A Portrait of the Relationship between Mechanization and Work in the U.S. Economy in 1980

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Debates over the effects of technological change on work continue to generate a wide and confusing array of findings. One reason for the lack of consensus is that empirical research based on large samples has yet to adequately address the core issue: the relationship, if any, between the level of mechanization and the characteristics of work. This relationship is explored using data from the 1980 Census of Population to link measures of the level of mechanization with measures of work characteristics for manufacturing industries. The results are mixed; work characteristics in more mechanized industries compared to less mechanized industries are higher in some dimensions and lower in others. A path model approach allows aggregation of these mixed results. Using wages as a yardstick, and controlling for other determinants of wages, we find that the work characteristics of more mechanized industries are upgraded in the aggregate, compared to those in less mechanized industries.

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Studies of the evolution of work in the face of technological change have generated a wide and confusing array of findings. Debates continue over how the historical trend toward mechanization has affected work -- or indeed whether any discernible relationship exists at all. Our approach is to examine *what* are the effects of mechanization on work; the question of *whether* there are such (strong) effects is treated as the null hypothesis.

Of those who hypothesize strong influences of mechanization, some argue that political forces have led managers to use new technologies to “deskill” workers (Braverman, 1974; Noble, 1984). Their argument is that political demands for increased control over workers comes at the expense of workers' autonomy and skill. A corollary is the polarization thesis, which argues that deskilling of some (groups of) workers is accompanied by upgrading of others (e.g., technicians), leading to an increasingly dichotomous skill distribution.

Others argue an upgrading hypothesis. One variant, developed by Bell (1960) and others and reworked in the 1980s by Hirschhorn (1984), Adler (1986), and Zuboff (1988), is that although new technologies reduce traditional craft skills, they make even greater conceptual demands on workers. Another variant is that jobs may be deskilled in the initial stages of technological development, but with further advances in technology, the trend reverses and an overall pattern of upgrading emerges (Blauner, 1964; Sorge and Streeck, 1988).

The null hypothesis about the relationship between mechanization and work is that managers have a wide latitude of choice in technological implementation, and a wide variety of local conditions affect both technology implementation and skill labeling. This "contextualist" hypothesis argues that the relationship between mechanization and work is idiosyncratic to particular firms (Kelley, 1986; Form, et al., 1988) or countries (Maurice et al., 1986), and thus there is no general historical trend to be found.

For all three schools, what is at stake is the effect of technological change on *jobs,* and through the changing nature of jobs, on the workers who inhabit those jobs. To measure such an effect, one must be able to assess the technological and skill-related characteristics of jobs in a broad sample. Existing empirical research falls short of resolving these debates due to three difficulties (Vallas, 1990; Spenner, 1990).

First, researchers have lacked a robust notion of skill or, more broadly, of the appropriate dimensions of work. Industrial engineers focus on the range of conventional skills -- manual, cognitive, perceptual, etc. -- demanded for the technically efficient use of new technologies (Crossman, et al., 1966; Hazlehurst, et al., 1969). Those who focus attention on the politics of the workplace highlight substantive complexity and autonomy/control as the central characteristics of skilled work, emphasizing their role as a source of power in labor-management conflict (Braverman, 1974; Edwards, 1979; Shaiken, 1984). Another line of research criticizes both approaches for failing to recognize that labels such as "skilled" and "unskilled" reflect idiosyncratic constellations of institutional and cultural forces more than they do broad technological or political-economic realities (Elbaum, 1984).

Each of these approaches is based on contestable theory (Hirschhorn, 1984; Adler, 1986); moreover, none is supported by systematic data. Following Cain and Treiman (1981) and Parcel and Mueller (1983), we shall use the measures of a rich set of work characteristics supplied by the Dictionary of Occupational Titles (U.S. Department of Labor, 1977) (DOT) to identify empirically some underlying dimensions of work. It is this empirical characterization that we shall use in measuring the relationship between mechanization and the dimensions of work.

Second are methodological difficulties. Richer, more fine-grained case studies are hampered by inadequate samples; while studies employing broader samples gloss the issue of causality. Case-study research is insufficient to address the question at the heart of this paper. The forces that link mechanization and work clearly allow considerable variation from case to case (Spenner, 1988). If competitive pressures tend to drive firms to employ human and technical capital efficiently and if efficient use has determinate form, it will still be the case that not all firms will be at equilibrium at any given point in time and there may therefore be a wide range of technology utilization patterns.

When we look to broader statistical studies, however, we find that the question of mechanization has been supplanted by a focus on temporal change in work characteristics. Attributing temporal changes in work to mechanization assumes a relatively strong causal role for technology in which temporal trends in mechanization are widespread, consistent, and outweigh other forces shaping work (such as shopfloor politics and rising education levels). While some find such a model plausible, many others do not (Kelley, 1986; Noble, 1984; MacKenzie and Wajcman, 1985).

Of the studies reviewed by Spenner (1988) on the "effects of technology on skill requirements," only that by Mueller et al. (1969) incorporates any measure of technology. Mueller and her colleagues analyzed 2662 jobs representative of the U.S. labor force. In the 228 cases in which the worker had been in the same job for the 5-year span of the survey and in which the job had experienced a "machine change" during that time, they found evidence of upgrading of both "skill" and "influence." Apart from the very small final sample, the Mueller et al. study suffers from two other difficulties. First, it is difficult to extrapolate to the broader universe of jobs, since for those workers who changed jobs during the five years, skill changes may be attributable either to changes in mechanization or changes in job (Spenner, 1988). Second, it could be plausibly argued that if technological change does affect job requirements, the incumbent is more likely to be replaced if the change reduces requirements than if it increases requirements.

In order to avoid conflating the effects of mechanization and the effects of other forces (e.g., rising education levels, work mobility) the present study focuses on the cross-section relationship between mechanization and skill, examining the entire U.S.

manufacturing workforce in 1980. Limitations of data and space prevent us from exploring mining, agricultural, transportation and service industries. We shall not, however, restrict the range of occupations studied since occupations typically associated with the service sector are often found in manufacturing industries and are affected by mechanization. A quantitative measure of mechanization (equipment stock per worker) will be supplemented by qualitative measures -- proportion of output produced in small batches, in large batch or assembly-line production, or through continuous process technology -- similar to those used in previous studies of mechanization and work (e.g., Woodward, 1965; Blauner, 1964; Hull, et al., 1982).

We thus draw our data from the 1980 U.S. Census, thus covering all reported job holders in that year; we measure not only the skill level, but also the mechanization level, of each job. We then test whether there is a discernible statistical relationship between mechanization and work; and if so, whether the relationship is consistent with the deskilling or upgrading hypotheses.

A third problem is that existing research lacks a scheme for weighting the relative contributions of different work characteristics in order to assess the aggregate changes in work (Vallas, 1990). In most research on mechanization and work, more than one dimension of work is at issue, creating the need for some form of aggregation scheme. The industrial engineering approach decomposed work into constituent skills, but lacked a method for evaluating the relative contribution of each dimension to an overall measure of skill (Crossman et al., 1966; Hazlehurst et al., 1969; Bright, 1958). As a result these researchers were unable to draw any overall conclusions. Similarly, those who emphasize substantive complexity and autonomy/control have difficulty aggregating the two. Their theoretical model presumes that the two dimensions are highly correlated and that management pressure to reduce the latter also tends to reduce the former (Braverman, 1974). But this correlation is asserted, not tested and has been con-tested by Friedman (1977). The problems associated with aggregating disparate dimensions of work has led some to abandon the search. These agnostics posit a "mixed effects" model in which the final aggregate outcome is either uncertain or contingent upon organizational variables (Form, et al., 1988).

We approach the aggregation problem with a socio-economic method that takes wages as the final arbiter of skill. Our strategy is decidedly "positivist," in Attewell's (1990) framework, taking productive ability — and its quantification in wages — as the grounding of our concept of skill. Nonetheless, we are not blindly positivist; we recognize the other influences on wages besides productive ability, controlling for such factors.

First, we measure the effect of mechanization on each of several dimensions of work. We find mixed results: there is some evidence of upgrading, some of deskilling. Second, we estimate the wage return to each of several underlying dimensions of work, controlling for social and institutional influences. This captures the labor market valuation of each of these dimensions of work and thus provides an implicit weighting scheme: the higher the wage return, the greater the productive contribution and thus the greater the overall skill content.

Thus, by measuring the association between mechanization and skill for all reported job holders in the U.S. in 1980, and by weighting the differentially distributed components of skill, we can assess the degree of upgrading or deskilling due to mechanization in the overall U.S. economy. We find that the deskilled dimensions of work tend to be devalued, relative to the upgraded dimensions. On net, we find that the mixed effects of mechanization generate a slight overall upgrading effect. While we do not assume that wages are an unambiguous indicator of skill, we find that this approach generates some important lessons for the skill debates.

DATA AND METHODS

Our unit of analysis is the job, and our sample is all jobholders reporting their employment on the 1980 U.S. Census. For each job we shall need a measure of skill and a measure of mechanization. The former is obtained from the DOT; the latter from the Bureau of Economic Analysis. We can associate each of these data sources with our Census data because each jobholder reported his/her occupation and the industry in which s/he worked. The major hurdle in doing so is that the taxonomies employed by the Census, the DOT and the BEA are not isomorphic. Fortunately, bridges between them exist which provide a suitably accurate mapping.

The fulcrum of our dataset is the Census Bureau's industry-occupation matrix (U.S. Bureau of Census, 1984), in which rows represent industrial categories and columns represent occupations. Each cell of the matrix contains the number of employees in that particular industry-occupation mix. The cell frequencies come from the 1980 U.S. Census and represent the self-reported occupation and industry of employment for over 94 million employees. These employees are allocated into 447 Census occupations and 225 Census industries; this creates a matrix with 100575 unique industry-occupation combinations. After selecting the manufacturing subset (20 industries) we are left with 20.3 million employees categorized into 8940 unique industry-occupation combinations.

Measuring work characteristics

We use the Dictionary of Occupational Titles (DOT) as our source of measures of work characteristics. The DOT is not without problems; however, its breadth of coverage, standardization and detail make it invaluable for the type of large-scale analysis presented here. The DOT variables measure physical capacities such as manual dexterity; managerial and social aspects of work (e.g., "People"; "Direct, Control, Plan"; "Deal with People"); and socio-cultural aspects (e.g., "Preference for Prestige") (Table 1).

These measures are gathered through field studies conducted by the United States Employment Service, which periodically updates both the measures and the occupational classification scheme.

<u>Put Table 1 here.</u>

The most exhaustive examinations of the limitations of the DOT dataset is found in Miller et al. (1980) and Spenner (1990). Miller et al. argue that since the DOT classification is based on incremental, decennial updates of previously existing schemes, it underrepresents occupations in emerging industries. Since our data represent jobs, rather than occupational categories, and this is a cross-sectional study, this problem is not a threat here.

Miller et al. also suggest that there is not as much differentiation among the DOT measures as is apparent, due to halo effects caused by the use of a single rater for each occupation. We follow their advice and use factor analysis to reduce these measures to a set of more distinct measures. Miller et al. also report low inter-coder reliability of the DOT measures, finding that the major source of unreliability is inter-rater differences. This would be a threat to the validity of our results only if certain raters focused on certain occupations or certain industries; Miller et al., find no significant bias due to such a source. Thus for us, the lack of reliability results in noise, rather than bias (see also Spenner, 1990).

A more serious threat is posed by the influence of occupational prestige or desirability on evaluations of skill (Parcel and Mueller, 1983; Attewell, 1990; Spenner, 1990). As we discuss below in our discussion of estimation procedures, this potential model specification error has been ruled out empirically. Similarly, the validity problems cataloged by Spenner (1990) are either controlled for in this analysis (e.g., gender bias), or merely generate noise in our factor-analytic scheme (e.g., the questionable measurement of "strength" requirements).

The thorniest problem is that the occupational classification scheme employed by the Bureau of the Census in constructing the industry-occupation matrix differs from that used by the Bureau of Labor Statistics in constructing the DOT. The finer grain of the DOT classification results largely from distinguishing between similar occupations in different industries, which the Census classification does not. In order to use the DOT measures with the Census data, we employ a crosswalk between the two occupational classification schemes created by Paula England. The crosswalk translates the DOT variables into the Census occupational scheme by prorating the DOT measures for appropriate DOT occupations to each Census occupation. Each variable for each Census occupation is an average of that variable for the several corresponding DOT occupational categories weighted by the number of workers in each of the DOT categories. Thus, thanks to the efforts of Prof. England and colleagues, the problem of incommensurability is surmounted.

The factor structure for employees in the manufacturing sector is shown in Table 4 (all factor analyses are PROMAX oblique rotations, following Cain and Treiman, 1981). We find five statistically warranted and theoretically interpretable factors:

- Substantive Complexity encompasses the cognitive demands captured by intelligence, verbal, clerical, spatial, and numerical aptitudes, as well as training and education requirements (SVP and GED) and Data and People (thus our factor scheme is consistent with the cautions of Spenner, 1990).
- Motor Skills includes measures of dexterity and facility with things; it also includes negative loadings of Influence and Prestige, suggesting that (other work characteristics being equal) more manually-skilled occupations tend to have less authority and status. (The dexterity measures originally loaded negatively on the Motor

Skills factor and Influence loaded positively. We have changed the sign on this factor to make the results more intuitive.)

- Social Skills captures not only management skills (People, Influence, Preference for Business, and Use Judgment), but also communication skills (Talk, Verbal, Deal with People) and analytic skills (Data versus Things). Demanding Working Conditions captures both hazardous and physically demanding conditions.
- The fifth factor is more difficult to interpret. We call it Craftwork, because the combination of productive, creative and interpretive aspects, along with the negative loading of People, approximates the traditional concept of autonomous craftsmen. Occupations that scored particularly high on this factor included many of the traditional craft and creative occupations.

These factors are similar to those derived by Cain and Treiman, 1981. Minor differences reflect our narrower focus on manufacturing industries and our use of the jobholder, rather than the occupation, as the unit of analysis.

<u>Put Table 2 here.</u>

Sociological studies of work have tended to focus on the impacts of mechanization on non-managerial workers (Spenner, 1979; 1988). At the heart of the deskilling hypothesis is the assumption of increasing "separation of execution and control" (Edwards, 1979) and the different effects of mechanization on each element. In order to explore such differences we analyze two, successively narrower occupational subsets: all non-managerial occupations and non-managerial, non-professional occupations.

The factor structure for non-managerial employees is presented in Table 5. A comparison with the factor structure for all manufacturing employees in Table 5 illustrates the effects of status differences among non-managerial employees. While some form of Substantive Complexity accounts for most of the variance in both datasets, in the non-managerial subset, it does not include social skills or status. Status differences in the non-managerial subset turn up instead in the Motor Skill factor. This suggests that in the status hierarchy among non-management employees, those at the top are the less manually-skilled.

<u>Put Table 3 here.</u>

The factor structure for jobs in non-managerial, non-professional occupations is presented in Table 6. The major difference between this structure and that for the set of all occupations (Table 4) is that Substantive Complexity in the non-managerial, non-professional subset is decomposed into two factors that seem to reflect the white-collar/blue-collar distinction. The first factor, Cognitive Complexity, captures qualities such as clerical aptitude, use of judgment, and preferences for business and data (rather than for machines and things). This factor contrasts with the skills reflected in Technical Complexity, such as using measures, spatial and numerical aptitudes, and preference for science. Cognitive and Technical Complexity also differ on the social skills involved: the former includes people-processing skills ("Deal with People" and "Talk"), while the latter includes more properly supervisory responsibilities (i.e., "Direct, Control, Plan" and "Preference for Prestige"). Since the distinction between Cognitive and Technical Complexity appears only by excluding professionals, it appears that professional occupations combine these dimensions.

<u>Put Table 4 here.</u>

Measuring mechanization

We used the capital-labor ratio as a quantitative measure of the level of mechanization of each industry. We used this ratio since we are interested in the amount of mechanization available to average worker in the average job in an industry. For the numerator of this ratio, we use a five-year weighted average of the stock of "Equipment" for the years 1978 to 1982 (U.S. Dept. of Commerce, 1987). We thus exclude forms of capital less relevant to the mechanization and work debate, such as real estate and structures. Finer-grained candidates, such as the level of "office and computing equipment," each excluded important types of mechanized capital.

The measures we use are not depreciated. Since much mechanized equipment has a longer useful lifetime than the book life of accounting conventions (typically 5 years), measures of depreciated capital stock may underrepresent the actual level of equipment in use.

The denominator of the mechanization measure is the number of employees in each industry, calculated from the Census Bureau's industry-occupation matrix. The range of this measure is quite large; we use the logarithm of the capital-labor ratio in order to reduce scale effects.

A second measure of mechanization captures qualitative, rather than quantitative, industry distinctions. This is a measure of process type derived from the PIMS data service. Based on a survey of 3788 business units, the data indicate the proportion of output produced by each business unit using each of three process types: "small batch," "large batch/assembly" and "continuous process" (Strategic Planning Institute, 1978). We calculate the mean percentage of output produced through each category over the sample of business units in each of 49 industries.

Theories of organization assume that technological development results in a movement from small batch to large batch/assembly and then from the latter to continuous process (Woodward, 1970; Blauner, 1964). Confirming these assumptions, factor analysis of these three measures (using a PROMAX oblique rotation) generates two factors: the first factor ("Volume") distinguishes small batch from large batch/assembly-intensive industries; the second factor ("Process") distinguishes assembly from continuous process-intensive industries (see Table 2). These factors allow us to distinguish the relationships between work characteristics and the shift from batch to assembly, and between work and the shift from batch/assembly to continuous process.

<u>Put Table 5 here.</u>

The profile of industries on the qualitative and quantitative measures is given in Tables 3a , 3b, and 3c.

<u>Put Tables 6a, 6b and 6c here.</u>

We link the mechanization measures to the DOT measures using the industry-occupation matrix. This raises a problem similar to that raised by the DOT data: the Commerce Department's Standard Industrial Classification (SIC) scheme differs from the industrial classification scheme used by the Census Bureau in constructing the industry-occupation matrix. In this instance, however, bridging the two is much simpler. We used a published crosswalk (U.S. Bureau of Census, 1980). Since the 2-digit SIC categories are inclusive of the Census categories, we can convert from the Census to the 2-digit SIC scheme without having to prorate industries across categories.

Methods: Calculating correlations across the matrix

The resulting dataset represents each jobholder as reported in the 1980 U.S. Census, for whom we have a measure of skill (inferred from the jobholder's occupation) and of mechanization (inferred from his/her industry). (See Figure 1.)

<u>Put Figure 1 here</u>

We thus seek to measure how the distribution of skill throughout the U.S. economy reflects the distribution of mechanization (among other factors). The relative number of jobholders in each cell of our industry-occupation yield both distributions. By measuring the association between these distributions we can test the skill debates. The deskilling hypothesis, for example, claims that high-skill occupations will be more frequent in low-mechanization industries than in high-mechanization industries.

In our analyses the nominal unit of analysis is the Census respondent. The matrix represents over 20.3 million individuals; thus the dataset has over 20.3 million observations. Some of the variance in mechanization and work characteristics is lost, however, due to the structure of the dataset: the measures of work characteristics vary only between occupations and the mechanization measures vary only between industries. We thus adjust the degrees of freedom as appropriate, always assuming the most conservative test.

The first part of the analysis measures the association between mechanization and work. We first factor-analyze the DOT measures, isolating five factors. We then measure the correlations between mechanization (both quantitative and qualitative measures) and these five work factors. Our hypothesis, based on considerable empirical findings, was that this analysis would show mixed results, with some dimensions of work positively associated with mechanization and some negatively.

The final step in our analysis is thus to develop an aggregation scheme to account for the overall impact of mechanization on work. We do so by regressing the wage for each occupation on each of the work characteristic factor scores, controlling for occupational gender composition, and for industrial profitability and level of unionization (for a description of the control variables, see Hodson and England, 1986). Once we measure the marginal returns to each work characteristic, we can compare aggregate profiles of work characteristics and estimate overall upgrading or deskilling effects of mechanization through its effects on the composition of work.

RESULTS

The correlations between Mechanization and the dimensions of work for each of the three occupational subsets are presented in Tables 7a - c.

Put Tables 7a - c here.

We interpret each correlation as a measure of the increase in each particular skill required by a unit increase in Mechanization. Since our population is the same as our sample, except for Census department sampling error, we shall not draw much attention to tests of statistical significance. We report all correlations in the paper; the reader can see from the tables that the correlations are small, but given the large sample are nonetheless significant but for a few.

We find first that, contrary to the deskilling thesis, there is a small but positive correlation between complexity (whether Substantive, Cognitive or Technical) and Mechanization for all of the occupational subsets. (We examined the polarization corollary by measuring the association between the variation in each dimension of work and Mechanization. To be able to calculate a variance for each observation, we used the industry as the unit of analysis, for this analysis only; this severely reduces the number of independent observations. This analysis yielded no correlations that were either large or statistically significant.)

Second, we find a negative correlation between Mechanization and both Motor Skills and Craftwork in each occupational subset. This result is consistent with most prior research. Even the upgrading models allow for losses in manual skills and craft forms of work, hypothesizing that such losses are offset by gains in other types of skill.

The positive correlation between Mechanization and Demanding Working Conditions for each subset contradicts conventional wisdom. This may be due to the prevalence of machines that do indeed create poor working conditions. Alternatively, this correlation might reflect disequilibrium in implementation. If the most physically demanding tasks are the first candidates for mechanization, then higher-than-average levels of mechanization may be found in the most physically demanding areas in the short run, even if those areas become progressively more mechanized and less physically demanding over time. This disequilibrium hypothesis is consistent with the research on robotics that finds robots used most in particularly demanding environments of auto painting and welding (Hunt and Hunt, 1983).

Social Skills captures collegiality and people-processing skills. The positive correlation, weak as it is, between Mechanization and Social Skills is consistent with the hypothesis that mechanization increases interdependence among employees (Hirschhorn, 1984; Adler, 1986; Ray, 1989). While not directly capturing interdependence per se, this modest finding suggests that more mechanized work settings demand occupations with greater interpersonal (but not supervisory) skills.

The relationship between the qualitative measures of mechanization and work are presented in Tables 8a-c. These results summarize the effects of qualitative shifts in technology from small batch to large batch/assembly technology (measured by Volume) and from assembly to continuous process technology (Process).

Put Tables 8a-c here.

Not surprisingly, we find that Volume is negatively associated with Substantive Complexity in the all-occupations and the non-management datasets (Table 8a). However, we also find a positive correlation between Volume and both Cognitive and Technical Complexity among non-professional, non-managerial occupations (Table 8c). The latter finding challenges the widespread assumption that large batch/assembly line production allows for a finer division of labor which in turn reduces the substantive complexity of workers' jobs (Edwards, 1979).

The association between Process and each of the Complexity factors in each subset were statistically insignificant, except for a positive association between Process and Technical Complexity in the non-management, non-professional dataset.

Higher levels of both Volume and Process are associated with decreases in Motor Skills for all the occupational subsets. This is consistent with nearly all previous research and with the results of the quantitative measures examined above.

The relationship between Demanding Working Conditions and type of mechanization is weak in most cases. Poor Working Conditions are, however, negatively associated with Volume in the non-management non-professional subset (Table 8c), suggesting that assembly-line work is less hazardous and physically demanding than small batch production.

Craftwork is negatively associated with Process in the non-management non-professional subset (Table 8c). The craft aspects of work are in less demand in process-intensive than in assembly-intensive environments, challenging the "return-to-craftwork" upgrading arguments of Blauner (1964) and his followers. They are not significantly lower, however, in large batch/assembly than in small batch environments, challenging the deskilling arguments of Braverman (1974) and his followers.

Overall, all the significant regression coefficients on Volume and Process have the same sign; thus the two dimensions appear to have similar effects on work. We thus find no support for the curvilinear model proposed by Blauner (1964), in which the transition from small batch to assembly-line has a qualitatively different effect on work than the transition from assembly-line, large batch to continuous process. This suggests that the monotonic, uni-dimensional model suggested by Woodward (1965) model is a better conceptualization of mechanization for the purposes of analyzing its effects on work.

Aggregating the effects of Mechanization on Work

We thus find strong confirmation of a mixed-effects model: mechanization is associated with higher cognitive demands and lower physical demands. It remains to assess the aggregate result. The logic of our model is that mechanization affects wages through its effects on the underlying dimensions of work and their relative valuation (controlling for unionization, gender composition and industry profitability) (Figure 2).

Put Figure 2 here.

The central findings of this model proved robust procedures to correct data problems, as well as against alternative specifications (such as allowing for the effects of control variables on Mechanization). In addition, we tested for the effects of occupational status on both the raters of the DOT measures and on wages (Parcel and Mueller, 1983), anticipating that the influence of this unmeasured factor would lead to correlated errors in the Wage and the Work Characteristic equations. We could not reject the null hypothesis of no correlation between the residuals and thus rely on ordinary least square estimation.

Results of the equations in Figure 1 are presented in Tables 9a-c. The results are summarized in Table 10, which decomposes the covariance between Mechanization and Wage into its component paths, measured by their standardized regression coefficients. Since the work characteristics are factor scores they are dimensionless variables by construction and their variances are quite similar. The use of standardized coefficients allows us to compare the effects of work characteristics alongside those of the control variables (unstandardized coefficients suggest similar results).

Put Tables 9a-c and 10 here.

The central result is that in each of the three subsets we find a small but positive net relationship between Mechanization and Wage. Our contribution is not the identification of this relationship, however, but the ability of our model to decompose it into its component relationships. Closer examination of these suggests some new insights into mechanization's influence on work.

Substantive Complexity, Technical Complexity and Cognitive Complexity are all positively associated with both Mechanization and Wage. Consistent with the findings above, higher levels of Mechanization are associated with higher levels of Complexity. Since Complexity receives a positive wage return at the margin, the net effect of increases in Mechanization through this dimension of work on wages is positive. We will see that this robust effect, although small, outweighs the negative effects of other dimensions of work.

The path through Motor Skills is positive in the total sample and the non-managerial subsample — but not because of simple upgrading. Higher levels of Mechanization are associated with *lower* motor skills, but work with lower Motor Skill content in turn has *higher* wages than work with higher Motor Skill. Thus in the overall sample, mechanization is associated with increases in productive capacity accompanied by lower levels of Motor Skill. By contrast, for the non-management, non-professional subsample, we find a more traditional result: a net loss in Wages due to loss of Motor Skills. This supports the hypothesis of manual deskilling on which the deskilling approach focuses. Manual deskilling in the overall economy is not borne out due to the negative wage returns to manual skill in the managerial and professional occupations.

The Social Skills paths in the all-occupation and non-management subsets are positive (the third occupational subset lacks a comparable dimension). More mechanized environments place higher demands on Social Skills and these skills have positive marginal returns. Unfortunately the DOT focuses primarily on cognitive capabilities and physical competence. The measures loading on the Social Skills factor (e.g., "Deal with People," "People," "Influence," "Talk," "Verbal") do not tell much about the nature of these social demands.

In each subset Mechanization is associated with Demanding Working Conditions which in turn suffer a wage penalty in the labor market. The positive association of Mechanization and Demanding Working Conditions is somewhat surprising; earlier we suggested that this may be due to temporary disequilibria in the mechanization of jobs with poor working conditions. The negative correlation with wages, net of other components of skill, is also surprising; since we have controlled for manual and cognitive skills, it does not reflect the association of poor working conditions with low-skill jobs. It may instead be evidence of disequilibrium in the labor market for such work: jobs with poorer working conditions are more likely to suffer frequent turnover and to be filled by the unemployed and thus are more likely to have lower wages than jobs with better conditions.

The Craftwork component in the all-occupation dataset has a net negative effect, as mechanization reduces this positively-valued dimension of work. In the other two subsets more "negative upgrading" is found. Although mechanization reduces the craft content of work, there are negative marginal wage returns from Craftwork. The negative return to Craftwork is surprising; both upgrading and deskilling theorists hold up craft work as a exemplar of skilled work. One explanation is that since the Craftwork factor holds constant the substantive complexity normally associated with craft work, the creative and interpretive elements of craftwork are not themselves rewarded in the labor market.

Having assessed the results of the narrow model of Figure 2, we expand our model to include the controls as pathways between mechanization and wage (allowing a path from Mechanization to Control in Figure 2). These findings reinforce the upgrading hypothesis.

The first result is that the percentage of female workers is negatively associated with both mechanization and wages. The former is not surprising, given cultural gender norms on both the supply and demand side of the labor market. The latter is consistent with research on gender bias in the labor market.

Second, industry profitability is negatively associated with mechanization. This contradicts the conventional interpretation that the capital-labor ratio is associated with higher productivity (and, thus, profits). This may signal the failure of Fordist (Sabel, 1982) strategies of mechanization. Alternatively, it may be that high levels of mechanization are found in large "sunset" industries suffering from decline relative to large sunrise industries. Third, it may also reflect short-run adjustments (e.g., that profits are eroded by the high cost of new forms of mechanization).

Equally surprising is the wage penalty found in jobs in more profitable industries. To the extent that this is an artifact of the fact that declining, older industries have both lower profits and high-wage union contracts, it would be controlled for by Unionization. A simpler explanation is that profitable industries are those which are better able to control labor costs.

Third, Unionization is positively associated with both mechanization and wages, the former due to industry effects and the latter to the influence of collective bargaining.

On net, the small but positive relationship between Mechanization and Wage is robust against controls for unionization, gender composition and industry profitability.

DISCUSSION

Our market-based definition of skill as reflected in monetary returns distances our analysis from some studies of skill. But it speaks to the heart of the skill debates: the effect of mechanization on productive ability. Despite data difficulties that increased the noise of our models, we found small, but consistent results that support the upgrading thesis.

We do not wish to over-interpret the small positive correlation between Mechanization and Wage. It is, instead, merely the jumping-off point of our analysis. From there we adopted the mixed-effects assumption that manual skills decline, and cognitive skills increase, with mechanization. And we extended this analysis by assessing whether, and how, the upgrading and mixed-effects models were consistent.

We found that, in general, the gains brought by increases in positively valued cognitive and social skills outweighed the losses from decreases — brought both by losses of positively valued skills (e.g., manual skills) and by increases in negatively valued skills (e.g., Craftwork).

Some of the detailed results caused us to reconsider some of the less debated assumptions of existing theories. For one, we found that, controlling for the complexity of work, craft work *per se* is negatively valued in the labor market. This challenges the assumption that autonomy and control are themselves associated with productive ability (cf. Spenner, 1979). For another, we found a unexpected form of deskilling through working conditions: not only is Mechanization surprisingly associated with Demanding Working Conditions, but the latter suffers a wage penalty. We suggested some disequilibrium industry effects might be at the root of this finding.

Overall, however, we found a small but consistent upgrading effect. The more detailed examinations of our results indicate that the deskilling argument is borne out in the limited realm of blue-collar workers and manual skills; its extension to other areas of work seems unwarranted. The mixed effects argument, while supported by our initial explorations, appears incomplete. We have extended it through our path model to accommodate the upgrading thesis: while some aspects of skill are reduced and some are increased with increased mechanization, those that increase outweigh the others.

CONCLUSIONS

This study suffers from several limitations. It is cross-sectional, and so cannot measure the change in particular occupations brought about by mechanization. The path model may lack needed control variables. The DOT variables contain considerable noise and do not adequately capture some of the constructs at issue in the mechanization and work debate, such as "responsibility," considered by many to be an important characteristic of work that is upgraded by mechanization (Belitsky, 1978; Shaiken, 1984; Hirschhorn, 1984; Adler, 1986).

Nonetheless, we have uncovered some surprising and suggestive results. Using wages as a yardstick, jobs are upgraded in settings that are higher in both quantitative and qualitative levels of mechanization. This finding holds for jobs within occupations in all three major occupational subsets, including the non-management, non-professional employees who are at the center of the mechanization and work debate. In addition, in contrast to both the Braverman deskilling hypothesis and Blauner curvilinear hypotheses, we find that upgrading accompanies increases in both assembly- and process-intensity.

We have discussed limitations in data and methods that generated noise and inefficiency in our analyses. We have attributed the weaknesses of our results to these problems. An alternative attribution is the contextualist hypothesis, which argues that the effects of mechanization on work are simply weak. Despite this, we discovered that a cross-sectional view of the 1980 Census is consistent with several key corollaries of a naive upgrading interpretation of the “mixed results” model: deskilling in the manual and craft components of work is compensated for by upgrading in the cognitive, technical, substantive and social components.

While our methods do not allow us to decisively prove the upgraded mixed effects model, our results suggest that more attention be paid to the gains, as well as the losses, of skill to mechanization and to better methods for measuring and weighing the two. It thus suggests to managers that they ignore the potential upgrading effects of mechanization at their peril. Our analysis suggests to researchers that craft-based yardsticks for studying work are inappropriate and offers a method for rescuing the mixed effects model from its present agnosticism.

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Table 1:

DOT Variables

Name	Description and scale (counter-intuitive coding schemes are reversed)	Mean	S.D.
Data	Complexity of functioning with data. Scale: 0 (comparing) to 6 (synthesizing)	3.2	1.5
People	Complexity of functioning with people. 0 (taking instructions, helping) to 8 (mentoring)	6.3	1.5
Things	Complexity of functioning with things. 0 (handling) to 7 (setting-up)	4.1	1.9
GED	General Educational Development. 1 to 6: composite scale of reasoning, math, and language development.	3.7	0.9
SVP	Specific Vocational Preparation. 1 to 9: scale of time required to learn the job	5.4	1.5
Aptitudes:	Capacities or abilities required to learn some task or job duty. Occupation ranked by quintile (1 to 5)		
Intell	Intelligence	2.8	0.7
Verbal	Verbal	3.0	0.7
Numeric	Numerical	3.2	0.7
Spatial	Spatial	3.3	0.6
Form	Form perception	3.2	0.6
Clerical	Clerical perception	3.5	0.6
Motor	Motor coordination	3.4	0.4
Fingdex	Finger dexterity	3.4	0.5
Mandex	Manual dexterity	3.2	0.5
Eye/Hand	Eye, hand, foot coordination	4.5	0.6
Color	Color discrimination	4.3	0.5

Interests:	Percent of workers whose job requires preference for activities...		
Idata	concerning the communication of data	19.9	29.2
Iscience	of a scientific and technical nature	15.0	28.2
Icreate	of an abstract and creative nature	4.7	15.3
Iprod	resulting in tangible productive satisfaction	15.8	24.9
Ithing	dealing with things and objects	51.6	36.3
Ibusiness	involving business contact with people	26.0	32.0
Iroutine	of a routine, concrete, organized nature	38.0	34.2
Ipeople	involving working for the presumed good of people	7.2	21.0
Iprestige	resulting in prestige or the esteem of others	15.7	24.1
Polar interests:	Interests that are entailed in job performance. Scored on scale from -1 to 1: 1=first interest is relevant; -1=second interest is relevant; 0=dimension is irrelevant.		
Data/Thing	Preference for working with data or things.	-0.3	0.6
Create/Rout	Preference for abstract, creative work vs. routine, concrete, organized work.	-0.3	0.4
Mach/People	Preference for working with machines vs. working for the presumed good of people.	0.5	0.5
Product/Prest	Preference for activities resulting in tangible production vs those resulting in prestige.	0.0	0.4
Temperaments:	Percent of workers whose job requires the adaptability...		
Direct	for the direction, control, or planning of an activity.	18.8	25.9
Interpret	to situations involving the interpretation of feelings, ideas or facts.	2.8	12.3
Influence	to influencing people.	9.4	20.1
Judge	to making decisions based on sensory or judgmental criteria.	30.5	31.0
Measure	to making decisions based on measurable or verifiable criteria.	46.0	34.0
Dealw/people	to dealing with people beyond giving or receiving instructions.	35.8	36.5
Repeat	to performing repetitive work or to continuously performing the same work.	25.9	29.2
Stress	to performing under stress.	5.7	17.0
Standard	to situations requiring the attainment of set limits, tolerances or standards.	52.6	35.0
Variety	to performing a variety of duties, often changing from one task to another.	34.5	28.8

Physical demands:	Percent of workers whose job involves...		
Strength	physical strength.	2.4	0.7
Climb	climbing and/or balancing.	16.1	24.6
Stoop	stooping, kneeling, crouching, and/or crawling	27.9	30.7
Reach	reaching, handling, fingering, and/or feeling.	81.7	27.2
Talk	talking and/or hearing.	45.7	36.3
See	seeing.	65.7	29.1
Out	outdoor work.	7.9	17.8
Both	both indoor and outdoor work.	20.0	25.2
Cold	extreme cold.	0.9	4.6
Heat	extreme heat.	3.9	11.3
Wet	wet and/or humid conditions.	6.9	14.6
Noise	noise and/or vibrations.	22.6	28.5
Hazards	hazards.	19.3	26.3
Atmos	atmospheric conditions.	10.8	17.6

(Source: Roos and Price, 1981)

Table 2:

Measures of Process Type Intensity

Load on Two Factors

Factor 1 PIMS variable	Factor 2 Volume	Process
Large batch/assembly	.92	-.31
Small batch	-.86	-.53
Continuous process	-.02	.98
Proportion of common variance explained	.54	.46

Table 3:

Quantitative and Qualitative Indices of Mechanization by Industry

Quantitative index is capital-labor ratio (K/L) calculated for 2-digit SIC industries. Units are thousands of dollars per worker.

Qualitative indices are factor scores for 3-digit SIC industries in the PIMS sample. "Volume" contrasts assembly- and small batch-intensive processes; "Process" contrasts process- and small batch-intensive processes.

Industry	K/L	Volume	Process
Petroleum	133.4		
Chemicals	77.9		
Drugs		1.60	-0.69
Soaps		-0.16	0.38
Paints		0.56	-0.28
Agricultural chemicals		0.61	2.27
Industrial chemicals		-0.43	3.47
Paper products	77.6		
Paper pulp		-0.55	5.21
Misc. paper products		1.30	-0.19
Paper containers		1.45	-0.56
Primary metals	70.6		
Steel mills		0.11	0.14
Foundries		-1.29	-0.94
Primary aluminum		0.66	-0.66
Other primary metals		-0.87	0.52
Forgings		1.13	-0.73
Glass, cement and stone	50.0		
Glass		0.11	3.53
Cement		-0.37	4.47
Misc. stone products		-0.67	0.40
Tobacco	47.4		

Food Processing	40.7		
Canned vegetables		0.73	0.67
Milled grains		0.65	1.06
Bakeries		1.47	-0.23
Beverages		1.23	0.44
Misc. food		0.61	2.27
Rubber and plastics	39.6		
Plastics materials and synthetics		0.25	1.33
Misc. plastics		0.73	0.24
Rubber products		0.81	1.29
Fabricated metals	38.5		
Hardware		0.47	-0.57
Fabricated structural metals		-0.88	0.48
Screw machinery products		1.23	0.12
Misc. fabricated metals		-0.02	1.60
Transportation equipment	33.2		
Aircraft		-1.86	-0.86
Lumber and wood products	27.1		
Misc. wood products		0.38	2.86
Textiles	24.7		
Floor coverings		0.10	0.23
Fabrics		0.97	.47
Misc. textiles		0.40	2.25
Machinery, except electrical	22.8		
Engines		0.42	-0.74
Farm machinery		1.49	-0.70
Construction machinery	-2.12	-0.72	
Metalworking machinery		-1.11	-0.89
Office and computing equipment		-1.17	0.15
Non-electrical machinery, nec		-2.20	-0.78
Electrical machinery	21.0		
Household appliances		1.43	-.70
Radio/TV equipment		-0.77	-0.29
Electrical industrial machinery		0.06	-0.69

Instruments and precision equip.		16.5	
Scientific instruments		-2.28	-0.55
Optical supplies		-0.25	0.18
Photography equipment	-0.54	-0.07	
Printing	14.7		
Commercial printing		1.23	0.73
Misc. mfg. industries	12.3		
Toys		1.78	-0.67
Misc. manufacturing		0.86	0.74
Furniture	8.1		
Household furniture		0.50	-0.78
Leather products	5.8		
Apparel	5.2		

Table 3b
Descriptions of mechanization indices

Variable	Mean	Standard Dev.
K/L	41.5	22.7
Volume	.16	1.0
Process	.49	1.5

Table 3c
Correlations among the mechanization indices

	K/L	Volume	Process
K/L	1.00		
Volume	.124	1.00	
Process	.246	-.005	1.00

Table 4:

Factor Structure

(all occupations)

Percent of common variance accounted for by each factor is shown in parentheses. Only loadings of .40 or higher are shown. Method: oblique rotation (ROTATE = PROMAX in SAS).

Factor 1: Substantive complexity (32%)

Data	.97	SVP	.96	GED	.95	Intell	.90
Create/Rout	.89	Verbal	.88	Iroutine	-.88	Repeat	-.87
Numerical	.87	Direct	.80	People	.75	Talk	.69
Ithing	-.68	Variety	.67	Measure	.65	Clerical	.61
Iscience	.61	Spatial	.58	Iprestige	.57	Strength	-.49

Factor 2: Motor skills (16%)

Things	.89	Motor	.84	Fingdex	.83	See	.82
Standards	.81	Mandex	.75	Form	.67	Prod/Prestige	.62
Reach	.61	Influence	-.49	Mach/People	.49	Iproduct	.49

Factor 3: Social skills (25%)

Data/Thing	.93	Ibusiness	.92	Idata	.90	Dealw/peo	.89
Ithing	-.82	Talk	.79	Imachine	-.78	Judge	.75
People	.67	Verbal	.61	Influence	.57		

Factor 4: Demanding Working conditions (19%)

Climb	.86	Stoop	.86	Strength	.84	Physical	.77
Hazard	.76	Atmos	.61	Noise	.66	Clerical	-.63

Factor 5: Craftwork (8%)

Prod/Prestige	.66	Icreate	.60	Iprestige	-.57	Color	.52
Interpret	.45	People	-.42				

Inter-factor correlations

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Factor 1	1.00				
Factor 2	.00	1.00			
Factor 3	-.36	-.27	1.00		
Factor 4	-.26	-.16	.38	1.00	
Factor 5	-.09	-.27	.19	.04	1.00

Table 5:

Factor Structure

(non-managerial occupations)

Percent of common variance accounted for by each factor is shown in parentheses. Only loadings of .40 or higher are shown. Method: oblique rotation

Factor 1: Substantive complexity (30%)

GED	.96	Data	.94	SVP	.93	Numerical	.92
Intell	.91	Verbal	.86	Create/Rout	.82	Iroutine	-.80
Repeat	-.80	Iscience	.80	Direct	.80	Spatial	.69
Measure	.67	Form	.64	People	.61	Variety	.60
Clerical	.58						

Factor 2: Social skills (28%)

Data/Thing	.96	Dealw/people	.94	Idata	.93	Ibusiness	.92
Talk	.87	Ithing	-.87	People	.81	Judge	.79
Mach/People	-.72	Verbal	.71	Clerical	.68	Intell	.63

Factor 3: Motor skills (16%)

Things	.87	Standards	.81	Fingdex	.80	Motor	.80
See	.76	Form	.72	Mandex	.72	Prod/Prestige	.61
Influence	-.52						

Factor 4: Demanding Working conditions (18%)

Climb	.88	Stoop	.88	Strength	.80	Physical	.80
Hazard	.78	Noise	.62	Atmos	.60	Clerical	-.54
Both	.54	Wet	.52	Iproduct	.50		

Factor 5: Craftwork (8%)

Iproduct	.72	Interpret	.62	Create/Rout	.60	Prod/Prestige	.55

Inter-factor correlations

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Factor 1	1.00				
Factor 2	.38	1.00			
Factor 3	.22	-.13	1.00		
Factor 4	-.19	-.38	.17	1.00	
Factor 5	.16	.02	.18	.27	1.00

Table 6:

Factor Structure

(non-managerial, non-professional occupations)

Percent of common variance accounted for by each factor is shown in parentheses. Only loadings of .40 or higher are shown. Method: oblique rotation (ROTATE=PROMAX in SAS).

Factor 1: Cognitive complexity (30%)

Data/Thing	.95	Dealw/peo	.91	Idata	.91	Talk	.91
Ibusiness	.90	Ithing	-.89	Verbal	.86	People	.85
Judge	.82	Intell	.77	Clerical	.72	Repeat	-.70
Iroutine	-.61	Mach/People	-.62	Create/Rout	.60	Strength	-.56
Variety	.50	SVP	.51				

Factor 2: Technical complexity (23%)

GED	.87	SVP	.86	Data	.86	Numerical	.81
Repeat	-.76	Intell	.76	Iroutine	-.70	Iscience	.69
Measure	.69	Direct	.66	Icreate	.55	Spatial	.55

Factor 3: Motor skills (18%)

Standards	.85	See	.84	Things	.84	Fingdex	.81
Motor	.80	Form	.80	Mandex	.60	Influence	-.56

Factor 4: Demanding Working conditions (15%)

Climb	.88	Stoop	.85	Hazard	.81	Physical	.81
Strength	.75	Both	.62	Atmos	.58	Noise	.54
Heat	.52						

Factor 5: Craftwork (14%)

Prod/Prestige	.86	Iproduct	.86	Mandex	.65	Spatial	.65
Noise	.57	Clerical	-.54	Physical	.52	Things	.50

Inter-factor correlations

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Factor 1	1.00				
Factor 2	.39	1.00			
Factor 3	.07	.38	1.00		
Factor 4	-.29	-.01	.07	1.00	
Factor 5	-.18	.13	.27	.45	1.00

Table 7a:

Correlations between Mechanization and Work

(all occupations)

Mechanization: Ln (K/L).
N=8940
Correlations in **boldface** are significant at the .05 level.

Subst comp	**.10**	Motor skill	**-.10**	Social skills	**.04**	Demanding Wkg conds	**.13**	Craftwork	**-.05**
Data	**.11**	Things	**-.09**	Data/Thing	**.06**	Climb	**.17**	Prod/Prestige	**-.06**
SVP	**.09**	Motor	**-.08**	Ibusiness	**.04**	Stoop	**.16**	Icreate	-.00
GED	**.11**	Fingdex	**-.20**	Idata	.01	Strength	**.13**	Iprestige	**.05**
Intell	**.13**	See	**-.10**	Dealw/peo	**.05**	Physical	**.05**	Color	**-.09**
Creat/Rou	**.12**	Standards	**-.10**	Ithing	**-.08**	Hazard	**.16**	Interpret	**-.07**
Verbal	**.08**	Mandex	-.01	Talk	**.09**	Atmos	**.17**	People	**.09**
Iroutine	**-.13**	Form	**-.08**	Imachine	**-.08**	Noise	**-.07**		
Repeat	**-.13**	Prod/Prestige	**-.06**	Judge	**.05**	Clerical	**.13**		
Numerical	**.12**	Reach	**-.04**	People	**.09**				
Direct	**.08**	Influence	-.00	Verbal	**.08**				
People	**.09**	Mach/People	**-.08**	Influence	-.00				
Talk	**.09**								
Ithing	**-.08**								
Variety	**.10**								
Measure	**.11**								
Clerical	**.13**								
Iscience	**.09**								
Spatial	**.02**								
Iprestige	**.05**								
Strength	**.13**								

Table 7b:

Correlations between Mechanization and Work
(non-management occupations)

Mechanization: Ln(K/L).

N=8060
Correlations in **boldface** are significant at the .05 level.

Subst comp	**.10**	Social skills	**.06**	Motor skills	**-.08**	Demanding Wkg conds	**.17**	Craftwork	**-.10**
GED	**.11**	Data/Thing	**.05**	Things	**-.09**	Climb	**.18**	Iproduct	**-.04**
Data	**.10**	Dealw/peo	**.03**	Standards	**-.10**	Stoop	**.18**	Interpret	**-.08**
SVP	**.08**	Idata	**.02**	Fingdex	**-.21**	Strength	**.16**	Create/RoutT	**.11**
Numerical	**.12**	Ibusiness	**.02**	Motor	**-.07**	Physical	**.09**	Prod/Prestige	**-.05**
Intell	**.13**	Talk	**.08**	See	**-.10**	Hazard	**.17**		
Verbal	**.08**	Ithing	**-.08**	Form	**-.09**	Noise	**-.07**		
Creat/Rou	**.11**	People	**.09**	Mandex	.01	Atmos	**.18**		
Iroutine	**-.13**	Judge	**.04**	Prod/Prest	**-.05**	Clerical	**.13**		
Repeat	**-.13**	Mach/People	**-.10**	Influence	.00	Both	**.18**		
Iscience	**.09**	Verbal	**.08**			Wet	**.09**		
Direct	**.06**	Clerical	**.13**			Iproduct	**-.04**		
Spatial	**.02**	Intell	**.13**						
Measure	**.10**								
Form	**-.09**								
People	**.09**								
Variety	**.09**								
Clerical	**.13**								

Table 7c:

Correlations between Mechanization and Work
(non-management, non-professional occupations)

Mechanization: Ln(K/L).
N=5940
Correlations in **boldface** are significant at the .05 level.

Cog comp	**.08**	Tech comp	**.11**	Motor skills	**-.08**	Demanding Wkg conds	**.23**	Craftwork	**-.07**
Data/Thg	**.08**	GED	**.11**	Standards	**-.13**	Climb	**.19**	Prod/Prest	**-.05**
Deal peo	**.05**	SVP	**.08**	See	**-.11**	Stoop	**.20**	Iproduct	-.02
Idata	**.05**	Data	**.12**	Things	**-.12**	Hazard	**.18**	Mandex	.00
Talk	**.10**	Numerical	**.11**	Fingdex	**-.23**	Physical	**.10**	Spatial	.00
Ibusiness	**.04**	Repeat	**-.14**	Motor	**-.08**	Strength	**.17**	Noise	**-.07**
Ithing	**-.09**	Intell	**.15**	Form	**-.11**	Both	**.19**	Clerical	**.13**
Verbal	**.08**	Iroutine	**-.14**	Mandex	.00	Atmos	**.18**	Physical	**.10**
People	**.11**	Iscience	**.07**	Influence	.02	Noise	**-.07**	Things	**-.12**
Judge	**.06**	Measure	**.08**			Heat	**.10**		
Intell	**.15**	Direct	**.07**						
Clerical	**.13**	Icreate	**.03**						
Repeat	**-.14**	Spatial	.00						
Iroutine	**-.14**								
Mach/Peo	**-.12**								
Creat/Rou	**.13**								
Strength	**.17**								
Variety	**.08**								
SVP	**.08**								

Table 8a:

The Relationship between Work Factors and

Qualitative Measures of Mechanization

(all occupations)

Volume: distinguishes assembly-intensive from batch-intensive technology.
Process: distinguishes continuous process-intensive from batch-intensive technology.

Standard errors of regression coefficients are given in parentheses. Boldfaced coefficients are significant at the 5% level. N=20 industries.

Subst Comp = .054 -	**.100**(Volume) +	.000(Process)	R^2=.17
	(.027)	(.022)	
Motor Skill =.028 -	**.029**(Volume) -	**.044**(Process)	R^2=.27
	(.013)	(.011)	
Social skills =-.009 +	.004(Volume) +	.030(Process)	R^2=.03
	(.019)	(.016)	
Demanding =-.019 +	.010(Volume) +	.039(Process)	R^2=.02
Wkg Conds	(.028)	(.023)	
Craftwork =-.007 +	.010(Volume) -	.018(Process)	R^2=.01
	(.014)	(.012)	

Table 8b:

Regressing Work Factors on Qualitative Measures of Mechanization (non-management occupations)

Volume: distinguishes assembly-intensive from batch-intensive technology.
Process: distinguishes continuous process-intensive from batch-intensive technology.

Standard errors of regression coefficients are given in parentheses. Boldfaced co-efficients are significant at the 5% level. N=20 industries.

Subst Comp = .063 -	**.115**(Volume) -	.007(Process)	R^2=.17
	(.031)	(.026)	
Social Skills =-.001 -	.014(Volume) +	.028(Process)	R^2=.01
	(.022)	(.019)	
Motor Skill =.042 -	**.040**(Volume) -	**.047**(Process)	R^2=.33
	(.013)	(.011)	
Demanding =-.008 -	.002(Volume) +	.040(Process)	R^2=.01
Wkg Conds	(.028)	(.023)	
Craftwork =-.045 +	.032(Volume) -	.005(Process)	R^2=.03
	(.017)	(.014)	

Table 8c:

Regressing Work Factors on Qualitative Measures of Mechanization

(non-management, non-professional occupations)

Volume: distinguishes assembly-intensive from batch-intensive technology.
Process: distinguishes continuous process-intensive from batch-intensive technology.

Standard errors of regression coefficients are given in parentheses. Boldfaced co-efficients are significant at the 5% level. N=20 industries.

Cog Comp = -.058 +	**.065**(Volume) -	.018(Process)	R^2=.09
	(.023)	(.019)	
Tech Comp =-.021 +	**.034**(Volume) +	**.054**(Process)	R^2=.31
	(.014)	(.012)	
Motor Skill =.015 +	.012(Volume) -	.035(Process)	R^2=.02
	(.024)	(.020)	
Demanding =.007 -	**.034**(Volume) -	.017(Process)	R^2=.10
Wkg Conds	(.014)	(.012)	
Craftwork = .063 -	.024(Volume) -	**.049**(Process)	R^2=.18
	(.017)	(.014)	

Table 9a:
Path Model Regression Results:
All occupations

Standardized regression coefficients. T-statistics presented in parentheses. Boldface indicates significant at 0.05 level.
N=447 occupations.

Wage=**0.65**(SubComp) -**0.06**(Motor) +**0.15**(Social) -**0.23**(WkgCond)+**0.03**(Craft)
(134) (14) (37) (-45) (10)
-**0.24**(Gender) -**0.02**(Profit) +**0.02**(Union).
(-43) (-7) (7)
Adjusted R^2=0.77

SubComp	=	+0.10(Mech) (15)
Motor	=	-0.10(Mech) (15)
Social	=	+0.04(Mech) (6)
WkgCond	=	+0.13(Mech) (20)
Craft	=	-0.05(Mech) (-8)
Gender	=	-0.29(Mech) (-44)
Profit	=	-0.18(Mech) (-27)
Union	=	0.19(Mech) (28)

Table 9b:
Path Model Regression Results:
Non-management occupations

Standardized regression coefficients. T-statistics presented in parentheses. Boldface indicates significant at 0.05 level.
N=403 occupations.

Wage = **0.65**(SubComp) +**0.23**(Social) -**0.02**(Motor) -**0.17**(WkgCond) -**0.05**(Craft)
(115) (51) (4) (-29) (-13)
-**0.27**(Gender) -**0.02**(Profit) +**0.03**(Union).
(-42) (-6) (7)

AdjustedR^2=0.74

SubComp	=	+0.11(Mech) (15)
Social	=	+0.05(Mech) (8)
Motor	=	-0.08(Mech) (12)
WkgCond	=	+0.17(Mech) (25)
Craft	=	-0.10(Mech) (-14)
Gender	=	-0.30(Mech) (-44)
Profit	=	-0.18(Mech) (-25)
Union	=	0.19(Mech) (27)

Table 9c:
Path Model Regression Results:
Non-management, non-professional occupations

Standardized regression coefficients. T-statistics presented in parentheses. Boldface indicates significant at 0.05 level.
N=297 occupations.

Wage=	**0.60**(CogComp)	+**0.16**(TecCom)	+**0.18**(Motor)	-**0.23**(WkgCond)
	(108)	(23)	(26)	(-33)
	0.02(Craft)	-**0.46**(Gender)	-**0.02**(Profit)	-**0.04**(Union).
	(-3)	(-55)	(-4)	(8)

Adjusted R^2=0.62

CogComp	=	+0.09(Mech)
		(12)
TechComp	=	+0.11(Mech)
		(13)
Motor	=	-0.08(Mech)
		(11)
WkgCond	=	+0.20(Mech)
		(27)
Craft	=	-0.07(Mech)
		(-9)
Gender	=	-0.30(Mech)
		(-41)
Profit	=	-0.17(Mech)
		(-22)
Union	=	0.19(Mech)
		(26)

Table 10:

Decomposition of Variance between Mechanization and Wages

(standardized regression coefficients)

All occupations

Work Characteristic	(1) From Mech	(2) To Wage	Total (1)x(2)
Substantive Complexity	0.10	0.65	0.065
Motor Skill	-0.10	-0.06	0.006
Social Skills	0.04	0.15	0.006
Working Conditions	0.13	-0.23	-0.030
Craftwork	-0.05	0.03	-0.002
Total covariance			0.045
Control			
Gender	-0.29	-0.24	0.070
Profitability	-0.18	-0.02	0.004
Unionization	0.19	0.02	0.004
Total covariance with controls:			0.123

Non-management occupations

Work Characteristic	(1) From Mech	(2) To Wage	Total (1)x(2)
Substantive Complexity	0.11	0.065	0.072
Social Skills	0.05	0.23	0.012
Motor Skill	-0.08	-0.02	0.001
Working Conditions	0.17	-0.17	-0.029
Craftwork	-0.10	-0.05	0.005
Total covariance			0.061
Control			
Gender	-0.30	-0.27	0.081
Profitability	-0.18	-0.02	0.004
Unionization	0.19	0.03	0.006
Total covariance with controls:			0.152

Table 10:

Decomposition of Variance between Mechanization and Wages

(standardized regression coefficients)

Non-management non-professional occupations

Work Characteristic	(1) From Mech	(2) To Wage	Total (1)x(2)
Cognitive Complexity	0.09	0.60	0.054
Technical Complexity	0.11	0.16	0.018
Motor Skill	-0.08	0.18	-0.014
Working Conditions	0.20	-0.23	-0.046
Craftwork	-0.07	-0.02	0.001
Total covariance			0.013
Control			
Gender	-0.30	-0.46	0.138
Profitability	-0.17	-0.02	0.003
Unionization	0.19	0.04	0.008
Total covariance with controls:			0.162

Figure 1
Data Matrix

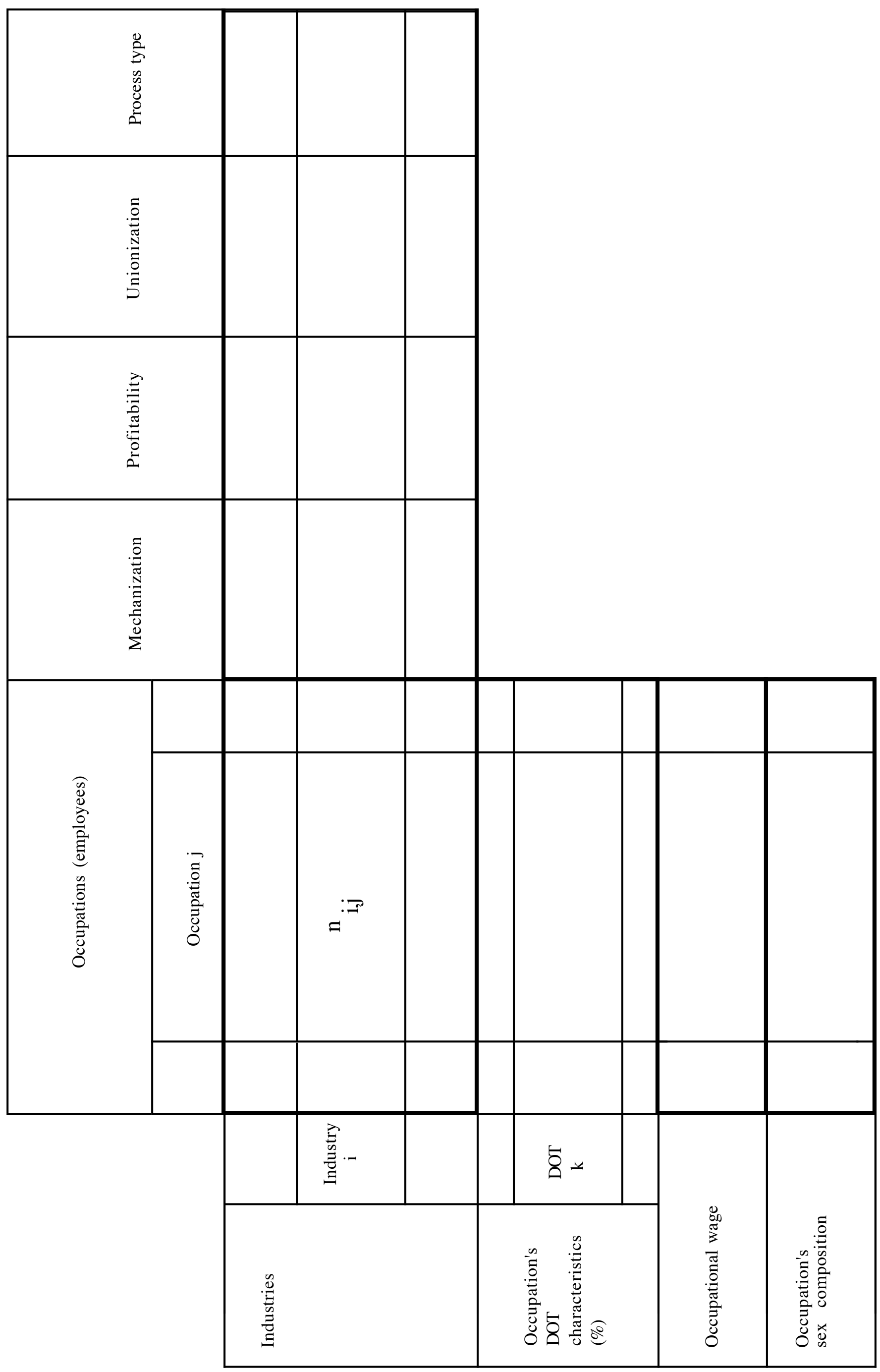

Figure 2
Path Model