upgrading the quality of K-12 education is the need to increase the number of students who enter and complete college and in particular increase the supply of scientists and engineers who are so critical to the nation's competitiveness. It is to this issue we now turn.

2.1--THE PAYOFF TO COLLEGE: IS THERE A SHORTAGE OF COLLEGE GRADUATES?

In the American labor market shortages of a particular type of labor cause its relative wage to rise; surpluses cause relative wages to decline. The wage premium for attaining a college degree fell during the 1970s--a period of surplus for college graduate labor--but then rose dramatically during the 1980s. In May/June CPS data, real hourly wage rates of workers with 16 years of schooling and 1 to 10 years of experience rose 14.7 (12.2) percent for males (females) between 1980 and 1988 while real wage rates of workers with 12 years of schooling and similar levels of experience fell 16 (5.4) percent for males (females) (Kosters 1989). Blackburn, Bloom and Freeman (1989) report that between 1979 and 1987 the real full time earnings of 25 to 34 year old white male college graduates rose 9.2 percent while the earnings of their high school graduate counterparts fell 9.4 percent. Katz and Murphy's (1990) study of March CPS data found that between 1980 and 1987 real weekly earnings of college graduates with 1 to 5 years of work experience rose 10.6 (12.9) percent for females (males) while the real earnings of high school graduates with similar levels of experience fell 3.2 and 15 percent respectively. They conclude that "changes in education differentials ...reflect changes in 'skill prices' rather than changes in group composition. We find that rapid secular growth in the relative demand for 'more skilled' workers is a key component of any consistent explanation..." of these changes in wage structure. While unemployment rates for college graduates were unchanged at very low levels (1.5 percent for 25-64 year olds) in both 1980 and 1988, they rose from 4.7 to 5.4 percent for high school graduates and from 7.4 to 9.2 percent for those who had not completed high school (Freeman 1991).

Not all analysts, however, take the view that the nation is currently experiencing a shortage of college graduates. Ronald Kutscher, Associate Commissioner of the Bureau of Labor Statistics, argues that there existed "an
oversupply of college graduates during the 1980's (Kutscher 1991)." He sights as evidence for this view recent increases in the number of people with 16+ years of schooling who are coded by the Current Population Survey as having jobs which are not "traditional" for holders of a bachelors degree. He reports that between 1983 and 1988 workers claiming to have completed 16 years of schooling increased by 41,000 in secretarial and typist jobs, by 59,000 in factory operative jobs, and by 6,000 in bartender, waiter and waitress jobs. But what about the opposite kind of mismatch: workers who have substantially fewer years of schooling than are required by the job. This kind of mismatch also increased between 1983 and 1988. The number of workers claiming to have fewer than 16 years of schooling increased by 23,000 among physicians, by 18,800 among lawyers and judges, by 14,500 among college teachers, by 125,000 among other teachers and by 99,000 among mathematical and computer scientists (U. S. Bureau of Labor Statistics 1990). Don't these statistics imply a growing shortage of qualified college graduate workers?

But one should not give much credence to any of these estimates of mismatches between schooling and occupation. The reporting and coding of occupation is quite unreliable. Those coded as a professional, a technician or manager by a Census interviewer have a 15 to 21 percent chance of being coded in a lower level occupation by a second interviewer a few months later (U.S. Bureau of the Census 1972). Ten percent of those who report completing 16+ years of schooling also claim not to have received a bachelors degree. Errors in measuring education are also quite common and the incidence of such errors appears to have risen during the 1980's (Bishop and Carter 1991). Many of the discrepancies between an individual's schooling and occupation found in CPS data are caused by reporting and coding errors. How else can one explain the 9.6 percent of college teachers and the 5.4 to 6.5 percent of lawyers, physicians and secondary school teachers who claim not to have completed 16 years of schooling (U.S. Bureau of Labor Statistics 1990, Table F-3). The unreliability of individual measures of occupation and education means that counts of mismatches between schooling and occupation derived from microdata have almost no validity at all. The fact that the BLS keeps track of only one kind of mismatch makes matters worse. True mismatches between education and occupation are a lot less common than these statistics suggest.

This is not to deny that mismatches occur. College graduates are incredibly diverse and seek work in very distinct labor markets. College graduates who major in subjects which have little value in the labor market, who get C's and D's in undemanding courses, who are not geographically mobile, who have a substance abuse problem or who make a poor impression in interviews, will sometimes have to accept jobs which do not appear to "require" a college degree. These graduates are included in the averages and despite the drag they represent on the mean, the average college graduate is doing very well and compared to
those who did not go to college she is doing extremely well.

Projecting the Future: The wage premium for attaining a college degree is higher now than ever before. Despite the increase in college attendance rates stimulated by the high wage premium, the supply of college graduate workers is fated to grow more slowly in the 1990s than in the 1980s. The cause of the slowdown in supply is the small size of the college age cohort during the 1990s and the growing number of retirements by workers who obtained degrees during the 1950s under the GI bill. The Bureau of Labor Statistics predicts that the rate of growth of demand for college graduate skills will slow as well (Silvestri and Lukasiewicz 1991). If their prediction is correct, the current balance between the growth of supply and demand will be maintained.

However, the BLS projection methodology is unable to anticipate the within industry shifts in occupational employment demand that are driving the explosion of college level occupations. The BLS grossly underpredicted the growth of professional, technical and managerial occupations during the 1980s. Projected to account for 28 percent of employment growth, these occupations actually accounted for 52 percent of growth between 1978 and 1990. Their projections of growth for high level occupations during the 1990s are probably biased as well. Using an econometric methodology of projecting occupational shares, Bishop and Carter (1991) predict that the growth of professional, technical and managerial employment will not diminish during the 1990s. If their prediction is correct, the labor market for college graduates, is fated to become even tighter than it is now.

2.2--Which College Specialties Generate the Largest Economic Payoff?

College graduates who have majored in physical science, engineering and business earn substantially more than graduates who have majored in education, humanities or social sciences other than economics. The first four columns of Table 5 present data from the College Placement Council on how field of study effected the starting salaries received by college graduates whose placement outcomes were reported to the school's placement office for 1963, for 1969-70, for 1979-80 and for 1989 (College Placement Council 1985; 1991). The differences across field are sometimes as large as the wage gains accruing to those obtaining higher level degrees. Relative to majors in humanities and social sciences other than economics, engineers received 45-70 percent higher starting salaries in 1991, computer scientists received a 38 percent premium, physical science majors received a 24 percent premium and business majors received a 10 percent premium. Studies of the earnings of adults indicate that the salaries of business majors tend to catch up with the engineers, but education and liberal arts majors remain far behind those with engineering, physical science and business degrees (see column 5 and 6).

Largely because of these large wage differentials, there has been a
dramatic growth in the relative supply of graduates in engineering, computer science and business administration. For males degrees in engineering, computer science and business which accounted for 33.2 percent of all BA's in 1973 rose to 50.8 percent of all bachelors degrees in 1986. For women degrees in engineering, computer science and business grew from 3.5 percent to 26.6 percent of degrees awarded. In 1973 degrees in education, humanities and social science accounted for 50.5 percent of bachelors degrees awarded to men and 83.5 percent of the bachelors degrees awarded to women. By 1986 these percentages had dropped to 35.1 percent and 54.7 percent respectively. As a result, the ratio of degrees awarded in engineering and computer science to degrees awarded in humanities, social science or education grew 5.2 percent per year in the 1970s and 10.7 percent per year in the 1980s. The ratio of business degrees to humanities, social science, and education degrees grew 5.8 percent per year in the 1970s and 5.1 percent in the 1980s.

The very rapid growth during the last 20 years of the relative supply of college graduates trained in business and engineering fields has surprisingly not significantly diminished the wage premiums these fields command. Trends in starting wage premiums for business and technical degrees can be followed by comparing the first four columns of Table 5. Relative to humanities majors, wage premiums for engineering degrees grew dramatically during the 1970s and then dropped slightly by 1991, but remained significantly above the levels that had prevailed in the 1960s. Wage premiums for chemistry and mathematics majors over humanities majors rose from 17 percent in the 1960s to 36 percent in 1979-80 and then fell to 24 percent in 1991. Starting wage premiums for business majors rose from essentially zero in the 1960s to 10-11 percent during the late 1970s and 1980s.

Trends in the effect of college major on salaries of college graduates who have been working for many years can be examined by comparing columns 5 and 6. In 1967 male college graduates 21-70 years old who had majored in business earned 28 percent more and engineers 52 percent more than those who had majored in humanities (U.S Bureau of the Census, 1967). In 1964 college graduates who had majored in physical science earned 93 percent more, engineers earned 114 percent more and business majors 103 percent more than humanities majors (U.S. Bureau of the Census, 1987). Clearly, the economic payoff to business and technical education is considerably greater than the payoff to majors in the humanities and social sciences other than economics and the advantage of these fields of study has not diminished appreciably in the face of the massive increase in the number of students choosing these fields of study. Clearly, there has been a substantial shift in market demand favoring graduates with business and technical degrees over graduates with liberal arts and education degrees. In addition, the most important externalities of university education--technological advances--are generated by the education of scientists and engineers.
Final Thoughts: Part 1's review of the evidence on the wage and productivity payoff to various skills generated very similar conclusions. Mathematical and technical skills of average workers generate much greater wage and productivity benefits than verbal and scientific skills. The policy implications of these findings are that mathematics particularly algebra, geometry and statistics should receive much greater emphasis in the secondary school curriculum. Students also need to be given more exposure to computers and other technologies. There is no data on the productivity consequences of greater knowledge of history, geography and foreign languages. The economic case for greater emphasis on English and science in high school rests largely on the pipeline argument--these competencies are necessary for success in college. These conclusions must for now be tentative for much more research is required on the contribution of particular skills and competencies to productivity of individuals and competitiveness of nations.
Table 1

Effect of Competencies on
Log Wage Rates and Earnings

<table>
<thead>
<tr>
<th>Competencies</th>
<th>Technical Speed</th>
<th>Clerical Speed</th>
<th>Computation Speed</th>
<th>Math Reasoning</th>
<th>Verbal</th>
<th>Science</th>
<th>$R^2$</th>
<th>Number of Obs</th>
<th>F Test on Academic Coef.</th>
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</thead>
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<tr>
<td><strong>MALES</strong></td>
<td></td>
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<td></td>
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<tr>
<td>Wages--1986</td>
<td>.080***</td>
<td>.005</td>
<td>.064***</td>
<td>-.007</td>
<td>-.021</td>
<td>-.008</td>
<td>.264</td>
<td>4272</td>
<td>4.35**</td>
</tr>
<tr>
<td></td>
<td>(6.10)</td>
<td>(.51)</td>
<td>(5.75)</td>
<td>(.51)</td>
<td>(1.49)</td>
<td>(.60)</td>
<td></td>
<td></td>
<td>neg</td>
</tr>
<tr>
<td>Earnings-1985</td>
<td>.133***</td>
<td>.004</td>
<td>.119***</td>
<td>-.037*</td>
<td>.014</td>
<td>-.021</td>
<td>.358</td>
<td>4564</td>
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<td></td>
<td>(6.26)</td>
<td>(.21)</td>
<td>(6.55)</td>
<td>(1.78)</td>
<td>(.61)</td>
<td>(.93)</td>
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<tr>
<td><strong>FEMALES</strong></td>
<td></td>
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<td></td>
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<tr>
<td>Wages--1986</td>
<td>.006</td>
<td>.028***</td>
<td>.024**</td>
<td>.027*</td>
<td>.027*</td>
<td>.012</td>
<td>.275</td>
<td>4080</td>
<td>12.6***</td>
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<td></td>
<td>(.31)</td>
<td>(2.60)</td>
<td>(2.04)</td>
<td>(1.94)</td>
<td>(1.75)</td>
<td>(.81)</td>
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<tr>
<td>Earnings-1985</td>
<td>-.020</td>
<td>.022</td>
<td>.053***</td>
<td>.065***</td>
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<td>.009</td>
<td>.328</td>
<td>3888</td>
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<tr>
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<td>(.64)</td>
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<td>(1.40)</td>
<td>(.34)</td>
<td></td>
<td></td>
<td>pos</td>
</tr>
</tbody>
</table>

Source: Analysis of the 1986 National Longitudinal Survey of Youth. Sample excluded individuals who were in the military in 1979 but included students both full and part time if they had a job in 1985 or 1986. School attendance was controlled by four separate variables: a dummy for respondent is in school at the time of the interview; a dummy for respondent has been in school since the last interview; a dummy for part time attendance and the share of the calendar year that the youth reported attending school derived from the NLS’s monthly time log. Years of schooling was controlled 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. Reports of weeks spent in civilian employment were available all the way back through 1975. For each individual, these weeks worked reports were aggregated across time and an estimate of cumulated civilian work experience was derived for January 1 of each year in the longitudinal file. This variable and its square was included in every model as was age, age squared and current and past military experience. The individual’s family situation was controlled by dummy variables for being married and for having at least one child. Minority status was 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.
Table 2. Effect of competencies on job performance (SQT).

<table>
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<tbody>
<tr>
<td>Skilled technical</td>
<td>0.092***</td>
<td>0.017</td>
<td>0.132***</td>
<td>0.174***</td>
<td>0.024</td>
<td>0.031</td>
<td>0.215***</td>
<td>0.062***</td>
<td>0.121***</td>
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<td>0.548</td>
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<td>(1324)</td>
<td>(3.07)</td>
<td>(0.58)</td>
<td>(4.28)</td>
<td>(5.09)</td>
<td>(1.12)</td>
<td>(1.17)</td>
<td>(6.77)</td>
<td>(1.96)</td>
<td>(3.76)</td>
<td>(1.83)</td>
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<td>Skilled electronic</td>
<td>0.086</td>
<td>0.098</td>
<td>0.246***</td>
<td>0.045</td>
<td>0.084</td>
<td>-0.013</td>
<td>-0.004</td>
<td>-0.021</td>
<td>0.261***</td>
<td>0.072</td>
<td>0.426</td>
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<td>(349)</td>
<td>(1.30)</td>
<td>(1.49)</td>
<td>(3.64)</td>
<td>(0.60)</td>
<td>(1.81)</td>
<td>(0.22)</td>
<td>(0.06)</td>
<td>(0.30)</td>
<td>(3.67)</td>
<td>(1.05)</td>
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<tr>
<td>General (const.)</td>
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<tr>
<td>(879)</td>
<td>(0.11)</td>
<td>(2.34)</td>
<td>(3.25)</td>
<td>(3.05)</td>
<td>(1.76)</td>
<td>(2.19)</td>
<td>(1.80)</td>
<td>(2.73)</td>
<td>(1.70)</td>
<td>(3.67)</td>
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<tr>
<td>Mechanical</td>
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<tr>
<td>(131)</td>
<td>(0.38)</td>
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<td></td>
<td></td>
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<tr>
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<td>(0.01)</td>
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<td>(3.99)</td>
<td>(1.10)</td>
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</tbody>
</table>

Source: Reanalysis of Maier and 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 and Grafton.
Table 3

Raw Validity Coefficients

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<tr>
<th></th>
<th>Mechanical Comprehension</th>
<th>Intelligence</th>
<th>Arithmetic</th>
<th>Spatial Relations</th>
<th>Perceptual Accuracy</th>
<th>Psychomotor Abilities</th>
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<tbody>
<tr>
<td>Foreman</td>
<td>23&lt;sup&gt;a&lt;/sup&gt;</td>
<td>28&lt;sup&gt;a&lt;/sup&gt;</td>
<td>20&lt;sup&gt;a&lt;/sup&gt;</td>
<td>21&lt;sup&gt;a&lt;/sup&gt;</td>
<td>27&lt;sup&gt;a&lt;/sup&gt;</td>
<td>15&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>Craftworkers</td>
<td>26&lt;sup&gt;a&lt;/sup&gt;</td>
<td>25&lt;sup&gt;a&lt;/sup&gt;</td>
<td>25&lt;sup&gt;a&lt;/sup&gt;</td>
<td>23&lt;sup&gt;a&lt;/sup&gt;</td>
<td>24&lt;sup&gt;a&lt;/sup&gt;</td>
<td>19&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>Industrial Workers</td>
<td>24&lt;sup&gt;a&lt;/sup&gt;</td>
<td>20&lt;sup&gt;a&lt;/sup&gt;</td>
<td>21&lt;sup&gt;a&lt;/sup&gt;</td>
<td>21&lt;sup&gt;a&lt;/sup&gt;</td>
<td>20&lt;sup&gt;a&lt;/sup&gt;</td>
<td>22&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>Vehicle Operators</td>
<td>22&lt;sup&gt;a&lt;/sup&gt;</td>
<td>15&lt;sup&gt;a&lt;/sup&gt;</td>
<td>25&lt;sup&gt;a&lt;/sup&gt;</td>
<td>16&lt;sup&gt;a&lt;/sup&gt;</td>
<td>17&lt;sup&gt;a&lt;/sup&gt;</td>
<td>25&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>Service Occupations</td>
<td>----</td>
<td>26&lt;sup&gt;a&lt;/sup&gt;</td>
<td>28&lt;sup&gt;a&lt;/sup&gt;</td>
<td>13&lt;sup&gt;a&lt;/sup&gt;</td>
<td>10&lt;sup&gt;a&lt;/sup&gt;</td>
<td>15&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>Protective Occupations</td>
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<td>23&lt;sup&gt;a&lt;/sup&gt;</td>
<td>18&lt;sup&gt;a&lt;/sup&gt;</td>
<td>17&lt;sup&gt;a&lt;/sup&gt;</td>
<td>21&lt;sup&gt;a&lt;/sup&gt;</td>
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<td>Clerical</td>
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<td>30&lt;sup&gt;a&lt;/sup&gt;</td>
<td>26&lt;sup&gt;a&lt;/sup&gt;</td>
<td>16&lt;sup&gt;a&lt;/sup&gt;</td>
<td>29&lt;sup&gt;a&lt;/sup&gt;</td>
<td>16&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
</tbody>
</table>

Source: Ghiselli (1973) compilation of published and unpublished validity studies for job performance. The raw validity coefficients have not been corrected for restriction of range or measurement error in the performance rating. The Perceptual Accuracy category includes number comparison, name comparison, cancellation and perceptual speed tests. They assess the ability to perceive detail quickly. Psychomotor tests measure the ability to perceive spatial patterns and to manipulate objects quickly and accurately. This category of tests includes tracing, tapping, doting, finger dexterity, hand dexterity and arm dexterity tests.

<sup>a</sup> Less than 100 cases.
<sup>b</sup> 100 to 499 cases.
<sup>c</sup> 500 to 999 cases.
<sup>d</sup> 1,000 to 4,999 cases.
<sup>e</sup> 5,000 to 9,999 cases.
<sup>f</sup> 10,000 or more cases.
<table>
<thead>
<tr>
<th></th>
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<th>High Skill Clerical</th>
<th>Low Skill Clerical</th>
<th>Craft Workers</th>
<th>Operatives</th>
<th>Service</th>
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<td>(.033)</td>
<td>(.026)</td>
<td>.017</td>
<td>(.018)</td>
<td>(.039)</td>
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<tr>
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<td>.070**</td>
<td>-.018</td>
<td>.012</td>
<td>.078*</td>
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<tr>
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<td>(.038)</td>
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<td>(.030)</td>
<td>(.020)</td>
<td>(.023)</td>
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<td>Spatial Perception</td>
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<td>.075***</td>
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<td>.039</td>
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<td>(.014)</td>
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<td>.082***</td>
<td>.063*</td>
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<td>(.031)</td>
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<td>(.019)</td>
<td>(.038)</td>
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<tr>
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<td>Yrs. of Schooling</td>
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<td>-.020</td>
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<tr>
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<td>.019</td>
<td>.042***</td>
<td>.040***</td>
<td>.036***</td>
<td>.082***</td>
</tr>
<tr>
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<td>(.015)</td>
<td>(.012)</td>
<td>(.005)</td>
<td>(.010)</td>
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<tr>
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<td>-.00072***</td>
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Source: Analysis of GATB revalidation data in the US Employment Services Individual Data File. Deviations of job performance ratings from the mean for the job/establishment are modeled as a function of deviations of worker characteristics from the mean for the job/establishment. The test scores are in a population standard deviation metric. The metric for job performance is the within job/establishment standard deviation.
Table 5  
Wage Premiums by College Major  
(Relative to Bachelors Degree in Humanities)

<table>
<thead>
<tr>
<th></th>
<th>Starting Salaries</th>
<th>Median Earnings</th>
<th>Average Monthly Earnings</th>
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</tr>
<tr>
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<td>--</td>
<td>--</td>
<td>8%</td>
</tr>
<tr>
<td>Other Social Sciences</td>
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<td>-1</td>
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<td>--</td>
</tr>
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<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Agriculture</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Health</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Bachelors in High Wage Major</td>
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<td></td>
</tr>
<tr>
<td>Physical Science</td>
<td>17%</td>
<td>17%</td>
<td>36%</td>
</tr>
<tr>
<td>Mathematics</td>
<td>18%</td>
<td>15%</td>
<td>36%</td>
</tr>
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<td>Engineering</td>
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<td>23%</td>
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<td>17%</td>
<td>21%</td>
</tr>
<tr>
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<td>2%</td>
<td>11%</td>
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</table>

*a* Percentage differential between the starting salary in the designated major over that received by humanities majors. The College Placement Council "Inflation and the College Graduate" 1985 and CPC Salary Survey, Sept. 1991.

*b* Percentage differential for median yearly earnings of males whose highest degree is a BA or BS in the designated major relative to median earnings of humanities majors. Current Population Reports, P-20, No. 201.

*c* Percentage differential for mean monthly earnings of men and women whose highest degree is a BA or BS in the designated major relative to earnings of humanities and liberal arts majors. Current Population Reports, P-70, No. 11, p. 13.
Bibliography


Hunter, John E.; Schmidt, Frank L. and Judiesch, Michael K. "Individual Differences in Output as a Function of Job Complexity." Department of Industrial Relations and Human Resources, University of Iowa, June 1988.


Klein, Roger; Spady, Richard; and Weiss, Andrew. Factors Affecting the Output and Quit Propensities of Production Workers. New York: Bell Laboratories and Columbia University, 1983.


Secretary's Commission on Necessary Skills.


ENDNOTES

1. The survey was of a stratified random sample of the National Federation of Independent Business membership. Larger firms had a significantly higher probability of being selected for the study. The response rate to the mail survey was 20 percent and the number of usable responses was 2014 (Bishop and Griffin, forthcoming).

2. Studies that measure output for different workers in the same job at the same firm, using physical output as a criterion, can be manipulated to produce estimates of the standard deviation of non-transitory output variation across individuals. It averages about .14 in operative jobs, .28 in craft jobs, .34 in technician jobs, .164 in routine clerical jobs and .278 in clerical jobs with decision making responsibilities (Hunter, Schmidt & Judiesch 1988). Because there are fixed costs to employing an individual (facilities, equipment, light, heat and overhead functions such as hiring and payrolling), the coefficient of variation of marginal products of individuals is assumed to be 1.5 times the coefficient of variation of productivity. Because about 2/3rds of clerical jobs can be classified as routine, the coefficient of variation of marginal productivity for clerical jobs is 30% \[1.5\times(0.33\times0.278+0.67\times0.164)\]. Averaging operative jobs in with craft and technical jobs produces a similar 30% figure for blue collar jobs. The details and rationale of these calculations are explained in Bishop 1988b and in Appendix B.

3. Only deviations of rated performance \((R_{ij}^m - R_m)\) from the mean for the establishment \((R_m)\) were analyzed. The variance of the job performance distribution was also standardized across establishments by dividing \((R_{ij}^m - R_m)\) by the standard deviation of rated performance, \(SD_{R_{ij}^m}\), calculated for that firm (or 3 if the sample SD is less than 3). Separate models were estimated for each major occupation. They were specified as follows:

\[
\frac{R_{ij}^m - R_m}{SD_{R_{ij}^m}} = \beta_0 + \beta_1 (T_{ij} - T_j) + \beta_2 (S_{ij} - S_j) + \beta_3 (X_{ij} - X_j) + \beta_4 (D_{ij} - D_j) + \nu_{ij}
\]

where \(R_{ij}\) = ratings standardized to have a zero mean and SD of 1.

\(T_{ij}\) = a vector of the five GATB aptitude composites

\(S_{ij}\) is the schooling of the \(i^{th}\) individual.

\(X_{ij}\) = a vector of age and experience variables—age, age\(^2\), total occupational experience, total occupational experience\(^2\), plant experience and plant experience\(^2\).

\(D_{ij}\) = a vector of dummy variables for black, Hispanic and female.

\(T_j, S_j, X_j\) and \(D_j\) are the means of test composites, schooling, experience variables and race and gender dummies for the \(j^{th}\) job/establishment combination.
Effect of Competencies on Earnings, 1984-1985
Young Men

<table>
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<th>Competency</th>
<th>Effect</th>
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<tbody>
<tr>
<td>Mechanical</td>
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</tr>
<tr>
<td>Electronics</td>
<td>2.1%</td>
</tr>
<tr>
<td>Clerical</td>
<td>1.4%</td>
</tr>
<tr>
<td>Computational</td>
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<tr>
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<td>-1.3%</td>
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Effect of Competencies on Wage Rates, 1983-1986
Young Men

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</tr>
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<td>Electronics</td>
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</tr>
<tr>
<td>Clerical</td>
<td>0.4%</td>
</tr>
<tr>
<td>Computational</td>
<td>6.2%</td>
</tr>
<tr>
<td>Verbal</td>
<td>-3.2%</td>
</tr>
<tr>
<td>Math</td>
<td>-0.9%</td>
</tr>
<tr>
<td>Science</td>
<td>-0.6%</td>
</tr>
</tbody>
</table>

Source: Analysis of NLS Youth data. The figure reports the effect of a one population standard deviation increase in Armed Services Vocational Aptitude Battery subtest while controlling for schooling, school attendance, age, work experience, region, SMSA residence and ethnicity.
Effect of Competencies on Earnings, 1984-1985
Young Women

- Mechanical: 1.6%
- Electronics: -0.3%
- Clerical: 2.8%
- Computational Speed: 5.3%
- Verbal: 3.8%
- Math: 6.6%

Effect of Competencies on Wage Rates, 1983-1986
Young Women

- Electronics: -1.3%
- Clerical: 1.7%
- Computational Speed: 2.9%
- Verbal: 1.7%
- Math: 3.1%

Source: Analysis of NLS Youth data. The figure reports the effect on a population standard deviation increase in Armed Services Vocational Aptitude Battery subtest while controlling for schooling, school attendance, age, work experience, region, SMSA residence and ethnicity.
Effect of Competencies on Job Performance (SQT) of Clerical

<table>
<thead>
<tr>
<th>Competency</th>
<th>Percent</th>
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<tr>
<td>Science</td>
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<tr>
<td>Math Know</td>
<td>20.6</td>
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<tr>
<td>Arith Reasn</td>
<td>24.1</td>
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<tr>
<td>Word Know</td>
<td>11.8</td>
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<tr>
<td>Comput Speed</td>
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<tr>
<td>Cler</td>
<td>1.5</td>
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<tr>
<td>Elect Info</td>
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<tr>
<td>Shop Info</td>
<td>-3</td>
</tr>
<tr>
<td>Auto Info</td>
<td>8.7</td>
</tr>
<tr>
<td>Mech Comp</td>
<td>-6.8</td>
</tr>
</tbody>
</table>
Effect of Competencies on Job Performance (SQT) of Skilled Technical

- Science: 5.7
- Math Know: 12.1
- Arith Reasn: 6.2
- Word Know: 21.5
- Comput Speed: 3.1
- Cler: 2.4
- Elect Info: 17.4
- Shop Info: 13.2
- Auto Info: 1.7
- Mech Comp: 9.2

Percent

30
20
10
0
-10
Effect of Competencies on Job Performance (SQT) of Skilled Electronic Workers

- Science: 7.2
- Math Know: 26.1
- Arith Reasn: -2.1
- Word Know: -0.4
- Comput Speed: -1.3
- Cler: 8.4
- Elect Info: 4.5
- Shop Info: 24.6
- Auto Info: 9.8
- Mech Comp: 8.6

Percent
Effect of Competencies on Job Performance (SQT) of General Maintenance

- Science: 13.4%
- Math Know: 44.1%
- Arith Reasn: -10.1%
- Word Know: 6.6%
- Comput Speed: 6.8%
- Cler: 4.3%
- Elect Info: 12.1%
- Shop Info: 11.7%
- Auto Info: 8.2%
- Mech Comp: -0.4%

Percent
Effect of Competencies on Job Performance (SQT) of Mechanical Maintenance

- Science: 9.6%
- Math Know: 6.1%
- Arith Reasn: -6.8%
- Word Know: -0.4%
- Comput Speed: 23.5%
- Cler: 5.5%
- Elect Info: -8.9%
- Shop Info: 20.6%
- Auto Info: 31.4%
- Mech Comp: 4.2%
Effect of Competencies on Job Performance (SQT) of Missile Battery Operators

- Science: 7.6
- Math Know: 10.6
- Arith Reasn: 11.4
- Word Know: 6.1
- Comput Speed: -3.7
- Cler: 5
- Elect Info: 10
- Shop Info: 6.2
- Auto Info: 17.9
- Mech Comp: 10.9

Percent