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Abstract

Trade and other economic models often hinge on skill distinctions in the labor force, and empirical studies commonly use production-nonproduction worker, rather than education, data to measure skill. We argue that empirical work in trade should measure skill with education data by industry. With 1995 and 1996 data from U.S., Mexican and Canadian manufacturing we demonstrate that the production-worker share, while significantly related to skill level, is in most cases not a good proxy for the latter. Furthermore, the relation between the production-worker share and skill level differs systematically between "advanced-technology" and other manufacturing. The relationship between production-worker shares and skill displays deep and pervasive cross-sectoral differences within national manufacturing sectors and across countries. JEL J0, J3, F1.

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Measuring Skill Intensity: Production Worker vs. Education Data in the NAFTA Countries

Measuring workers' skills is a central component of several important research areas in economics. The distinction between skilled and less-skilled workers, for example, plays a particularly prominent role in theoretical and empirical studies of wage and income inequality trends, in the OECD and in developing countries, by trade and labor economists.[1]

But what is the best way to measure skill? Empirical studies in trade or labor economics typically require data on both the absolute level of demand for labor by skill and also on the relative intensity of skilled-labor use across industries and across countries. By far the most commonly used measure of skill in trade studies is data on industries' use of production and nonproduction workers, in share or level terms. These data are also used frequently in studies of wage dispersion and technological change in labor markets. The production-nonproduction distinction, it is argued, corresponds to an unskilled-skilled divide in an industry's workforce, and so production-nonproduction data are routinely used as a skill proxy without much by way of theoretical or empirical justification. It also frequently assumed, often implicitly, that all manufacturing industries share a similar relationship between worker skills and production- worker shares, and further that in other economies the relationship between these occupational and educational measures is similar to that in the United States.

Although the labor economics literature provides some examples of the use of the production-nonproduction worker distinction as a worker-skill proxy,[2] labor economics theory suggests that worker-education data by sector may be a better measure of skill than the production-worker share. Studies of income distribution trends, for example, routinely measure the skill premium with earnings differentials across levels of education. The widening of the skill premium between the least-educated workers and

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[1] For a review of this literature, see Collins (1998).
[2] See the articles cited in Dunne, Haltiwanger and Troske (1997), especially Hamermesh (1993).

those with college degrees (or more) provides the most potent evidence of increasing U.S. income inequality over the 1980s and 1990s.

Which approach is better, and does it matter? To answer these questions this paper does three things. First, we survey the existing evidence on, and debate about, the use of production-nonproduction worker data as a skill proxy. Second, we provide a fresh empirical investigation of the relationship between manufacturing industries' production-nonproduction worker data and their workers' education levels in the United States, and provide for the first time evidence from Canada and Mexico. In contrast to previous studies, we directly test the assumptions underlying the use of production worker data as a skill proxy by using cross-section data which allow estimation of the relationship across all manufacturing. Finally, we consider the implications of these findings for best-practice empirical work.

We find that production-nonproduction worker data is indeed statistically significantly related to education-based skills measures, and highly so. But while production workers are on average less-skilled than nonproduction workers, the share of production workers in any given manufacturing sector is not, in many circumstances, a good predictor of education-based skill measures. The production-nonproduction worker data has a mixed ability to predict U.S. education-based skills measures, and a poor ability to predict Canadian and Mexican education-based skills measures. We therefore argue that on both empirical and theoretical grounds education data should be the preferred proxy for skill.

Additionally, we find that there is substantial heterogeneity in education levels among production workers, and this heterogeneity is related to industries. Some industries, in particular those generally considered high-skill industries, employ more educated production workers than do other industries. Among these high-skill industries, moreover, a change in production-worker share implies a much different change in education shares than that found in the rest of manufacturing. In this sense, then, all industries are not alike, and use of the production-worker data across industries implies a type of systematic mismeasurment of skill intensity.

Finally, we find large differences in the relationship between the two skill proxies in the United States, Canada, and Mexico. For any given industry, the relationship in the United States between production-worker shares and education is not typical of the experience in the rest of NAFTA. The lesson here, we will argue, is that the U.S. production-worker data should never be ascribed to either Canada or Mexico (to, for example, rank industries based upon skill intensity). More generally, even own-country production-worker data should only be used with extreme caution as a skill proxy.

The paper proceeds as follows. Section I addresses the debate about using production-nonproduction worker data as a proxy for skill, and assesses the empirical evidence that has been brought forward to date. Our own empirical results follow in section II. Section III considers the practical implications of these results for economists' research efforts. We offer recommendations about circumstances in which it may be reasonable to use the production-worker proxy and cases when it is not so. We then make concluding comments.

I. The Debate About Skill Measures in Manufacturing

The labor economics literature suggests strongly that education is a superior measure of skill than the production/nonproduction worker share. While "skill" is an elusive concept, the literature identifies three sources of workers' skills: total years of work experience, job tenure in their current occupation, and educational attainment.[3] A carefully drawn study, then, would use micro data on these three sources to measure and compare industries' skill distributions. This data requirement is beyond the scope of most studies. The good news, however, is that worker educational attainment is correlated with the other two skill sources. More educated workers show a greater commitment to the labor force (and

[3] See Becker (1975) on "general" vs. "specific" training, and Schultz (1975) on education.

have, on average, more total years in the workforce[4]), and have a higher propensity to enroll in formal on-the-job training (OJT).[5] This collinearity may be trouble for a labor economist's wage equation, but it simplifies the task facing economists looking for a single measure of labor's skill. Educational attainment measures its own contribution, and proxies the remaining contributions, to worker skills. Thus, the distribution of workers' educational attainment comports closely to labor's skill distribution and labor economists frequently rely on education alone as a skill proxy.[6]

If years of education is a useful proxy for skill, that has not stopped some labor economists, and many trade economists, from using the production-nonproduction distinction as a skill measure. This is problematic for those economists whose theoretical models hinge on distinguishing labor factors on the basis of skill, since the production-worker data only allows two skill divisions. Some economists have also expressed qualms about using production-worker data as a proxy for skill on the grounds that the production worker category includes many highly-skilled workers and, likewise, that the nonproduction worker category includes many unskilled workers.[7] But, more commonly, researchers have defended its use. Production-worker data has been used to measure the share of unskilled workers in each industry, to rank industries by skill intensity, and to measure unskilled workers' wage changes.[8]

Berman, Bound and Griliches (1994) provide the most frequently-cited evidence in favor of this proxy. They argue that

> …both conceptually and empirically, the production/nonproduction worker distinction closely mirrors the distinction between blue- and white-collar occupations…The blue-collar/white-collar

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[4] This holds true for the United States and, we may assume, for Canada. It does not hold true for Mexico, however. Mexican workers with more education tend to have less labor-market experience because there has been an upward trend in completion years. As a result, the oldest workers are typically the least educated.

[5] See Pencavel (1986) and Bowen and Finegan (1969) on the positive response of hours to education; see Altonji and Spletzer (1991), Mincer (1988) and Lillard and Tan (1986) on education and OJT.

[6] See Wolff (1996) and Howell and Wolff (1991).

[7] The most pointed criticism is found in Leamer (1994) and Lawrence (1996).

[8] Sachs and Shatz (1994, 1998), Feenstra and Hanson (1999), Lawrence and Slaughter (1993), and Krugman and Lawrence (1993) are notable examples. Baldwin and Cain (2000) stand out as one of the few trade studies which reject the use of production-nonproduction-worker data; Pryor (1999) uses both skill proxies.

classification, in turn, closely reflects an educational classification of high school/college (pp. 371-372).

This is a two-part argument. The first part, that the production-nonproduction worker distinction mirrors the blue- and white-collar distinction, is supported by aggregate data for the manufacturing sector in 1973, 1979, and 1987. In each of these years the total proportion of nonproduction workers is quite close to the proportion of white-collar workers, and both display a strikingly similar upward trend. Their evidence for the second part of their argument, that the blue-collar/white-collar distinction mirrors the high-school/college educational distinction, comes from the 1987 Current Population Survey which indicates that a smaller share of blue-collar workers have more than a high-school diploma than is true for white-collar workers.[9]

In a related issue, Berman, Bound and Griliches also make the case that "…a large part, though not all, of the skill upgrading that occurred in the 1980s can be accounted for by the shift to…nonproduction labor" (pp. 373-374). This implies, as Berman, Bound and Machin (1998) summarize it, that "the proportion of nonproduction workers follows the same trend increase as the proportion of skilled workers in U.S. manufacturing," a point often cited as evidence in favor of using production worker data as a skill proxy. Sachs and Shatz (1994, Appendix B) use essentially this argument when they cite the closely similar trends in education shares and production-nonproduction worker shares between 1967 and 1987.

Dunne, Haltiwanger and Troske (1997) also provide evidence on the relationship between production worker data and skill levels. Using 1990 data from the Worker-Establishment Characteristics Database, they find that in plants in the lowest nonproduction share quintile only 7.4 percent of workers

[9] Their complete statement of evidence on this point is "…only 17 percent of blue-collar workers had more than a high-school education, as opposed to 35 percent of clerical workers, 70 percent of sales workers, and 78 percent of managers and professionals" (p. 372).

are college graduates, while 21.1 percent of workers are college graduates in plants in the highest nonproduction share quintile.

None of the defenders of production-worker data claim that the data are ideal; in fact, Jensen and Troske (2000) allow that this evidence "is by no means ideal." In our view, a central defect of the existing literature is that it does not provide direct estimates of the relationship, across all manufacturing sectors, between the production-nonproduction share and education shares.[10] The existing literature supports the view that on average across manufacturing the production-nonproduction worker distinction corresponds to a meaningful skill distinction. Nonproduction workers – who include supervisory workers, management, and research staff – *are* on average more skilled than production workers.[11] But this is not equivalent to a demonstration that the production/nonproduction worker distinction is a good proxy for skill distinctions in all circumstances. That is, Berman *et al*'s evidence noted above demonstrates a positive correlation between the production-nonproduction worker share and educational measures for all of manufacturing, not for individual manufacturing industries. Do changes in production worker shares from industry to industry, for instance, correspond to meaningful differences in industries' use of skilled labor? Will a rank ordering of manufacturing sectors by production worker shares correspond closely enough to a rank ordering by education shares (say, by the share of workers without a high school degree) for the former to proxy the latter?

Finally, whatever the weaknesses of the literature linking U.S. production-worker data to education data, there has been nothing comparable done to link these two skill measures for non-U.S.

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[10] Sachs and Shatz (1994, Appendix B) is a partial exception. They estimate the cross section relation between Howell and Wolf's education index and production worker shares in 1980.

[11] The Census Bureau's *Annual Survey of Manufacturing* (ASM) definition separates workers into those directly engaged in production and all others. Production workers are "…workers (up through the line-supervisor level) engaged in fabricating, processing, assembling, inspecting, receiving, storing, handling, packing, warehousing, shipping (but not delivering), maintenance, repair, janitorial and guard services, product development, auxiliary production for plant's own use (power plant, etc.), record-keeping, and other services closely associated with these production operations…" (U.S. Census Bureau).

countries. Since the production-nonproduction worker data are now being used in studies of other countries, it is necessary , then, to examine this relationship outside of the United States.

In sum, the popularity of production-worker data is not attributable to a wide consensus regarding its empirical suitability. It is rooted, instead, in the data's ready availability[12] and its basic correspondence to a meaningful skill division. The literature has left almost entirely unexplored all questions about the underlying cross-sectional relationship between production-worker shares and skill and about differences in that relationship across countries.

II. Production-Worker Data as a Proxy for Skill: Empirical Results

Focusing exclusively on manufacturing, we assembled production worker share (PWS) data at a detailed industry level for each NAFTA member, matched with educational attainment data. For the United States we used 3-digit U.S. SIC data for 1995 and 1996, pooling the observations for the calculations reported below. Data on a 3-digit Canadian SIC basis, for 1995 only, was constructed for Canada; for Mexico we again pooled annual 3-digit data, on a Mexican CMAP (Clasificacion Mexicana de Actividades y Productos) basis, for 1995 and 1996.[13]

We focus on the lower end of each country's skill distribution as measured by educational attainment. For the United States and Canada we included detailed industry-level measures of the share of workers with less than a high-school degree (LHS) and the share with a high-school degree or less (HS).[14] For Mexico, we used measures of the share of workers with 7 years or less of education (E7) and those with 12 years or less (E12). In each country these can be thought of as the share of the least

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[12] The Department of Labor's Bureau of Labor Statistics (BLS) and the ASM both provide production-nonproduction worker data.

[13] We concorded the U.S. education data, which comes from the Current Population Survey, to conform to the SIC-based categories used by the BLS to report the production/nonproduction worker data. Similar concording was necessary for the Canadian and Mexican data. (The data appendix provides details.)

[14] These categories are slightly different in the United States and Canada, as the HS category in Canada includes individuals who, in U.S. terms, have finished a year of schooling beyond high-school.

skilled, and that of low-skilled, workers, respectively. By putting PWS up against two education-based skill measures, we are giving the production-worker data an opportunity to prove that it adequately proxies at least one such measure.

Table 1 displays the averages in manufacturing, for all three countries, of the various measures. In the United States and Canada average production-worker shares are substantially higher than the shares of low and least-skilled workers as measured by educational attainment. In the United States in 1996, for instance, the production-worker share was 69.1 percent while only 55.4 percent of manufacturing workers had a high-school degree or less, and only 15.4 percent had less than a high-school degree. For Canada and the United States, in other words, the absolute level of the production-worker share overstates the unskilled-worker share by a wide margin. In Mexico in 1996 the average production-worker share in manufacturing is at 70.0 percent but the share of workers with 12 years of education or less is higher (86.9 percent) and the share of workers with 7 years of education or less is lower (33.7 percent). Thus here, too, in absolute terms the production worker share does not correspond to educational attainment shares.

That levels of PWS do not correspond one-for-one with education shares does not mean that PWS is a poor proxy for measuring the relationship across industries between these variables. The production-worker data may be useful if it displays a consistent, reliable relationship to education shares. In estimating this relationship our concern is not exclusively that of finding a statistically significant relation between the two variables, though without that there would be no case at all for using PWS. Nor are we exclusively concerned with the nature of the relationship revealed by the estimated slope coefficients, though that will be of interest. What's most important is the extent of the correlation – the standard "goodness of fit" – which measures the accuracy of PWS data in predicting educational shares across manufacturing sectors. If the variance in PWS cannot explain much of the variance in education shares, PWS will not predict education shares well no matter how significant the relationship, or what the slope.

We therefore ran a series of regressions using PWS as the independent variable and either LHS or HS as the dependent variable; each equation was estimated twice, with variables in level form and in logs, using ordinary least squares. (In the pooled data sets, each regression included a constant term to control for possible 1996 fixed effects. This term was never significant.) We also calculated the Spearman rank correlation between industries' PWS and education shares.

We begin with the United States (Table 2). In all the regressions, in levels or logs, the coefficients on PWS are positive and highly significant. In level terms a one percentage point increase in PWS is associated with a 0.46 percentage point increase in LHS (equation 1) and a 0.90 percentage point increase in HS (equation 5). The double log regressions reveal the relationship more vividly: the coefficient on PWS is 1.95 when LHS is the dependent variable (equation 3) and 1.06 when HS is the dependent variable (equation 7). This suggests that for the U.S. the cross-industries elasticities of the LHS and HS shares with respect to PWS are around 2 and 1, respectively. While *levels* do not correspond one-for-one, *changes* in PWS apparently do with respect to HS shares.

Equations (3) and (7) have adjusted r-squareds of 0.47 (LHS) and 0.70 (HS), respectively. For LHS the low r-squared indicates a large amount of noise in the data, and translates into a correlation with PWS of less than 0.69. This should suggest caution to economists, who are aware of the difference between statistical significance (which is high in this case) and actual predictive usefulness. The ability of changes in PWS from sector to sector to predict changes in LHS shares is not high. For HS the adjusted r-squared may be high enough to suggest a useful correlation (approximately 0.84) between PWS and HS. We conclude that for the United States the merits of PWS as a skill proxy depend on what level of skill one considers.

There is also evidence of important cross-industry differences in the relation between PWS and education shares. That is, there's bias. Table 2's equations (2) and (4) for LHS, and (6) and (8) for HS, again in levels and logs, include in addition to the independent variable PWS 18 intercept dummies corresponding to each two-digit SIC category represented in U.S. data.[15] The industry intercept dummies dramatically improve the regressions' goodness of fit compared to the single variable models, and change the coefficients on the PWS terms. These changes suggest that the former equations correct for omitted variable bias in the latter. The elasticity of LHS with respect to PWS falls to around 1.3 (equation (4)), while that of HS with respect to PWS drops a much smaller proportion, down to around 0.9 (equation (8)).

But the most striking aspect of the multisector regressions is the distinctive pattern in the estimated industry intercept coefficients, a pattern displayed in all these equations. Coefficients for sectors that are commonly identified as "high-technology" sectors[16] – SICs 28 (chemicals), 29 (petroleum refining), 35 (machinery), 36 (electrical equipment), 37 (transportation equipment), and 38 (professional and scientific instruments) – are all negative and virtually all are statistically significant.[17] At the same time, the coefficients on sectors commonly regarded as "low-technology" sectors – SICs 20 (food products), 22 (textiles), 23 (apparel), and 24 (lumber and wood products) – are all positive and statistically significant. Advanced technology industries evidently use less low-skilled labor (whether LHS or HS) than other sectors, for any given level of PWS. This is evidence of what we label a "high-

[15] For the U.S. data here, and for subsequent Canadian and Mexican regressions which employ sector-specific dummies, we estimate unique coefficients for each 2-digit category without excluding one of the categories, which would normally be required in traditional estimation techniques. Using the STATA regression package, the "grand2.ado" command allows estimation of differential effects for all dummies; it calculates the average of a group of dummy variables and the difference of each dummy variable from the grand mean. Coefficient estimates and standard errors are corrected as suggested by Haisken-DeNew and Schmidt (1997).

[16] See Brauer and Hickock (1995).

[17] All the signs are as expected, and the only coefficients not statistically significant at 5% among these SICs are the coefficients for SIC 28 in equation (4) and for SICs 35 and 37 in equation (8). All of these are significant at 10%.

technology" bias in the use of PWS to measure skill: PWS in general overstates low-skill education shares, but the overstatement is particularly large in high-tech sectors.[18]

Results for Canada are in Table 3 (arrayed in the same manner as in Table 2's U.S. results). Consider first the results for the single-variable models which use only PWS as an independent variable. The relationship between PWS and the education measures is highly statistically significant in both level and log terms. The elasticity of HS with respect to PWS appears to be close to unity (1.17, in equation (7)), as it is for the United States; the elasticity of LHS is higher (at 1.82, equation (3)) but is not as high as the 1.95 estimated for the United States. Goodness of fit, however, as measured by the adjusted r-squared, is quite low, ranging from 25.4 percent for LHS levels to 33.4 percent for logged HS. These translate into low correlation coefficients between the education shares and PWS – between 50 percent and 58 percent – which hardly seems adequate for good proxying.

When sector-specific intercept dummies are added, adjusted r-squared rises somewhat but is still less than 50 percent in all regressions. The estimated elasticities of HS and LHS with respect to PWS fall only slightly to 1.04 and 1.57, respectively, and remain highly significant. The sectoral coefficients reveal high-tech bias, as in the United States, across both levels and logged specifications. Canadian SICs 18 (primary textiles), 19 (textile products) and 24 (clothing) have large, significant positive signs[19], while the SICs commonly thought of as advanced-technology intensive, such as 32 (transportation equipment), 33 (electrical equipment) and 36 (refined petroleum), exhibit negative coefficients and are usually statistically significant. This yields the same kind of differential observed for the United States:

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[18] To test the robustness of this high-tech bias to a different definition of advanced technology sectors we ran additional regressions which omitted the 2-digit intercept dummies and included a single pair of slope and intercept dummies for the industries identified by the USITC (1990) as high-technology industries on the basis of higher than average ratios of R&D to sales. We again found clear evidence of bias. Double-log regressions indicated an elasticity of LHS with respect to PWS of 1.95 for non-advanced technology industries but only 1.15 for the technology-intensive industries. The elasticities of HS with respect to PWS are 0.84 to 0.68 for the two types of industries, respectively. As a sector's PWS grows, advanced technology industries see less growth in their share of low-skill workers than do non-advanced technology sectors. In levels both the LHS and HS shares are predicted to be lower in high-tech than non-high-tech industries over the relevant range of observed PWS.

[19] With the exception of SIC 18 in the two logged equations (4) and (8), though the signs are correct.

for a given level of PWS, advanced technology sectors use less low-skilled labor than other sectors. Nevertheless this bias does not appear to be as sharp in the Canadian data as for the United States. SICs 37 (chemicals) and 31 (machinery) usually show the negative sign that would be expected on the basis of their advanced technology status, but are not statistically significant.

Mexican regressions are in Table 4 (again, in the same format as Tables 2 and 3). What is equally striking about all of the Mexican regressions, despite the positive and highly significant coefficients on PWS, is how poorly PWS performs in a predictive sense. Adjusted r-squareds range only from 11.2 percent to 32.6 percent, hardly high enough to inspire confidence in using PWS to predict individual sectors' use of workers by education level.

The log regressions indicate that the elasticity of E7 with respect to PWS is in the 0.56 to 0.77 range (from the multisector model, equation (4), and the single variable model, equation (3), respectively). This is less than half of the comparable elasticity in the United States or Canada. The elasticity of E12 with respect to PWS ranges from 0.22 to 0.28 (from the multisector model, equation (8), and the single variable model, equation (7), respectively). This range is an order of magnitude lower than that observed for the United States and Canada (which were close to unity).

The Mexican data also exhibit high-tech bias. At any given level of PWS, textiles and apparel sectors are significantly more intensive in the use of E7 and E12 labor than are the chemicals, basic metals and machinery sectors.

A final measure of the suitability of PWS as a skill proxy is provided by its rank correlation with education measures across industries. This is worth considering, as some cross-sectional studies need simply to rank industries by their skill intensity. Table 5 presents these results. Two generalizations can be made. First, in each country the rank correlation between PWS and the low education share (HS or E12) is higher than PWS's rank correlation with the least education measure (LHS or E7). Second, rank correlation is highest in the United States (where, at its maximum, it is 0.81 with respect to HS in 1995) and lowest in Mexico (at 0.35 for E7 in 1995). This is consistent with the range in the national regressions' adjusted r-squareds. A rank correlation on the order of 0.80 may be high enough for researchers to use PWS with confidence to rank industries by skill in education terms; but rank correlations in the 0.35 to 0.45 range, as is the case with Mexico, are probably not good enough to provide reasonable skill rankings.

Our empirical results can be summarized as follows. For all NAFTA members the relationship between production-worker shares and education intensity is positive and significant. There is a lot of noise, however, in the relationship across industries. In terms of rank correlation and adjusted r-squareds the fit appears strongest for the United States, less strong for Canada, and substantially weaker for Mexico. For the United States and Canada the elasticity of the HS education share with respect to production worker share appears to be in the neighborhood of unity; the elasticity of the LHS share with respect to PWS is larger. Both these elasticities are an order of magnitude smaller in Mexican manufacturing. All three countries give evidence of using less low-skilled labor in advanced-technology sectors than other sectors.

III. Implications for Empirical Work

While the overall empirical evidence is not encouraging, researchers need not avoid the production- worker data. Instead, we argue that this convenient and readily available data can play a useful, though limited, role in economists' empirical work. In this section we note how economists might continue to use the production-nonproduction distinction, and where its use is inadvisable.

The link between educational achievement and the production-nonproduction distinction is strongest in the United States when "unskilled" is defined as a worker with a high-school degree or less (that is, when the HS data is used). The elasticity between HS and the production-worker share is almost exactly one. The goodness of fit measure is perhaps acceptable at 0.7, and the rank correlation between industry HS data and industry PWS data is quite good at 0.8. So, when it is appropriate to group together U.S. workers with and without a high-school diploma, the good news from this study is that researchers can confidently use the PWS data. But it is important for researchers to make a careful judgement, for their particular question, that a high-school-educated worker is unskilled. As we note above, PWS is not a good proxy for the LHS data.

The second piece of good news is that, even if the question involves a comparison of industries inside manufacturing, it still might be possible to use this data. The inter-industry bias breaks fairly cleanly on a high-tech low-tech basis. We therefore recommend breaking the industries into the two groups for separate estimation, when possible, when using the production-worker data. This may be particularly important for economists who, in studying U.S. wages, face the challenge of separating technology-driven from trade-driven wage trends. This labor is made more difficult if a proxy for skill is used that systematically misstates the skill demand of high-technology industries, the very sectors in which technological change may be most pronounced.

While this is provisional good news for those in need of U.S. labor skill measures, researchers should be mindful of a subtle link between available data and the models economists employ. The focus on the production versus nonproduction worker distinction has encouraged researchers to model labor as two factors of production – skilled and unskilled – at the cost of losing much important detail about the *extent* of skill differentials between workers. As this, in our view, is the most serious problem with this data, we offer a detailed example of where its use can lead to erroneous conclusions.

Decades-long wage declines for U.S. unskilled workers have provoked economists to measure its extent, and to seek its source. One hypothesized source is import competition from low-income countries. Much of the modeling in this literature uses a two-tier skill definition for labor, which allows the empirical analysis to use the production-nonproduction worker data. A comparison of this data with the education data, however, casts strong doubt on whether this approach is appropriate. High-school dropouts in the United States have seen their average weekly wages fall by over 19 percent between 1979 and 1996. Production workers, by contrast, saw only a 9 percent decline over a similar period. This difference in outcomes likely results from the production worker category mixing dropouts, high-school graduates (whose weekly wages declined by only 6 percent), and even better-educated workers (such as advanced-technology line supervisors) whose wages rose.

The nonproduction worker category suffers from the same problem. College graduates saw their weekly wages rise by 23 percent over the period noted above, while nonproduction workers saw their wages increase by a more modest 12 percent. This lower wage increase may come from mixing college graduates with high-school graduates, and with high-school graduates with some post high-school training. This latter category saw their wages rise by only 1.5 percent. In short, the dramatic differences in wage trends by education level suggest that this data reflects real skill distinctions, while the production-nonproduction categories eliminate much inequality by mixing together workers with very different skill levels.[20]

The use of production-nonproduction categories may also make it difficult to assess properly the effect of international competition on inequality. Many low-income countries are abundant in workers most like those at the very bottom of the U.S. skill distribution. The typical conclusion that trade has not diminished the wages of unskilled workers may be sensitive to the gross skill categories trade economists favor. For instance, since 1980 U.S. imports from China and Mexico have surged, so much so that these countries are now among the top 4 sources of all U.S. imports. The average years of education in these countries was 5.0 and 4.9 in 1992, respectively.[21] Even allowing for equal quality schooling, these workers would be near the bottom of the U.S. education distribution. Textiles and apparel have been

[20] We thank Rebecca Blank for these Current Population Survey tabulations of real wages by education; the production/nonproduction worker real wage data is calculated from nominal data in the *Annual Survey of Manufactures* (1992 and 1996) deflated using CPI data from the *Economic Report of the President 1998*.

[21] See UNDP (1994).

major components of these new imports. The shares of U.S. workers in these industries without a high-school diploma are 28 percent and 36 percent respectively (in 1996), making them the two manufacturing sectors most intensive in the use of non-high-school graduates – though they do *not* have the highest production-worker shares of U.S. industries. The education data, in short, allows for a more carefully drawn definition of those possibly harmed by international trade.[22]

The point again from this example is that while the production-nonproduction worker data "works" for the United States in that it reasonably closely proxies a division of the manufacturing labor force between those with a high-school degree or less, and all others, this might not be the right place to draw the line. Careful regard must still be given to whether it is appropriate to model labor as having only two skill divisions.

Using the production-nonproduction distinction as a skill proxy outside the United States is much more problematic. For Canada the elasticity is, like the United States, close to one when comparing production shares and HS shares. But the low goodness of fit (33 percent) should be enough to give researchers pause. Mexico's regressions inspire even less confidence. The elasticity in the log-linear regressions is less than half that found for the U.S. and Canada. And the goodness of fit measures are worrisomely low. Both the Canadian and the Mexican data exhibit the high-tech bias found in the United States.

[22] Anderson and Smith (2000), for example, find that the predictions for wage loss by "low-skill" workers in Canada, attributable to increased imports from developing countries, is highly-sensitive to the number of skill distinctions employed, with the very *least*-skilled workers – those with less than a high school education – most vulnerable to adverse wage movements.

IV. Conclusion

Empirical economic research almost always involves difficult choices about proxy variables to measure important theoretical distinctions. Though production-worker data are readily available, the evidence in this paper is that on both empirical and theoretical grounds education-based skill measures will usually be superior. Furthermore, the evidence presented here suggests extreme caution in making international comparisons based upon production-worker data. While at a practical level it is more cumbersome to use education-based skill measures than the occupational-based measure (as indicated in the Data Appendix), the data are, in fact, available and we recommend that it become the standard for best practice in this area.

Table 1. Production Worker and Educational Attainment Shares in Manufacturing
Figures are percentages

United States			Canada		Mexico		
Measure	1995	1996	Measure	1995	Measure	1995	1996
PWS[1]	69.2	69.1	PWS	75.1	PWS	69.3	70.0
HS[2]	56.5	55.4	HS	51.6	HS	87.6	86.9
LHS[3]	157	15.4	LHS	26.8	LHS	35.4	33.7

[1] PWS: production worker share.
[2] HS: share (%) of workers with high school education or less; E7: share of workforce (%) with 7 years of education or less; E12: share of workforce (%) with 12 years of education or less.
[2] LHS: share (%) of workers with less than high school education.

Source: Authors' calculations from sources described in the Data Appendix.

Table 2. Predicting Education Shares with Production Worker Shares: United States

Pooled 1995 and 1996 3-digit SIC data for manufacturing; standard errors in parentheses. "Levels" ("Logs") indicates that all variables used in the reported regression are in levels (natural logs, except dummies).

	Dependent variable							
	LHS				HS			
	Levels		Logs		Levels		Logs	
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-15.763*	-1.607	-5.644*	-2.826*	-3.959	0.641*	-0.447	-0.341*
	(2.988)	(2.602)	(0.756)	(0.698)	(3.843)	(0.033)	(0.256)	(0.254)
PWS	0.460*	0.258*	1.954*	1.289*	0.899*	0.283*	1.062*	0.876*
	(0.041)	(0.036)	(0.178)	(0.165)	(0.053)	(0.047)	(0.060)	(0.060)
Intercept dummies by 2-digit U.S. SIC:								
20 Food		4.058*		0.276*		4.192*		0.087
		(1.053)		(0.086)		(1.503)		(0.031)
22 Textiles		9.354*		0.495*		7.967*		0.116*
		(1.342)		(0.108)		(1.916)		(0.039)
23 Apparel		13.196*		0.619*		9.338*		0.135*
		(2.092)		(0.171)		(2.987)		(0.062)
24 Lumber and wood		8.143*		0.454*		10.183*		0.147*
		(1.485)		(0.121)		(2.120)		(0.044)
26 Paper		-4.376*		-0.232		-3.078		-0.043
		(1.673)		(0.137)		(2.388)		(0.050)
27 Printing		-0.248		0.235		1.348		0.134*
		(2.191)		(0.180)		(3.128)		(0.065)
28 Chemicals		-3.307*		-0.187		-5.127*		-0.090*
		(1.240)		(0.100)		(1.771)		(0.036)
29 Petroleum and coal		-6.700*		-0.443*		-12.718*		-0.255*
		(2.054)		(0.168)		(2.933)		(0.061)
30 Rubber, plastic		-1.755		-0.000		-1.449		-0.016
		(1.673)		(0.137)		(2.388)		(0.050)
31 Leather		8.436*		0.478*		10.380*		0.155*
		(1.686)		(0.138)		(2.407)		(0.050)
32 Stone, clay, glass		0.792		0.145		2.019		0.038
		(1.449)		(0.119)		(2.069)		(0.043)
33 Primary metal		-2.496		-0.051		0.640		0.015
		(1.687)		(0.138)		(2.408)		(0.050)
34 Fabricated metal		-1.190		0.059		4.731*		0.095*
		(1.268)		(0.104)		(1.810)		(0.038)
35 Industrial machinery		-5.325*		-0.342*		-3.459*		-0.064
		(1.179)		(0.096)		(1.683)		(0.035)
36 Electronic machinery		-5.747*		-0.301*		-9.944*		-0.178*
		(1.664)		(0.136)		(2.376)		(0.050)
37 Transport equipment		-3.836*		-0.206*		-4.507*		-0.067
		(1.175)		(0.097)		(1.678)		(0.035)
38 Instruments		-8.419*		-1.118*		-14.768*		-0.283*
		(1.712)		(0.140)		(2.444)		(0.051)
39 Misc. manufacturing		0.420		0.163		-4.371		-0.060
		(2.917)		(0.240)		(4.165)		(0.087)
1996 fixed effects		0.335		0.044		-0.406		-0.009
		(0.713)		(0.059)		(1.018)		(0.021)
Adjusted R^2	0.476	0.778	0.467	0.728	0.680	0.833	0.695	0.821
SE	6.3386	4.156	0.478	0.341	8.213	5.934	0.162	0.124
n	136	136	136	136	136	136	136	136

LHS: share (%) of workers with less than high school education; HS: share (%) of workers with high school education, or less; PWS: production worker share (%); see text for complete description.

*Significant at 5%.

Table 3. Predicting Education Shares with Production Worker Shares: Canada

1995 3-digit Canadian SIC data for manufacturing; standard errors in parentheses. “Levels” (“Logs”) indicates that all variables used in the reported regression are in levels (natural logs, except dummies).

	Dependent variable							
	LHS				HS			
	Levels		Logs		Levels		Logs	
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-20.515*	-12.447	-4.583*	-3.484*	-8.620	-5.114	-1.088	-0.545
	(8.092)	(10.686)	(1.107)	(1.554)	(8.565)	(11.966)	(0.679)	(0.996)
PWS	0.660*	0.551*	1.821*	1.566*	0.828*	0.780*	1.167*	1.040*
	(0.108)	(0.143)	(0.257)	(0.361)	(0.114)	(0.160)	(0.158)	(0.231)
Intercept dummies by 2-digit U.S. SIC:								
10 Food		4.101		0.170		6.354		0.127
		(2.972)		(0.111)		(3.329)		(0.071)
11 Beverages		1.791		0.161		0.521		-.068
		(5.353)		(0.202)		(5.995)		(0.130)
12 Tobacco		16.458		0.786*		21.141		0.470*
		(9.790)		(0.367)		(10.964)		(0.235)
15 Rubber		-2.275		-0.001		-0.968		0.013
		(5.309)		(0.198)		(5.945)		(0.127)
16 Plastics		-6.311		-0.173		-3.740		-0.050
		(4.596)		(0.171)		(5.147)		(0.110)
17 Leather		22.375*		0.586		14.823		0.258
		(9.322)		(0.347)		(10.440)		(0.222)
18 Primary textiles		14.939*		0.278		12.206*		0.158
		(5.321)		(0.198)		(5.959)		(0.127)
19 Textile products		19.133*		0.520*		17.130*		0.278*
		(4.626)		(0.172		(5.180)		(0.110)
24 Clothing		19.641*		0.525*		14.119*		0.247*
		(4.722)		(0.175)		(5.288)		(0.112)
25 Wood		-2.271		-0.011		2.309		0.065
		3.934)		(0.145)		(4.405)		(0.093)
26 Furniture		4.265		0.191		1.313		0.055
		(5.418)		(0.201)		(6.068)		(0.129)
27 Paper		-4.133		-0.097		-1.514		-0.007
		(4.582)		(0.171)		(5.131)		(0.110)
28 Printing		-2.440		0.011		4.350		0.117
		(5.340)		(0.199)		(5.980)		(0.127)
29 Primary metal		-4.271		-0.147		-5.261		-0.075
		(3.564)		(0.132)		(3.992)		(0.085)
30 Fabricated metal		-3.139		-0.056		-7.622*		-0.131
		(2.991)		(0.111)		(3.350)		(0.071)
31 Machinery		-5.721		-0.163		-5.219		-0.090
		(5.314)		(0.198)		(5.951)		(0.127)
32 Transport equipment		-4.856		-0.099		-7.159*		-0.126
		(3.161)		(0.118)		(3.540)		(0.075)
33 Electrical		-5.180		-0.231*		-7.146*		-0.158*
		(2.982)		(0.111)		(3.339)		(0.071)
35 Non-metallic mineral		1.705		0.096		3.439		0.086
		(3.169)		(0.118)		(3.548)		(0.076)
36 Refined petroleum		-11.941		-0.897*		-15.074*		-0.447*
		(6.820)		(0.2550		(7.638)		(0.163)
37 Chemical		-2.820		-0.146		0.632		0.007
		(3.294)		(0.147)		(4.394)		(0.094)
39 Other manufacturing		-6.498		-0.185		-4.706		-0.066
		(4.056)		(0.151)		(4.542)		(0.097)
Adjusted R^2	0.254	0.495	0.315	0.484	0.326	0.489	0.334	0.454
SE	11.28	9.286	0.399	0.346	11.939	10.399	0.245	0.222
n	108	108	108	108	108	108	108	108

LHS: Share of workers with less than high school education; HS: Share of workers with high school education, or less; PWS: Production worker share; see text for complete description.

*Significant at 5%.

Table 4. Predicting Education Shares with Production Worker Shares: Mexico

Pooled 1995 and 1996 data, 3-digit Mexican manufacturing industries; standard errors in parentheses. “Levels” (“Logs”) indicates that all variables used in the reported regression are in levels (natural logs, except dummies).

	Dependent variable							
	E7				E12			
	Levels		Logs		Levels		Logs	
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	7.433	18.136*	-4.356*	-3.400*	56.654*	64.090*	-1.380*	-1.101*
Constant	(0.043)	(4.483)	(0.433)	(0.437)	(3.032)	(3.319)	(0.146)	(0.159)
	0.393*	0.239*	0.768*	0.557*	0.391*	0.283*	0.283*	0.216*
PWS	(0.061)	(0.064)	(0.102)	(0.104)	(0.043)	(0.047)	(0.035)	(0.038)
Intercept dummies by 2-digit Mexican CMAP**:								
31 Food/beverages		2.156		0.074*		2.466		-0.000
		(1.277)		(0.037)		(9.453)		(0.013)
32 Textiles/apparel		9.170*		0.295*		6.390*		0.079*
		(1.581)		(0.045)		(1.171)		(0.016)
33 Wood products		11.860*		0.304*		5.335		0.071
		(3.692)		(0.105)		(2.734)		(0.039)
34 Paper/printing		-3.827		0.014		-0.059		0.122
		(2.888)		(0.084)		(2.138)		(0.031)
35 Chemicals		-5.160*		-0.153*		-4.186*		-0.054*
		(1.576)		(0.046)		(1.167)		(0.017)
36 Non-metallic minerals		7.149*		0.149*		-1.605		-0.022
		(2.391)		(0.069)		(1.770)		(0.025)
37 Basic metals		-7.878*		-0.280*		-5.436*		-0.063*
		(3.026)		(0.087)		(2.240)		(0.032)
38 Machinery/		-5.638*		-0.162*		-1.012		-0.012
metal products		(1.025)		(0.030)		(0.759)		(0.011)
39 Other		-1.559		-0.015		3.080		0.038
		(5.747)		(0.165)		(4.255)		(0.060)
1996 fixed effects		-1.644	-.050	-0.045	-1.058	-0.977	-0.013	-0.012
		(1.278)	(0.042)	(0.037)	(1.000)	(0.946)	(0.014)	(0.013)
Adjusted R^2	0.112	0.281	0.147	0.326	0.202	0.285	0.167	0.236
SE	12.851	11.565	0.373	0.332	9.048	8.561	0.127	0.122
n	328	328	322	322	328	328	328	328

E7: share of workforce (%) with 7 years of education or less; E12: share of workforce (%) with 12 years of education or less; PWS: production worker share.

*Significant at 5%.
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Table 5. Rank Correlation Between Production Worker Shares and Education Measures, 1995-1996

Each entry in the table represents the Spearman rank correlation between production worker share and the indicated education measure, using national 3-digit manufacturing data.

Year	United States (n = 68 annually)		Canada (n = 108)		Mexico (n = 164 annually)	
	LHS	HS	LHS	HS	E7	E12
1995	0.748	0.811	0.602	0.628	0.349	0.454
1996	0.797	0.805	n.a.	n.a.	0.380	0.460

LHS: share of workers with less than high school education; HS: share of workers with high school education, or less; E7: share of workforce with 7 years of education or less; E12: share of workforce with 12 years of education or less.

Data Appendix

United States

The Bureau of Labor Statistics provided the data on production-worker shares on its web page; they are also in *Employment and Earnings*. This establishment survey data is classified by three digit SIC.

The BLS also provided the industry data on employment by education. These data, unpublished tabulations from the Current Population Survey, dissect each industry's employment into ten non-overlapping education categories. The data are collected by industry codes that are close to, but not always the same as, the three-digit SIC codes used for the production-worker data. We therefore concorded the education data to the SIC; to match the data several three digit codes had to be combined. One observation for LHS (which is measured in percentages) equaled 0 and was changed to 1 to permit log-linear estimation. The final data set has 68 annual observations each for 1995 and 1996.

The CPS education data have one liability: the household survey misclassifies some workers' industries. The error can occur if workers do not know which industry they work for, or a member of the worker's household provides erroneous information. This error will not systematically bias this skill measure if it occurs randomly across industries. As the establishment survey polls plant managers, the production-worker data does not have this problem.

Canada

Statistics Canada provided the three-digit (Canadian) SIC data on production worker shares (from the Industry Division's Census of Manufactures, an establishment survey) and on educational attainment (from the Household Survey Division's Labor Force Survey, a household poll). As with the

CPS education data in the U.S., the household poll introduces some error into the education data, but in our view these errors result in noise, not bias.

Mexico

The Mexican education data are from the National Urban Employment Surveys (Encuesta Nacional de Empleo Urbano). These surveys are used by the Mexican government to calculate employment and other measures of labor market activity. The surveys are quarterly and cover a broad geographic range throughout Mexico. The Mexican production-worker data come from the Monthly Industrial Survey (Encuesta Industrial Mensual). These data survey over 3000 manufacturing firms and do not include maquiladoras. Industries are concorded at roughly the three digit level.

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