Abstract

The distribution of earnings and the distribution of skills vary widely among advanced countries, with the major English-speaking countries, the US, UK, and Canada, having much greater inequality in both earnings and skills than continental European Union countries. This raises the possibility that cross-country differences in the distribution of skills determine cross-country differences in earnings inequality. Using the International Adult Literacy Survey, we find that skill inequality explains only about 7% of the cross-country difference in inequality. Most striking, the dispersion of earnings in the US is larger in narrowly defined skill groups than is the dispersion of earnings for European workers overall. The bulk of cross-country differences in earnings inequality occur within skill groups, not between them

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Does Inequality in Skills Explain Inequality of Earnings Across Advanced Countries?

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Introduction

The distribution of earnings varies widely among major advanced countries, with the major English-speaking countries (the US, UK, and Canada), having much greater inequality than continental European Union countries. The distribution of cognitive skills, measured by adult literacy and numeracy, also varies more in the US, UK, and Canada, than in continental EU countries. These two facts raise the possibility that the wider dispersion of skills in some countries may be the primary cause of their wider dispersion of earnings (Nickell and Bell, 1995; Nickell, 1997; Leuven *et al*, 2000).

As Figure 1 shows, the coefficient of variation in test scores across countries from the International Adult Literacy Survey (OECD and Statistics Canada, 1998) is positively correlated with 90-10 earnings differentials across countries reported by the OECD (OECD, 1996), consistent with a skills interpretation of earnings inequality across advanced countries. But test scores are more weakly related to earnings among individuals within countries (Jencks, 1972; Griliches and Mason, 1973), even though their impact on earnings has risen over time (Murnane, Willett, and Levy, 1995; Jencks and Phillips, 1998). Many analysts interpret the differing distribution of earnings as reflecting differences in wage-setting institutions rather than the distribution of skills (Freeman and Katz, 1994; Blau and Kahn, 1996; 2000).

How much do differences in the dispersion of skills across countries in fact contribute to differences in the dispersion of earnings across countries? What explains the divergence between the seemingly strong cross-country relation between skill inequality and earnings inequality and the weaker links between measured skills and earnings in micro data?

This paper examines these questions using the best internationally comparable data on skills and earnings: the OECD's International Adult Literacy Survey. We focus on the US, Sweden, Germany, and Holland because we have obtained good measures of earnings for individuals in these countries. We reject the claim that inequality of skills explains much of inequality of earnings across countries on three grounds:

1. Literacy tests in the home country language understate the labor market skills of immigrants who speak a different language. Inequality of skills in the country with the highest level of inequality, the US, falls markedly when we exclude immigrants from our sample, while the dispersion of earnings does not perceptibly change.

2. Decomposition of the difference in the standard deviation of earnings between the US and Germany, Sweden, and the Netherlands shows that inequality in skills explains 7% of the cross-country difference in inequality. A much greater part of the difference, around 36%, is explained by the higher skill premium in the US. However, most of the difference in dispersion across countries occurs in the residuals from earnings equations.

3. In narrowly defined skill groups, dispersion of pay is higher in the US than in low inequality EU countries and indeed is higher for US workers in narrowly defined groups than for European workers overall.

If the distribution of skills does not explain cross-country differences in earnings inequality, what does? Many analyses examine how national collective bargaining and state interventions limit wage dispersion in the low-inequality EU countries (Blau and Kahn, 1996) but few ask the reverse question: why does competitive wage setting produce huge dispersions of pay among narrowly defined skill groups in high-inequality countries? We conclude the paper with some hypotheses about possible reasons for this pattern.

2. The Distribution of Measured Skills

For the distribution of skills to help explain the dispersion of earnings across countries, skills must be more unequally distributed in high-earnings-inequality countries than in low-earnings-inequality countries. Years of schooling, the usual measure of skills in labor economics, fails this criterion because years of schooling is less dispersed in the country with the greatest inequality among advanced countries, the US, than in low-inequality EU countries.[1] Hence, proponents of the argument that inequality in skills explains inequality in earnings look at an alternative measure of skills, adult literacy test scores, which is more highly dispersed in the high inequality US, UK, and Canada than in other countries. To give the skills hypothesis its best chance of being supported, we will focus on these literacy scores as well.

[1] In the International Adult Literacy Survey, the coefficient of variation in years of schooling was 0.22 for the US, 0.28 for Germany, 0.29 for the Netherlands, and 0.30 for Sweden.

The principal source of data on adult literacy scores is the OECD's International Adult Literacy Survey (IALS).[2] The IALS administered the same battery of questions[3] to adults in 12 OECD countries. The questions measure three kinds of skills:

1. prose literacy – ability to understand and use information from texts, including editorials, news stories, poems, and fiction;
2. document literacy – ability to locate and use information in various formats, including job applications, payroll forms, transportation schedules, maps, tables and graphics;
3. quantitative literacy – ability to use arithmetic operations, such as balancing a checkbook, computing a tip, or determining the amount of interest on a loan from a bank.[4]

Scores in the three areas are highly correlated, so that it makes little difference if one analyzes document, prose, and quantitative literacy separately or together. We use the simple mean of the scores on all three parts of the IALS test as our general measure of literacy skills. Empirical results are not sensitive to the relative weight given to each category.

Table 1 summarizes the cross-country variation in the scores. Panel A gives the coefficient of variation in scores for all adults and for workers in each country, in ascending order by the level of inequality.[5] In all countries, the coefficients of variation are higher for the total adult population than for workers, reflecting the fact that the jobless tend to be lower skilled than workers. This difference is particularly pronounced in the US and is least pronounced in the continental Western European countries.[6] The countries with high skill inequality are all English-speaking countries.

[2] The survey consisted of a 20-minute questionnaire and a 45-minute test that covered the three domains. For each domain, literacy is reported as a score between 0 and 500. Each country used a probability sample to derive results representative of the civilian non-institutionalized population aged 16-65. See Blum, A. and Guerin-Pace, F. (2000) for a general discussion of the problems with the IALS.

[3] The test was given in the common language of each country. Goldstein (2000) has criticized the comparability of the survey across countries, but the IALS is the best available source of information on the skills of adults across countries.

[4] The survey gave some different questions to each individual. Item Response Theory (IRT) scaling was used to simulate the latent proficiency of individuals for each domain of literacy. The survey designers used a three-parameter logistic IRT model to estimate the probability of answering a particular item correctly, where the probability depended on the individual's proficiency, and three variables describing each test item The IALS generated five simulated proficiency values and averaged the five to estimate the true proficiency. A useful description of IRT theory is Lord (1980).

[5] Poland, which we have not included in this study, has higher inequality in adult literacy than even the US and a very low average level.

[6] In Germany, there is virtually no difference among the test scores of the employed, the unemployed, and non-labor force participants while in the US the differences are large (Freeman and Schettkat, 2000).

Panel B of the table gives the scores for workers in the various countries by quintile of the score distributions. It shows that the main reason that the English-speaking countries have such high dispersion of skills is that persons in the low end of their distribution score exceptionally low. In the lowest quintile, workers in the US, Canada, Ireland, Northern Ireland and Great Britain average 30-40 points below in the bottom quintile than workers in the Netherlands, Germany, and Sweden. In the highest score quintile, by contrast, persons in these countries score similarly to those in the low-inequality countries.

One reason that a large number of Americans have exceptionally low scores is that immigrants score very poorly on the IALS, which is given in English. In all countries, immigrants are heavily over-represented in the lowest quintile, but in the US the percent of persons in the lowest quintile who are immigrants is an extraordinary 33%. Figure 2 shows that the distribution of literacy scores for US immigrants is double-peaked, with the higher peak close to the mean for the native-born and the lower peak far below the average. A similar but less pronounced pattern also appears in the UK and in English-speaking Canada.

In the US the majority of immigrants with exceedingly low skills report themselves to be Hispanic or Latin Americans.[7] To the extent that Spanish-speaking or other immigrants can work in ethnic enclaves or in workplaces adapted to them, measures of literacy in English will understate true workplace skills[8]. In fact, conditional on IALS scores immigrants earn less than natives, suggesting that literacy scores actually understate immigrant skills.[9]

We take account of the problem of mismeasurement of the skills of immigrants in ensuing analyses by controlling for immigrant status in all regressions; and by repeating each calculation for samples that exclude immigrants. We do not report both sets of results, since they are quite similar.

[7] Latin American immigrants constitute 10.4% of the US sample but 48.4% of persons scoring below 200 on the NALS literacy test, which contains more observations than the IALS. The IALS gives similar results.

[8] Since many US immigrants have limited education, it is useful to factor out the independent contribution of immigrant status as opposed to low education on the probability of falling in the lower tail of the score distribution. We estimated a probit equation linking presence in the bottom quintile of scores to age, years of education, race, and immigrant status, and obtained a significant 0.22 coefficient on immigrant status in the IALS.

[9] The immigrant premium is -.24. Controlling for education, it is -.18; controlling for test score, it becomes .12. Controlling for both education and test score, it is .01, or statistically insignificant (the standard error in all cases is about .02). Thus, it appears that years of education overstate immigrant skills, but test scores actually understate their skills.

3. Skills and Earnings

To assess how much skill inequality contributes to earnings inequality, we must supplement the IALS literacy skills files with good measures of earnings for individuals. The public OECD data file reports the position of workers in the income distribution not in precise figures but in income quintiles. In many cases, moreover, the distribution of people across quintiles is uneven, which makes analysis of the link between skills and income problematic. We remedied this problem by obtaining the original earnings data from the underlying country surveys for the US, Germany, the Netherlands, and Sweden. The earnings data are precise for the US and Sweden, but earnings for Germany and the Netherlands are reported in 20 unevenly-represented categories.[10] We made the data comparable among the four countries by generating a random component to the earnings of workers in the Netherlands and Germany.[11]

Table 2 describes the main patterns in the data. Overall, the dispersion of earnings and the dispersion of skills are higher in the US than in the EU countries, whereas the dispersion of years of schooling is less in the US than in the EU countries. Limiting the comparisons to natives reduces the dispersion of skills more in the US than in the other countries, which cuts the difference in standard deviations of skill between the US and the other countries from 14-19 points to 8-12 points.[12] If the distribution of skills were a major factor in earnings inequality, we would expect a comparable reduction in the standard deviation of ln earnings in the US and in the difference in standard deviations between the US and the other countries. But eliminating immigrants from the analysis has no discernible impact on the dispersion of earnings in the US! This is our first indication that the micro IALS data will not support the aggregate cross-country relations in Figure 1.

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[10] Moreover, earnings data for Germany are monthly, rather than yearly, so earnings inequality in Germany is probably overstated relative to the other countries due to the more transitory nature of monthly than of yearly income.

[11] We randomly assigned earnings from a uniform distribution to persons within each category. We experimented with other ways of making the data comparable, for instance by grouping the US and Swedish data to the categories in Germany and the Netherlands, and obtained results comparable to those reported here. None of our conclusions are sensitive to alternative ways of making the data comparable.

[12] This pattern is even more striking if we look on the bottom part of the skill distribution. The ratio of the mean scores of workers in the middle quintile (Q3) to the mean score of workers in the bottom quintile (Q1) declines from 1.50 to 1.38 in the US with the elimination of immigrants while it barely changes in EU countries.

In all countries the correlation between years of schooling and earnings exceeds the correlation between adult literacy skills and earnings. This indicates that years of schooling is a better predictor of earnings than the literacy score measure. All of the correlations are lower in the EU countries than in the US. The link between skills and earnings is weaker in the low inequality EU countries compared to the high-inequality US. This difference in the skill premium across countries will be important for our decomposition analysis in the next section.

Table 3 records the literacy scores of workers by quintiles of the income distribution of each country. In the US, test scores rise substantially as we move up the income scale: the average increase in scores is 17 points per income quintile. By contrast, in the three EU countries, scores in the bottom quintile are only slightly lower than those at the top and are higher in some cases than in the middle quintiles. The average literacy scores of Europeans in the 2nd, 3rd, and 4th quintiles of the income distribution are barely distinguishable (the average difference is 3 points) whereas the average scores of Americans in those quintiles differ by more than 20 points.[13] Something very different is evidently going on in the US labor market than in the market in these other countries.

4. The Impact of Skills on the Distribution of Earnings

We use a two-stage analysis to estimate the impact of the distribution of skills on the distribution of earnings across countries. First, we estimate the effect of skills on earnings for each country with a standard log-linear regression. These estimates give us coefficients for the effect of skills on earnings and estimates of the residual variation of earnings within countries. Second, we use these coefficients and residual variances to estimate how much the dispersion in one country would change if it had another country's distribution of skills.

Table 4 records the coefficients and standard errors on measures of skill in separate earnings equations for each country, conditional on sex, immigrant status, age, and quadratic age. For ease of presentation, we divided the test scores by 100. Column 1 uses the individual's test score as the sole measure of skill. This column gives us the largest coefficient on literacy skill and thus accords the skill inequality hypothesis its greatest

[13] For the UK and Canada, income is reported in uneven quintiles. However, from what we can tell Canada looks very much like the US. The UK is somewhere in between North America and continental Europe, with scores roughly 12 points higher in each successive income quintile.

opportunity to explain the cross-country patterns. The regressions show different estimated coefficients between the US and the other countries. A 100-point change in the adult literacy score (about 1.5 standard deviations) raises earnings in the US by about 50%. This is three times the estimated coefficient for Germany, more than three times the coefficient for Sweden, and 50% greater than that for the Netherlands.

The regressions with years of schooling as the sole measure of skills in column 2 show that schooling also has a larger effect on earnings for the US than for the other countries. Similarly, when we include both scores and years of schooling in the equation, column 3 shows that the estimated effects of both measures are higher in the US than in the other countries.[14] Any explanation of the greater dispersion of earnings in the US than in the EU must take account of the greater impact of skills and most other determinants of earnings on ln earnings in the US than in the EU. Note also that in the column 3 regressions, years of schooling is more strongly linked to earnings than test scores in Germany and Sweden, while both schooling and test scores are closely related to earnings in the US and the Netherlands.

What magnitude of coefficients on literacy scores in earnings equations would be needed to explain fully the cross-country differences in dispersion of earnings by the observed differences in the dispersion of skills? Taking the figures for all workers in Table 2, the standard deviation of ln earnings in the US averages 0.25 ln points greater than the standard deviation in the EU countries. The standard deviation of the literacy score averages 0.17 points greater. This implies that the coefficient in a regression of ln earnings on skills/100 would have to be 1.47 (= .25/.17) to explain fully the US-low inequality countries difference in earnings inequality. But taking only native-born workers the dispersion in skills in the US is 10 points higher than in the EU countries. This would require a skills premium of 2.50 (= .25/.10) to explain the 0.25 difference in earnings inequality.[15] By contrast, the largest coefficient on literacy scores in Table 4 is 0.48, for the US, far below these values.[16]

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[14] The coefficients on the age variables are also larger in the US in the various regressions.

[15] If we compare native white workers to EU workers, the skills premium that would explain all of the dispersion in skills would have to be 3.33 (= .20/.06).

[16] Might the higher coefficient on skills in the US be due to the greater variation in wages relative to skills? Or could it reflect greater range of skill variation in the US, in part because we included immigrants in our regressions? We examined these possibilities in several ways. We estimated the same model excluding immigrants, whose test scores may understate their skills. We obtained very similar results to those reported in the table. We also eliminated the lowest quintile of workers, and again obtained a greater coefficient in the US than in the EU countries. Finally, we replaced the actual earnings and test scores data with the rank of people according to their test score and earnings in their respective national distributions. The US once again had

At most 1/3rd to 1/5th of the difference in the dispersion of earnings between the US and the low inequality EU countries can be attributed to differences in the dispersion of skills.

4.1 Variance decomposition

More formally, we use a variance decomposition to estimate the dispersion of earnings the US would have if US workers had the distribution of skills (other characteristics) in the low inequality EU countries; and the dispersion of earnings in the low inequality EU countries if they had the distribution of characteristics in the US. In the former case, we take the equation for variance of earnings in the US (s^2_{lnW}) and replace the US dispersion of characteristics with the EU dispersion of characteristics:

(1) $$s^2_{\mathrm{lnW}} = b^2_{\mathrm{US}} s^2_{\mathrm{EU\ skills}} + s^2_{\mathrm{unexplainedUS}}$$

where the bs refer to the coefficients for the relevant characteristics and the s^2s are the variances of those characteristics. Whenever the dispersion of characteristics is less in the EU countries than in the US – as in the case of test scores – this analysis predicts that the US would have lower earnings dispersion if it had the EU dispersion. Similarly, we can estimate the distribution of earnings that the low-inequality EU countries would have if they had their own earnings equation and residual variation but the US distribution of skills:

(1') $$s^2_{\mathrm{lnW}} = b^2_{\mathrm{EU}} s^2_{\mathrm{US\ skills}} + s^2_{\mathrm{unexplainedEU}}$$

We can also ask what would happen to the US dispersion of incomes if the US had its own dispersion of skill characteristics but valued those characteristics by the coefficients from the EU earnings equation; and conversely, what would happen to the EU dispersion of incomes if skills were valued by the coefficient in the US earnings equation. In the former case, we replace the US coefficient on skills by the EU coefficient of skills in the US variance of earnings equation:

(2) $$s^2_{\mathrm{lnW}} = b^2_{\mathrm{EU}} s^2_{\mathrm{US\ skills}} + s^2_{\mathrm{unexplainedUS}}$$

In the latter case, we replace the EU coefficient on skills by the US coefficient in the equation for the variance of earnings in the EU (s^2_{lnW}):

(2') $$s^2_{\mathrm{lnW}} = b^2_{\mathrm{US}} s^2_{\mathrm{EU\ skills}} + s^2_{\mathrm{unexplainedEU}}$$

Whenever the EU coefficient in the earnings equation is less than the US coefficient - as in the case of test scores - this decomposition analysis predicts that the US would have lower

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higher coefficients on test scores. This result suggests that one reason the US gets higher coefficients on scores earnings dispersion if it had the EU earnings equation. Equivalently, the EU would have higher earnings dispersion if it had the US earnings equation.

Table 5 presents the results of these decomposition calculations. Since most analyses of dispersion use standard deviation of ln earnings, we transformed the variance decompositions into standard deviations, and report them in terms of the average difference they make to the US-EU country (Netherlands, Germany, Sweden) difference in standard deviations of ln earnings (0.256).

The first part of the table shows the change in the standard deviation of ln earnings in the US if the US maintained its earnings equation but had the dispersion of income determining characteristics of the low inequality EU countries. We computed this counterfactual for each of the three European countries, and then took the average of the results. We find that if Americans had a European distribution of scores, they would on average have .022 ln points less inequality.[17] The next line shows that when years of schooling is the only explanatory variable, and we replace the US dispersion of years of schooling with the EU dispersion, the predicted standard deviation of ln earnings in the US rises. The final line in this part of the table shows the dispersion of wages the US would have if the US population resembled the population of an EU in the entire set of characteristics in the US earnings equation. The drop in the standard deviation of log earnings is a modest -0.017, or less than 7% of the initial 0.256 difference in log earnings between the US and the EU countries.

The part of the table labeled "if the US had own distribution of scores" shows what happens when we value those characteristics by earnings equations for the EU countries. Again, we perform the analysis separately by country and give the average outcomes. Replacing the coefficient on scores in the US with the coefficient on scores in the EU in an equation where scores are the sole explanatory variable reduces inequality by 0.039 points. Altering the coefficient on years of schooling when schooling is the sole explanatory variable reduces the difference in standard deviations of ln earnings by .049 points. Finally, when we predict the dispersion of ln wages for the US sample using the full vector of estimated

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in the ln earnings equation is that the US sorts people by test scores more than any other country.

[17] When the ln earnings equation includes only test scores as an explanatory factor, the change in variance resulting from a drop in EU skills would be $(.45^2-.6^2)*.5^2 = -0.04$, where .6 is the standard deviation of test scores in the US, .45 is the average standard deviation of test scores in the EU countries, and .5 is the coefficient on test scores in the US earnings equation. This corresponds to a decline in standard deviation of ln wages from .93 to $/(.93^2-.04) = 0.91$.

coefficients for the EU countries, we obtain an average decline in dispersion of .093 or 36%. This is 5.5 times as great as the decline in the difference of dispersion of wages that we attribute to the differing dispersion of characteristics.

In short, the difference between the coefficients in the earnings equations between the US and low inequality EU countries explains much more of the greater dispersion of pay in the US than does the higher dispersion of skills in the US.

The remainder of Table 5 repeats our exercise for the EU country with the lowest level of inequality, Sweden. Since the earnings equation for Sweden has lower coefficients on test scores and years of schooling than does the US equation, transforming the distribution of skills in Sweden to the distribution of skills in the US has only a slight effect on the standard deviation of Swedish earnings. By contrast, replacing the coefficients on the earnings equations for Sweden with those for the US noticeably increases the standard deviation of ln earnings in Sweden. This supports our finding that differences in the impact of skills on earnings are more important than differences in the distribution of skills in differentiating high inequality US from low inequality EU countries.

Since changes in the dispersion of test scores or other wage-determining characteristics are themselves likely to alter the magnitude of the coefficients in the earnings equation, however, the variance decomposition arguably understates the effect of changes in the dispersion of skills. If through some educational innovation, the US lowered the dispersion of literacy scores, this would presumably reduce the premium to scores, just as an increased relative supply of educated workers would reduce the premium to education. This in turn would mean that some of the effect of the change in the coefficients on scores should be added with the estimated effect of the change in the dispersion of scores to obtain a more "general equilibrium" decomposition analysis. But even if we were to allot *all* of the difference in coefficients to the skill hypothesis, we could still explain at most 37% of the US-EU difference in the dispersion of earnings.[18]

[18] Adding together the estimated effects of changes in the variance of ln earnings due to changes in the distribution of skills and changes in the coefficients on skills gives us a predicted change in the variance of ln earnings in the US of .009, which translates into a change in the standard deviation of ln earnings of .095, which is just 36.9% of the 0.256 US-EU difference.

5. The Key Fact: Within-Group Inequality

The reason the skills hypothesis cannot account for more than a modicum of the US-low inequality EU difference in the dispersion of earnings is that roughly 2/3rds of the difference in the dispersion of earnings occurs *within* detailed skilled groups. This reflects the fact that the R^2s on these wage equations are all around 0.3. Even with equivalent test scores and equivalent test score premiums, unobservable factors are generating a much larger dispersion of wages in the US than in the EU countries.

We first demonstrate this aspect of earnings distributions across countries by calculating the dispersion of pay among workers in increasingly narrow skill categories. If the dispersion of skills were a major explanatory factor for country differences in the distribution of earnings, the difference in the dispersion of earnings would decline sharply as we examined workers in increasingly narrow skill bands. In the extreme, workers with exactly the same scores would have the same distributions of earnings.

Table 6 records standard deviations of ln earnings in the US, Germany, Netherlands, and Sweden for workers in five skill bands in the middle portions of the score distribution.[19] The figures show higher dispersion of earnings in the US than in EU countries in every category, with the largest differences occurring among lower skilled workers. The IALS sample is not large enough to allow us to calculate standard deviations of ln earnings within narrower skill bands, but we can do such computations for a much larger US-based literacy survey that strongly resembles the IALS. This is the 1992 National Adult Literacy Survey (NALS), which has roughly eight times as many persons as the IALS (Campbell *et al*, 1992). The distribution of scores and patterns in the data on the NALS are quite comparable to that on the IALS.[20]

Figure 3 shows the dispersion of earnings among Americans with the same test score in the NALS, where by the "same" we mean within a narrow band of 4 points on the scale, centered around the reported number. That is, when we report a score of 260, we include persons with scores between 258 and 262. In all but one of the narrow bands in the figure, the standard deviation of ln earnings in the US exceeds the standard deviation of ln earning

[19] We limit the analysis to the range of scores where there are sufficient observations to estimate the dispersion of pay in all of the countries with some confidence.
[20] For instance, the mean test score in the NALS in a sample of 24944 was 270 compared to the 272 reported in Table 1 on the IALS. The standard deviation of scores in the NALS was 64 compared to a standard deviation in the table on the IALS of 65.

for *all* workers in Germany, the Netherlands, and Sweden. *Earnings differ more among Americans with effectively the same literacy score than they differ among all workers in those countries.*

6. The Distributional Picture

There is another way to demonstrate the striking difference in earnings within the same skill groups between the US and low inequality EU countries. This is to compare the dispersion of pay among persons in the same parts of the skill distribution across countries – i.e. to compare Americans in the various quintiles in the US skill distribution with Europeans in the corresponding quintiles in the relevant European skill distribution. Table 7 records the results from such contrasts. With one exception (Germans in the highest quintile) the dispersion of earnings is higher in the US at each quintile of the earnings distribution than in the comparison countries. Moreover, the within-quintile differences in the dispersion of earnings are only modestly less than the dispersion of earnings for the entire work force.

Taking the distributional analysis a step further, we estimate a linear regression model in which the dependent variable is the ln of earnings and the independent variables are dummy variables that measure the location of workers in the distribution of scores with varying degrees of fineness:

$$\ln W_i = bD_i + u_i$$

where b is a (1xS) vector of coefficients, and D is an (Sx1) vector of dummy variables (d_1 ... d_S) for the percentile group of the individual in the distribution of scores. For instance, if S=2, the vector would distinguish whether or not the person was in the upper half of the score distribution; if S=5, the dummies would indicate in which score quintile a person was found; and so forth. The mean square error from the regression would reflect the residual dispersion. Increasing the size of the D vector necessarily reduces the dispersion of scores for each group, but does not necessarily reduce the residual dispersion of earnings. We calculate the average dispersion of within-group scores using the same regression procedure and then examine the relation between the dispersion of earnings and the dispersion of scores as we increase the number of groups.

Figure 4 summarizes the results of this analysis for the US in the NALS, where we have a sufficiently large sample to allow us to increase considerably. The horizontal axis measures the dispersion of test scores for each group, ranging from highest to lowest. The vertical axis measures the dispersion of ln earnings from lowest to highest. When the number of intervals is one, the standard deviation of log scores is 0.25 and the standard deviation of log earnings is 0.83. When we break the observations into five score quintiles, the mean standard deviation of log scores falls to 0.13; the mean standard deviation of log earnings falls modestly to 0.78. As we make the score intervals narrower and narrower, of course, score inequality approaches zero, but the mean standard error of ln earnings asymptotes at 0.77. Put differently, of the total variance in log earnings ($.83^2 = .69$), some 85% ($.77^2 = .59$, and $.59/.69 = .85$) seems to be due to something beyond observed scores.

Figure 5 repeats this exercise for our four chosen countries in the IALS data. The results for the US are consistent with those found in the NALS: in this case, the earnings dispersion starts at .93 and falls to about 0.85 as we narrow the score intervals. But the comparison with the other countries is striking: in the EU countries, where scores are more weakly related to earnings, the dispersion of pay barely falls as we increase the number of groups into which we divide the sample.

At any given level of dispersion of scores or number of differentiating groups, the dispersion of ln earnings is much higher in the US than in the EU. Most remarkably, the asymptote for the dispersion of earnings in the US exceeds the level of dispersion for the *entire* work force in the EU countries. This is true for the NALS data where dispersion of wages is lower than in the IALS, as well as for the IALS. Put differently, the dispersion of earnings among Americans with essentially *identical* skills is greater than the dispersion of earnings among the whole population of Europeans!

7. If Not Measured Skills, What?

Our analysis rejects the claim that differences in the dispersion of skills between the US and the low-inequality EU countries explains much of the difference in dispersion of earnings. By itself, the higher variance in literacy test scores in the US than in the Netherlands, Germany, and Sweden accounts for 7% of the greater dispersion of earnings among workers in the US than in those countries. Close to a quarter of the observed difference in the dispersion of earnings is due to differences in the magnitude of coefficients on earnings determining factor, though some part of this may reflect differences in the dispersion of skills. Our major finding, however, is that most of the difference in dispersion across countries occurs among workers who are identical by measured skill and other characteristics.

One possible explanation for the huge residual difference in the dispersion of income between the US and low inequality EU countries[21] is that Americans have greater heterogeneity of unobserved skills. Since the US has greater dispersion of measured skills, it is reasonable to expect the US to also have greater dispersion in unmeasured skills. But the finding that the dispersion of pay among Americans with the same literacy scores exceeds the dispersion of pay among all workers in EU countries makes this a highly dubious explanation of the bulk of the observed difference. It would require that Americans with the same observed skills have greater dispersion in unobserved skills than Europeans have in unobserved and observed skills.

Another possible explanation for the huge residual difference in the dispersion of earnings is that the premium on unobserved skills is higher in the US than in the other countries. This is consistent with the regression finding that observable measures of skill have greater effects on ln earnings in the US than in EU countries. One way to assess this explanation would be to obtain wages from persons who have worked in the US or other high inequality countries and in the low inequality EU countries. The residual from an earnings equation in each setting would reflect their unobserved characteristics. If each economy values the same unobservable skills, the residuals in the US and EU regressions should be highly positively correlated (the same person would have greater unobserved skills in both settings) but the dispersion of residuals should be higher in the US, reflecting the greater payoff to those skills.

The evidence that the dispersion of earnings among American workers with the same test score is higher than the dispersion of earnings of all workers in low inequality EU countries suggests, however, that even among persons with identical "unobserved skills" earnings varies considerably in the US. Why might this be? Since the US has a competitive labor market, the question becomes what might produce such a dispersion of earnings among persons with identical skills?

[21] We do not regard as credible one other possible explanation: that the differences in dispersion are due to compensating differentials associated with heterogeneity among workplaces. Because the EU has more centralized bargaining and regulations than the US, heterogeneity among workplaces is likely to be lower than in the US. In this case, the dispersion of earnings is more likely to understate rather than overstate the "true" difference in the dispersion of economic rewards among workers in the US and EU countries.

Jencks (1972) stressed the role of luck or chance in the determination of earnings. We propose a different explanation, based on the distinction between ex ante and ex post pay.[22] A competitive market should equalize ex ante payoffs among different jobs for persons with the same skills, but need not equalize ex post pay. Under some wage-setting institutions, indeed, a competitive market will produce considerable inequality for persons with the same skills. This will occur when, perhaps for incentive reasons, the market produces contracts that vary pay/chances of promotion with the performance of firms, even though firms will do better/worse in part for reasons beyond the control of employees.

The market for executives in the US, with extensive use of stock options, exemplifies such a situation. Equally able executives in two firms receive performance contracts that ex ante have the same worth. One firm prospers and the other does not. The result is a huge dispersion of earnings between them. Going beyond executives, the considerable variability in pay among US firms can produce similar differences for regular workers. If you got a job at Hewlett Packard as opposed to Xerox when you were young, your earnings are likely to be higher than your equally able mate who took the Xerox job, since Hewlett-Packard has done well while Xerox has not. EU wage-setting systems give market outcomes less leeway in determining wages by varying pay less across plants or sectors and make less use of bonuses, options, and other forms of variable pay. The key cause of greater dispersion in the US in this case is that there is a greater payoff to unanticipated economic shocks than in the EU.

Longitudinal data on the wages of workers in the US and EU are consistent with this notion. In its study of earnings mobility, the OECD (1997, Table 2.8) finds much greater dispersion of real earnings growth among American workers than among workers in Denmark, France, Germany, Italy, and the United Kingdom in the 1986-1991 period. But the OECD and other analysts (Burkhauser *et al*, 1997) also find that the US has a relatively higher level of inequality averaged over many years than EU countries. This suggests that the ex post-ex ante income distinction will not fully account for cross-country differences in earnings inequality, though the best test of this hypothesis would be to examine differences in earnings among people from their very first job, rather than from later in their careers, as these studies do.

[22] We thank Michael Schwarz for discussion of this argument.

Conclusion

Our analysis suggests that it is the difference in weights placed on wage-determining factors rather than differences in the distribution of skills that best explains why earnings inequality is higher in the US than in low inequality EU countries. We find sizable differences in the coefficients on literacy scores and on years of schooling between the US and low inequality EU countries and hypothesize that similar differences would be found on the coefficients on unobserved skills and on unanticipated economic shocks, given the appropriate data. The explanation for cross-country differences in inequality lies, not in the distribution of skills, but in the mechanism by which different pay systems produce dispersion among otherwise similar people in similar situations.

Table 1. Summary Measures of Average Adult Literacy Scores

A. Mean, Standard Deviation (Std Dev), Coefficient of Variation (CoV) in Literacy Scores

	All Adults				*Employed Workers*			
Country	N	Mean	Std Dev	CoV	N	Mean	Std Dev	CoV
Netherlands	3090	281	47	**0.17**	1815	295	40	**0.13**
Germany	2062	285	42	**0.15**	1120	291	40	**0.14**
Sweden	3038	293	55	**0.19**	1814	309	45	**0.15**
Belgium	2261	277	55	**0.20**	1166	287	49	**0.17**
New Zealand	4223	272	54	**0.20**	2224	284	49	**0.17**
Switzerland	2838	271	57	**0.21**	1930	277	51	**0.18**
Great Britain	3811	267	62	**0.23**	2505	281	53	**0.19**
Ireland	2423	263	57	**0.22**	1189	275	54	**0.20**
N. Ireland	2907	265	62	**0.23**	1767	278	56	**0.20**
Canada	5660	271	67	**0.25**	2604	291	59	**0.20**
US	3045	272	65	**0.24**	2047	283	60	**0.21**

B. Mean Score, by Within-Country Score Quintile (Employed Workers Only)

Score Quintile	1	2	3	4	5
Netherlands	235	280	299	317	343
Germany	235	271	291	313	345
Sweden	243	288	311	334	367
Belgium	212	271	295	315	345
New Zealand	211	262	288	311	345
Switzerland	200	262	285	305	334
Great Britain	200	256	287	313	347
Ireland	193	254	281	305	341
N. Ireland	194	253	284	311	347
Canada	204	271	298	323	362
US	191	261	291	318	355

Source: International Adult Literacy Survey (OECD and Statistics Canada, 1998). Reported scores are the average of scores on the document, prose, and quantitative tests; in all countries, the three tests are highly correlated.

Table 2. Comparing Test Scores, Earnings and Education

A. Dispersion of Literacy Scores and Earnings, by Demographic Group

	SD Scores			*SD Log Earnings*		
	All	Native	Native and White	All	Native	Native and White
Germany	0.41	0.39		0.68	0.68	
Nether.	0.40	0.38		0.68	0.69	
Sweden	0.45	0.42		0.67	0.68	
US	0.59	0.50	0.46	0.93	0.93	0.88

B. Dispersion of, and Correlations Among, Earnings, Education and Test Scores

	Coefficient of Variation			*Correlations*		
	Earnings	Years of schooling	Score	Earnings -Educ	Earnings-Score	Educ-Score
Germany	0.66	0.28	0.14	0.26	0.17	0.35
Nether.	0.66	0.29	0.13	0.21	0.15	0.45
Sweden	0.48	0.30	0.15	0.21	0.18	0.40
US	0.87	0.22	0.20	0.39	0.33	0.56

Source: International Adult Literacy Survey (OECD and Statistics Canada, 1998). See Table 1 for number of observations. The earnings data in Sweden are more left-skewed than in other countries, accounting for the low coefficient of variation relative to the standard deviation of ln earnings.

Table 3. Mean Score by Income Quintile

Income Quintile	Germany	Nether.	Sweden	US
Lowest	294	293	319	262
Next lowest	280	290	295	275
Middle	287	289	298	295
Next highest	287	296	301	318
Highest	308	310	322	329

Source: International Adult Literacy Survey (OECD and Statistics Canada, 1998). The five income quintiles within each country are of equal proportion; see Table 1 for number of observations.

Table 4. Ln Earnings Regressions: Coefficients on Score and/or Education

	Model 1: Test Score only	Model 2: Education only	Model 3: Score and Education
Germany			
Score	0.16** (0.05)		0.07 (0.05)
Educ		0.03** (0.01)	0.03** (0.01)
Nether.			
Score	0.32** (0.04)		0.23** (0.04)
Educ		0.03** (0.00)	0.02** (0.00)
Sweden			
Score	0.13** (0.04)		0.07* (0.04)
Educ		0.02** (0.00)	0.02** (0.00)
US			
Score	0.48** (0.04)		0.32** (0.04)
Educ		0.08** (0.01)	0.05** (0.01)

Notes: coefficients estimated from wage regressions, controlling for sex, immigrant status, and (quadratic) age. Sample size ranges from 918 to 1660; R^2 ranges from 0.21 to 0.39. Coefficients are significantly different from zero at the 1% level (**) or 5% level (*). More detailed regression output is available upon request.

Table 5. Predicted Change in Standard Deviation of Ln Earnings in the US, under Alternative Scenarios

Standard Deviation Ln US Earnings $s(\ln w_{US})$:		0.935
Predicted Change in Standard Deviation of Ln earnings…		
If the US had own earnings equation, but	EU distribution of scores[1]	-0.022
	EU distribution of education[2]	0.019
	EU distribution of all factors[3]	-0.017
If the US had own score distribution, but	EU coefficient on scores[4]	-0.039
	EU coefficient on education[5]	-0.049
	EU coefficients on all factors[6]	-0.093
Standard Deviation Ln Swedish Earnings $\sigma(\ln w_{SW})$:		0.679
Predicted Change in Standard Deviation of Ln earnings…		
If Sweden had own earnings equation, but	US distribution of scores[1]	0.002
	US distribution of education[2]	-0.001
	US distribution of all factors[3]	0.014
If Sweden had own score distribution, but	US coefficient on scores[4]	0.032
	US coefficient on education[5]	0.088
	US coefficients on all factors[6]	0.108
Average Difference in Standard Deviation Ln Earnings $s(\ln w_{US}) - s(\ln w_{SW})$:		0.256

1. Regress ln earnings on scores only; replace s^{US}_{score} with s^{EU}_{score}, or conversely.
2. Regress ln earnings on educ only: replace s^{US}_{educ} with s^{EU}_{educ}, or conversely.
3. Regress ln earnings on score and educ, sex, immigrant status and (quadratic) age; predict ln earnings using EU sample and US coefficients *or* predict ln earnings using US coefficients and Swedish sample.
4. Regress ln earnings on scores only; replace b^{US}_{score} with b^{EU}_{score}, or conversely.
5. Regress ln earnings on educ only; replace b^{US}_{educ} with b^{EU}_{educ}, or conversely.
6. Regress ln earnings on score and educ, sex, immigrant status and (quadratic) age; predict ln earnings using US sample and EU coefficients *or* predict ln earnings using Swedish ample and US coefficients.

Table 6. Standard Deviation Ln Earnings, by Within-Country Score Quintile

Score Quintile:	Q1	Q2	Q3	Q4	Q5
Germany	0.53	0.61	0.69	0.62	0.88
Nether.	0.63	0.62	0.69	0.68	0.76
Sweden	0.50	0.63	0.73	0.72	0.75
US	0.82	0.95	0.83	0.96	0.86

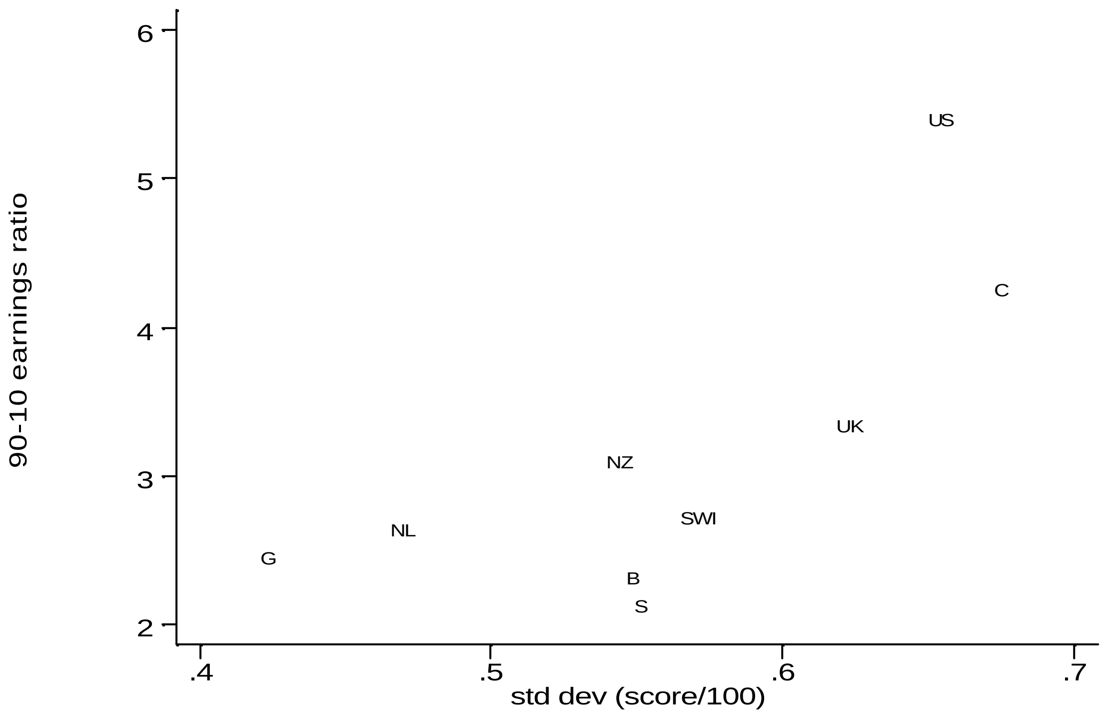
Source: International Adult Literacy Survey (OECD and Statistics Canada, 1998). The five score quintiles within each country are of equal proportion; see Table 1 for number of observations.

Table 7. Standard Deviation Ln Earnings, by Narrow Score Categories

Scores:	251-270	271-290	291-310	311-330	331-350
Germany	0.61	0.65	0.64	0.80	0.78
Nether.	0.67	0.59	0.68	0.69	0.76
Sweden	0.59	0.58	0.63	0.81	0.71
US	0.83	1.01	0.92	0.92	0.87

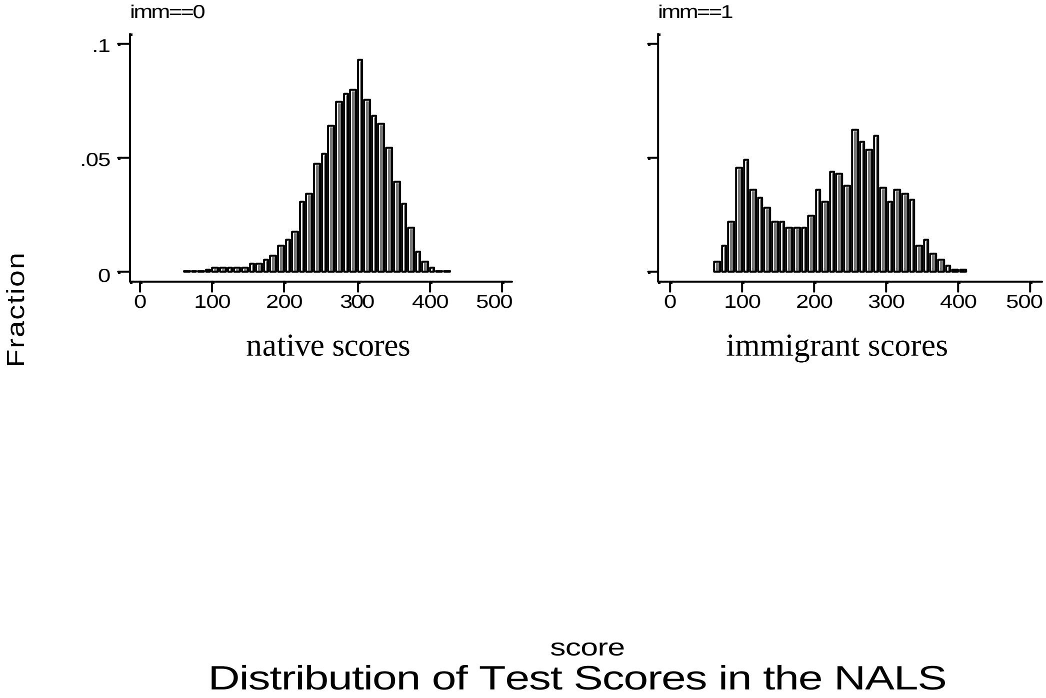
Source: International Adult Literacy Survey (OECD and Statistics Canada, 1998). The table lists the 20-point score intervals in the middle of the distribution, where observations are maximized. There are an average of 146 people in each score category.

Figure 1: Earnings Inequality vs. IALS Test Score Dispersion for Selected OECD countries, 1994



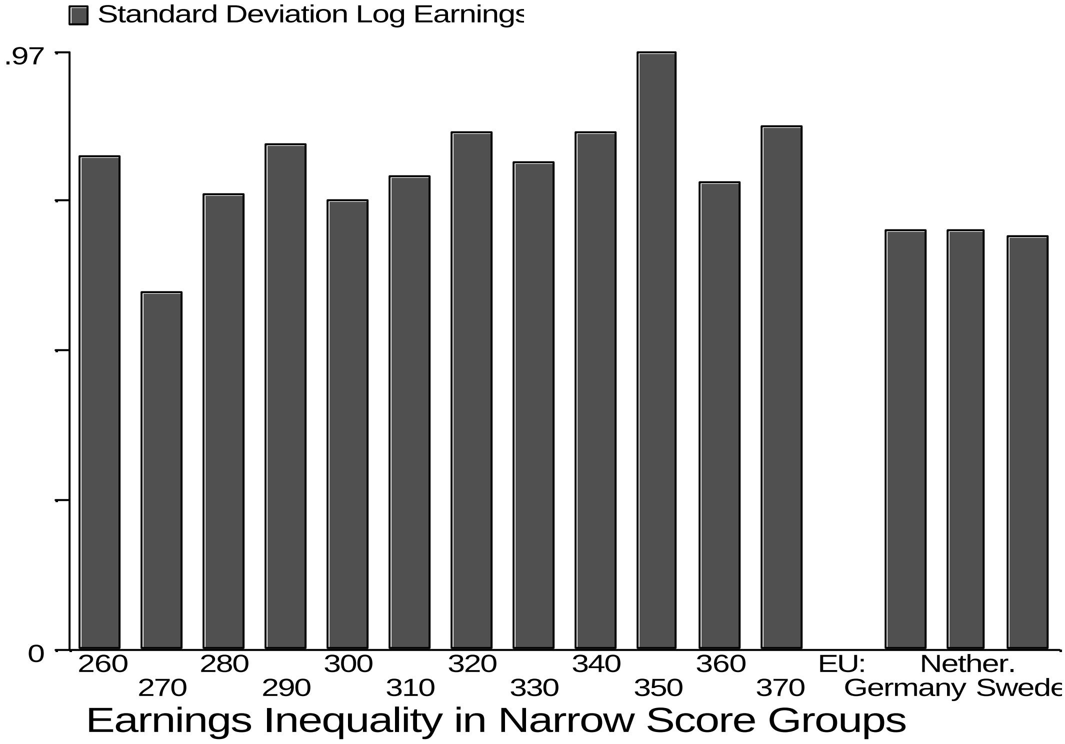
Notes: Standard deviation of score/100 for workers in the IALS, and 90-10 earnings ratio as reported by the OECD (1996).

Figure 2: Test Scores in the US, by Immigrant Status



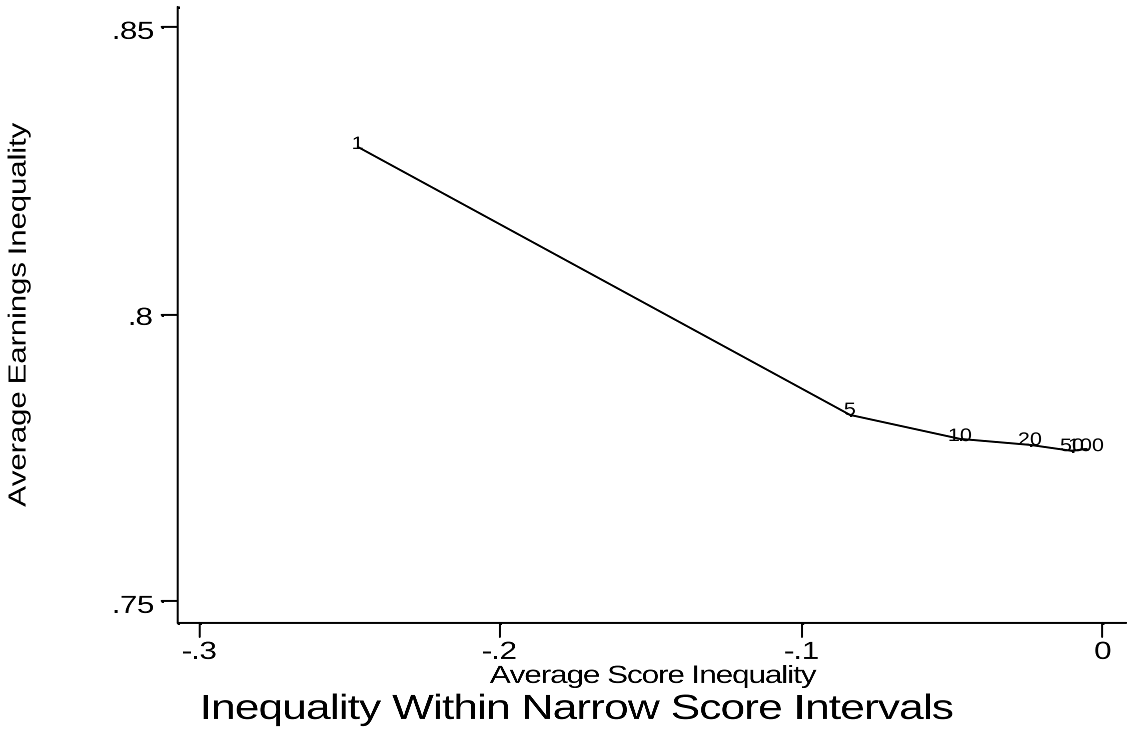
Source: National Adult Literacy Survey. The same patterns are found in the IALS, though with fewer observations.

Figure 3: Wage inequality in Narrow US Score Groups



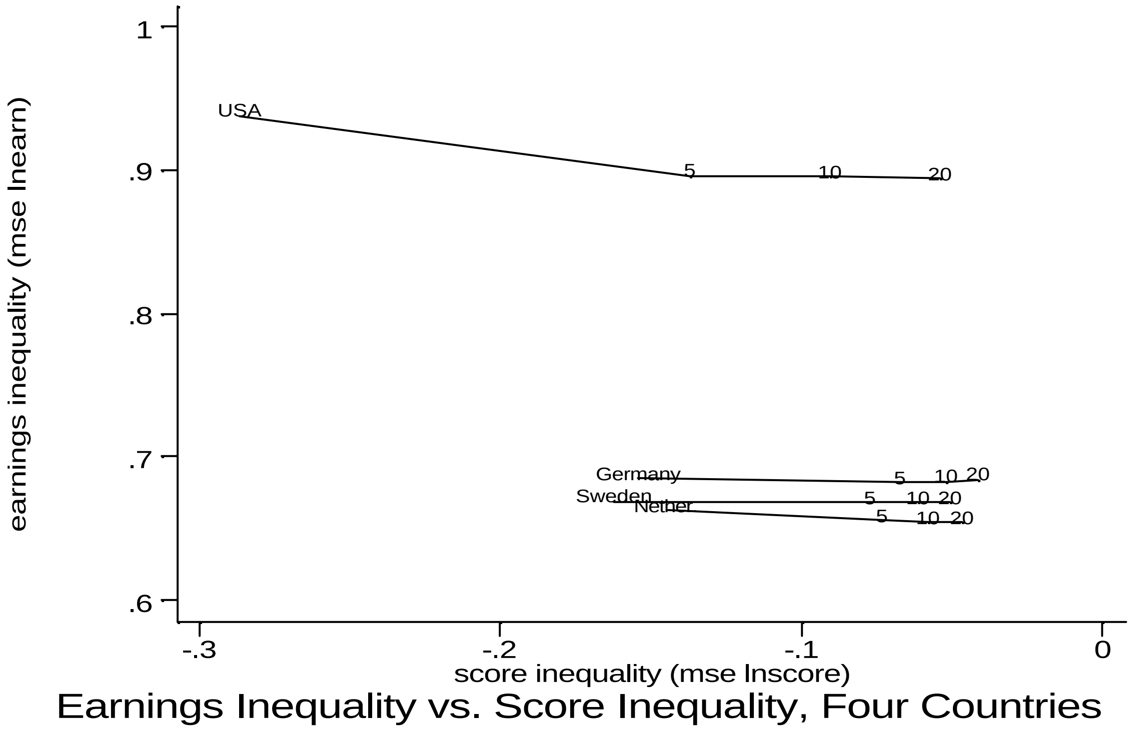
Source: National Adult Literacy Survey for US; International Adult Literacy Survey for other countries. We break the NALS sample of US workers into groups based on test score. For example, group 260 includes all persons with a score of 258-262. The average number of observations in each group is 286. We compare earnings inequality within each group to earnings inequality of each country. The average standard deviation of log earnings in these twelve groups is .79. The comparable figure for the four countries is Germany .68, Netherlands .67, Sweden .68, and US .86 (in the NALS, or .93 in the IALS).

Figure 4: Inequality Within Narrow Score Intervals



Source: Tabulated from National Adult Literacy Survey. We break the NALS sample into even groups based on test score. When there is only one group, mean standard error of ln earnings is .83 and average score inequality is .25. When we create 5, 10, 20 … groups, score inequality within the groups approaches zero – but earnings inequality asymptotes at .77. The total sample is 11,419, so when there are ten intervals there are approximately 1142 observations per interval.

Figure 5. Earnings Inequality vs. Score Inequality, Four Countries



Note: This figure replicates Figure 4 for all four countries in the IALS. As the number of groups into which we divide workers grows the earnings inequality asymptotes much as it did in Figure 4. But the asymptote is much higher in the US than in the European countries. Even as the score intervals get very narrow, within-group wage inequality in the US is still much higher than overall wage inequality elsewhere. (When there are ten intervals there are approximately 155 observations per interval, except in Germany where the figure is 92.)

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