Does Inequality in Skills Explain Inequality of Earnings Across Countries?

Dan Devroye and Richard Freeman

Harvard University

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The US has the most widely dispersed distribution of earnings among major advanced countries. The US also has a highly dispersed distribution of skills, as reflected in measures of adult literacy and numeracy. To what extent, if at all, does the wide dispersion of skills in the US explain the wide dispersion of earnings?

The hypothesis that greater inequality in skills explains the greater inequality in earnings in the US than in Western Europe or Japan is an appealing one. It suggests that the distribution of earnings is determined on the supply side, by the distribution of human capital. At a crude level, the hypothesis fits cross-country evidence remarkably well, as figure 1 shows. The coefficient of variation in test scores across countries from the widely used International Adult Literacy Survey (OECD, 1998) is positively correlated with 90-10 earnings differentials across countries reported by the OECD (OECD, 1997), and with standard deviation of ln earnings in the Adult Literacy Survey. But the argument that differences in the distribution of earnings across countries are largely due to differences in the distribution of skills across countries seems inconsistent with the weaker relation that analysts typically find between test scores and earnings within the US or other countries (Jencks, Griliches), and with widespread belief that much of the EU-US difference in the distribution of earnings reflects differences in wage-setting institutions (Freeman and Katz, 1996).

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 skill and earnings in micro data? Why does the US have such a wider dispersion of earnings among workers than other advanced countries?

This paper examines these questions using the OECD's International Adult Literacy Survey and the US National Adult Literacy Survey. It rejects the claim that inequality of skills explains much of inequality of earnings in the US on three grounds:

1. Inequality of skills in the US is overstated due to inclusion of immigrants whose skills are incorrectly measured by English literacy/numeracy exams. Limiting the US sample to native-born Americans greatly reduces the dispersion of skills but barely changes the dispersion of earnings.

2. Earnings differences associated with skills are much higher in the US than in Western Europe, but even using US returns to skill, differences in skill dispersion across countries explains only a modest proportion of differences in the dispersion of earnings across countries.

3. Dispersion of pay is higher for US workers than for EU workers in narrowly defined skill groups and indeed is higher for US workers in narrowly defined groups than for European workers overall. The dispersion of earnings within a group falls at a rapidly declining rate as the range of skills in the group narrows, asymptoting at a higher level of inequality in the US than in the EU.

If the distribution of skills does not explain the higher dispersion of pay in the US, what does? The standard institutional explanation is that inequality arises from differences in wage-setting systems, with the US relying more on decentralized markets compared to collective bargaining or state intervention than the EU. In our data, differences in the returns to skill across countries are more important than differences in the distribution of skills in explaining cross-country dispersion of earnings. But the biggest difference among countries is in the residual from earnings equations. There are several possible reasons for greater dispersion in wages among observably identically skilled workers, and we conclude the paper with a discussion of these hypotheses.

1. Distribution of Measured Skills

For the distribution of skills to help explain the greater dispersion of earnings in the US compared to the EU, skills must be more unequally distributed in the US than in the EU. The usual measure of skills in labor economics – years of schooling – fails this criterion. Years of schooling is less dispersed in the US than in most EU countries.[1] Accordingly, diverse analysts have looked at alternative measures of skills, notably adult literacy scores, to find support for the dispersed skill explanation for earnings differences (Edin; Nickell; Leuven *et al* (1999)). For much of this paper, we follow the same procedure: we look at adult literacy scores, which are more unequal in the US than in the EU. By concentrating on adult literacy scores, we give the skill hypothesis its best chance to prove itself.

Our principal source of data is the International Adult Literacy Survey (IALS). This is a cross country investigation of literacy skills among adults in 12 OECD countries. The IALS defines literacy in terms of a broad set of skills that can be grouped into three domains:

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.

Each country gathered data on adult literacy using a household survey. 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.

But the same set of questions was not given 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 (3PL) 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.[2] The IALS generated five simulated proficiency values and then took the average of the five to estimate the true proficiency.

Each country drew on a probability sample in order to derive results representative of the civilian, non-institutionalized population aged 16-65. While questions differed across individuals within each country, the same battery of questions was used for all countries in the survey. Great pains were also taken to guard against cultural bias in the results. While Goldstein (1999) has criticized the comparability of the survey across countries, it is the best available source of information on the skills of adults across countries. 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. In the interest of being concise but comprehensive, we use the average of the scores on all three parts of the IALS test as our general measure of skills.

Table 1 summarizes the dispersion of the total scores for all adults and for workers in the US and other advanced OECD countries in terms of the coefficient of variation in those scores. The table lists countries in ascending order by the level of inequality in the test outcomes for workers, from the Netherlands with the lowest inequality to the US with the highest inequality.[3] Among employed adult workers, the US has the highest coefficient of variation; however, it is only barely greater than that in Canada or the British Isles. The other countries with high coefficients of variation have one thing in common with the US: they are also English-speaking countries.

The coefficients of variation are higher in all countries 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. 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). For analyzing the impact of differences in the distribution of skills on the distribution of earnings, the figures for workers are more germane.

The last line in table 1 presents comparable figures for the US from the 1992 National Adult Literacy Survey (NALS). The National Center for Education Statistics designed this survey to measure the nature and extent of literacy skills among the U.S. adult population (16 years old and older). It is similar to the IALS in its basic structure. It assesses the literacy skills using three kinds of literacy tasks that adults would ordinarily encounter in daily life (prose literacy, document literacy, and quantitative literacy). Becasuse the NALS sample is roughly ten times as large as the IALS sample, we will use it to examine some issues which the IALS cannot resolve. The distribution of scores on the NALS is quite comparable to that on the IALS. The mean and standard deviation of scores have similar values in the two surveys.

Table 2 disaggregates literacy scores by score quintile for the various countries. It shows that the main reason that the US and the other countries with great inequality in adult literacy have such high dispersion of skills is that persons in the low end of their distribution score exceptionally low. In the highest score quintile, the high inequality countries do not fare much better than the low inequality countries. However, in the lowest quintile, the high inequality countries have much lower test scores. Americans and Canadians do exceedingly poorly at the bottom -- 40 to 50 points below the lowest-inequality countries. Before comparing the US with other countries, it is worth asking why it has so many people with particularly low test scores.

2. Who are the low-skilled Americans?

We examine next the characteristics of persons who fall in the lowest score quintile in the US. We compare their characteristics to those of persons in three countries which have both low inequality in scores and low inequality in earnings, Germany, Holland, and Sweden, and for whom we have reasonably good micro earnings data. Contrasting the US with Germany, Holland, and Sweden will give the skill hypothesis its strongest chance to explain the greater dispersion of pay in the US.

Table 3 records the proportion of persons with various characteristics who fall into the lowest score quintile and the proportion of those groups in the overall population in the US and other countries, and also gives the ratio of these proportions. When the ratio of representation in the lowest quintile to representation in the total group exceeds one, a group is disproportionately found among the least skilled. In all countries, immigrants are heavily overrepresented in the lowest quintile. In the IALS 33 percent of Americans in the lowest quintile are immigrants; in the NALS 27 percent in the lowest quintile are immigrants. Since both the IALS and NALS are given in English, the low score of immigrants presumably reflects in part their familiarity with the English language rather than any other potential skill deficiency. To the extent that these immigrants work in ethnic enclaves or have found employers who have adapted policies that make it easier for them to be productive with poor English skills, both the IALS and NALS understate their true workplace skills. The US also reports data by race, and minorities (defined here as self-reported non-whites) are also disproportionately represented among the lowest score quintile in the US. Not surprisingly, persons with low education levels (the bottom education quintile within each country) have lower scores as well, but this result is no more pronounced in the US than in other countries.

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 (0.18 in the NALS).[4]

But the difference in skills between immigrants and natives is more pronounced than this statistic suggests. As figure 2A shows, the distribution of literacy scores according to immigrant status in the United States is wider than that for natives. The immigrant distribution is double-peaked, with the higher peak close to the mean for the native-born and the lower peak sufficiently below the average to suggest that it does indeed reflect a very different population – for instance, one lacking English language skills.

In fact, the majority of immigrants with exceedingly low skills report themselves to be Hispanic or Latin Americans. Latin American immigrants constitute 10.4% of the US sample but 48.4% of persons scoring below 200 on the NALS literacy test. Figures 2C and 2D compare the distribution of skills for four race groups (White, Black, Latino and Asian); it appears that the lower immigrant scores come primarily from Latino and Asian immigrants. Thus, the low scores among immigrants may really be a reflection of poor English skills, not of poor labor market skills.

Consistent with this hypothesis, regressions of ln earnings on immigrant status, score on the literacy test, and sex and age, yield a positive 0.08-0.12 ln point coefficient on immigrant status (see Appendix A). By contrast, regressions of ln earnings on immigrant status, education, sex, and age yield a negative 0.15-0.18 ln point coefficient on immigrant status. The implication is that their education overstates their skills (presumably because it was in a different country and language) while their test score understates their skills. A probit equation linking presence in the bottom quintile of earnings to a quadratic in age, years of education, nonwhite, and immigrant status, yielded a 0.03 coefficient on immigrant status in the IALS (0.07 in the NALS) – substantially below the comparable coefficient for being in the lowest score quintile.

How much of the greater skill dispersion in the US compared to other countries can be attributed to the large influx of immigrants to the country?

The simplest way to answer this question is to compare the dispersion of skills in the US and other countries overall and for a population consisting solely of natives. Table 4 records the relevant statistics for the US and our three low-inequality EU countries. The table gives the standard deviation of literacy scores for all workers, for native workers only, and for native white workers only. Among all workers, the standard deviation of scores in the US is 14 points to 19 points higher than in the comparison countries in the IALS. Elimination of immigrants from the sample reduces the standard deviation of scores by 9 points in the US while elimination of immigrants from the samples of the EU countries reduces the standard deviation of scores by 2-3 points. The exclusion of immigrants reduces the US-EU country difference in dispersion of skills to 8-12 points – roughly 40%. If the American sample is further limited to native whites, the differences in dispersion of skills with native Europeans drops by an additional four points.

The right-hand panel of the table examines the effects of eliminating immigrants on the bottom part of the skill distribution, where Americans do poorly relative to Europeans. It records the ratio of the mean scores of workers in the middle quintile (Q3) to the mean score of workers in the bottom quintile (Q1) in the US and other countries. The Q3/Q1 score ratio declines from 1.50 to 1.38 in the US with the elimination of immigrants while it barely changes in EU countries.

In sum, one reason for the high measured inequality in skills in the US is that the US distribution combines two groups, natives brought up in the country, and immigrants, whose low scores reflect English language problems rather than some other skill deficiency. In what follows, we continue to include immigrants in the US sample, again to give the skills hypothesis its best chance. But one should keep in mind that a more accurate measure of labor market skills would make the US look even less exceptional in skill inequality.

3. The Effect of Skills on Earnings

To assess how much skill inequality may contribute to earnings inequality, we use the IALS files on earnings and skills for individuals rather than the aggregate data in figure 1. In the dataset available from the OECD, the only measure of earnings was the income in the quintile of the distribution in which the person was located, and even the five quintiles were not represented equally. Rather than working with such poor measures, we obtained the original earnings data for four countries: the US and our three low inequality EU countries, Germany, Holland, and Sweden. Even for these countries, however, the earnings figures are not ideal. First, while the earnings data are precise for the US and Sweden, earnings for Germany and Holland are reported in 20 unevenly-represented categories. 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.

To make the data comparable among the four countries, we can either amalgamate the US and Sweden to the group level of data for Holland and Germany, or we can give workers in those two countries a level of earnings associated with their group. We experimented with both procedures and found little difference in the results. In what follows, we have generated an earnings distribution for Germany and Holland by randomly imputing precise earnings from a uniform distribution to persons within each category. The results are easier to interpret and compare across countries. None of the substantive conclusions are sensitive to this procedure.

Table 5 describes the main patterns in the data: the standard deviations of the key variables that underlie our hypothetical and their correlations. The dispersion of earnings and the dispersion of skills are higher in the US than in the EU countries. But, as noted earlier, the dispersion of years of schooling is less in the US than in the EU countries -- the result of more rapid movement to universal education in the US. The correlations between earnings and skills is also notably higher in the US, as is the correlation between education and skills, and the correlation between skills and education. In all countries, moreover, the correlation between education and earnings exceeds the correlation between adult literacy skills and earnings.

Table 6 shows how scores are distributed through the income distribution. The results are striking. In the US, test scores rise by an average of 17 points per income quintile. The relationship is strongest among the middle income quintiles (20 points between Q2 and Q3; 23 points between Q3 and Q4), but also sizeable at the tails (13 points between Q1 and Q2; 11 points between Q4 and Q5). By contrast, in the three European countries, the relationship is exceedingly weak. While high-income people have somewhat higher scores, scores in the bottom quintile are only slightly lower than those at the top and are actually higher than in the middle quintiles. If we ignore the lowest score group, and focus only on Q2, Q3 and Q4, the average scores for these income groups in Europe are essentially indistinguishable, with an average difference among quintiles of 3 points compared to more than 20 points in the US. Scores and income are reasonably closely aligned in the US, but the relationship in the low-inequality European countries is extremely modest.

If dispersion of literacy skills is a major determinant of the dispersion of earnings, we would expect to find that reducing the dispersion of skills by narrowing the US sample to natives would be accompanied by a large decline in the dispersion of earnings. The bottom panel of table 4 shows the dispersion of ln earnings from the IALS for the US, Sweden, Germany, and the Netherlands. Remarkably, the elimination of immigrants from the US sample has no discernible impact on the dispersion of earnings in the US! Even when we narrow the US sample to native whites, removing earnings differences associated with discrimination, the dispersion of earnings falls only modestly.

What impact must literacy scores have on ln earnings if they are to explain the cross country dispersion of earnings? Taking all workers, the US has a dispersion of earnings that averages 0.25 ln points greater than the EU countries in table 4 and a dispersion of skills that averages 17 points greater. The coefficient in a regression on skills/100 in an ln earnings equation would have to be 1.47 (= .25/.17) to explain fully this pattern. But taking only native-born workers the US has a dispersion in skills that averages 10 points higher, which must explain the same difference in dispersion of earnings. This would require a skills premium of 2.50 (= .25/.10). Finally, 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).

Do skills have anything like these sized coefficients in actual micro earnings regressions? To answer this question, we estimated the effect of skills on earnings using standard ln earnings equations and then used the estimated coefficients on skills to assess how much the dispersion in earnings in the US would fall if the US had EU levels of dispersion of skill. We use the same regression models to assess how much differences in skill premium contribute to differences in the dispersion of earnings, also.

Table 7 records the results of our regression analysis in terms of the coefficients and standard errors on our measures of skill, conditional on sex, immigrant status, age, and quadratic age. Column 1 uses the individual's test score as the sole measure of skill. This column gives us the largest coefficient on the measure of skill where the US has greater inequality and thus gives the skill inequality hypothesis its greatest opportunity to explain the cross-country patterns. The regressions in this column show strikingly different estimated coefficients between the US and the other countries. The coefficient on literacy scores for the two US data sets are comparable: a 100 point change in the adult literacy score (about 1.5 standard deviations) raises earnings in the US by a sizable 0.50 ln points. 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. Though it is the largest coefficient on skills the 0.5 estimate for the US falls far short of the 1.2 to1.8 coefficients that we estimated are needed to explain all of the EU-US difference in the dispersion of earnings by the dispersion of skills.

The regressions with years of schooling as the sole measure of skills tell a similar story about the impact of skills on earnings. The effect of schooling on ln earnings is much greater in the US than in the other countries (column 2). Similarly, when we include both scores and years of schooling in the equation, the effects of both measures are higher in the US than in the other countries (column 3). In addition, in all of the regressions the coefficients on the age variables are also larger in the US. Any explanation of the greater dispersion of earnings in the US than in the EU cannot be complete without taking account of the greater impact of skills and most other determinants of earnings on ln earnings in the US than in the EU. Note finally that in the regressions with both schooling and literacy as measures of skill, years of schooling has a much stronger link to earnings than does the test score in Germany and Sweden, while both measures are closely related to earnings in the US and the Netherlands.

To what extent might the higher coefficient on skills in the US than other countries be due to the greater variation in wages relative to skills in the US, or to the fact that the US has a greater range of skill variation, in part because we included immigrants in our regressions? We examined these possibilities in several ways. First, 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 the same results. Regardless of the sample being used, scores have a more pronounced effect on earnings in the US than in the European countries, with coefficients in the ln earnings equations of about 0.50. Finally, we examined the possible effect of the varying dispersion of pay and skills across equations on the estimated coefficients in the earnings equation by replacing earnings and test scores with the rank of people according to their test score and earnings in their respective national distributions. Consistent with the higher correlation coefficients between scores and earnings in the other countries that we found in table 5, the US once again had higher coefficients on test scores. Put differently, one important reason for the higher coefficients on scores in the ln earnings equation is that the US sorts people by test scores more than any other country.

4. Decomposition Analysis

Given the estimated earnings equations and measures of the dispersion of skills and other wage determining factors in the US and EU countries we next calculate two types of counterfactuals that provide insight into how the differing characteristics of US and EU workers affect dispersion of pay. The first type of counterfactual calculates the dispersion of earnings the US would have if the US had the dispersion of skill characteristics of workers in EU countries, but weighted those characteristics by the coefficients from the US earnings equation. We do this by replacing the US dispersion of characteristics by the EU dispersion of skills in the equation for the variance of earnings in the US:

$$\sigma^2_{\text{lnW}} = b^2_{\text{US}}\,\sigma^2_{\text{EU skills}} + \sigma^2_{\text{unexplained US}}$$

where the *b*s refer to the coefficients for the relevant characteristics and the σ^2s are the variance of those characteristics. Whenever the EU dispersion of characteristics is less than the US dispersion of characteristics -- as in the case of test scores -- this analysis predicts that the US would have lower earnings dispersion if it had the EU dispersion while all else remained the same.

The second type of counterfactual asks what would happen to the US dispersion of wages if the US had its own dispersion of skill characteristics but if these characteristics were valued by the coefficients from the EU earnings equation. We do this by replacing the US coefficient on skills by the EU coefficient of skills in the equation for the variance of earnings in the US

$$\sigma^2_{\mathrm{lnW}} = b^2_{\mathrm{EU}}\,\sigma^2_{\mathrm{US\ skills}} + \sigma^2_{\mathrm{unexplainedUS}}$$

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 earnings dispersion if it had the EU earnings equation.

Table 8 presents the results of calculations of these types where we vary the dispersion or coefficients for various wage-determining characteristics. Since most analyses of dispersion concentrate on standard deviation of earnings, we have 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 line of the table shows the contribution of changing the dispersion of test scores in the US from the observed US level to the levels for the EU countries, based on an ln earnings equation in which the only explanatory factor was test scores. With an estimated *b* of about 0.5 in the US and with standard deviations of (score/100) in the US and EU of 0.6 and 0.45 respectively, the change in variance resulting from a drop in EU skills would be $(.6^2-.45^2)*.5^2 = 0.04$. This corresponds to a decline in standard deviation of ln wages of $\sqrt{(.93^2-.04)} = 0.02$, from 0.93 to 0.91. In the table, 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 .017 ln points less inequality. The next line shows the results for the counterfactual in which the only explanatory variable in the regression is years of education, and where we replace the US dispersion of education with the EU dispersion of education. Since the dispersion of years of schooling is lower in the US than in the EU, we get an increase in the predicted standard deviation of ln earnings in the US.

The final line under "if the US had the US earnings equation, but..." shows what happens if we replace the dispersion of *all* factors in the US with the dispersion of all factors in the EU contained in our earnings equations. Put differently, we estimate the dispersion of wages the US would have if the US population resembled the population of a European country in the entire set of characteristics in our earnings equation, but were paid by the US earnings equation. The drop in the standard deviation of log earnings is a modest -0.019, or 7% of the initial 0.256 difference in log earnings between the US and the EU countries.

The next part of the table examines what would happen to dispersion "if the US had US distributions of characteristics" but valued those characteristics by earnings equations for the EU countries. Again, we performed the analysis separately by country and give the average outcomes.
The major result here is that changing the coefficients in the earnings equation reduces the US-EU difference in dispersion by 2 to over 4 times as much as did changing the variance of characteristics. Simply 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 0.034 points. Altering the coefficient on years of schooling in an equation with only schooling as the explanatory variable reduces the difference in standard deviations of ln earnings by .044 points. Finally, when we predict the dispersion of ln wages for the US sample using the full vector of estimated coefficients for the EU countries, we obtain an average decline in dispersion of .088 or 34%. This is 4.6 times as great as the decline in the difference of dispersion of wages due to the differing dispersion of characteristics. In short, altering the US dispersion of skill by itself would cause only a very small reduction in earnings inequality; whereas atering the US wage equation would cause a more sizeable reduction. The higher skill premium explains more of the greater dispersion of pay in the US

than does the higher dispersion of skills.

Counterfactuals that vary the dispersion of skills without taking account of the potential effect of changes in that dispersion on the skill coefficients in earnings equations are, however, potentially misleading. Changes in the dispersion of test scores or other wage-determining characteristics are, after all, likely to affect the magnitude of the coefficients in the earnings equation. 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. With a good estimate of the potential impact of the effect of changing the dispersion of scores on the coefficient on score, we would include some of the effect of the change in the coefficients on scores with the estimated effect of the change in the dispersion of scores as the result of changing the dispersion of scores. But even if we were to take the full effect of the changes in scores, we would still not explain the bulk of the EU-US difference in the dispersion of earnings. This is because roughly 2/3rds of the difference in the dispersion of earnings occurs in the residual variation. 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.

5. A Non-Parametric Analysis

The analysis thus far has followed the standard parametric specification of earnings equations to assess how much reduced dispersion of skills would reduce the dispersion of earnings. But there is a natural non-parametric way to examine the data as well. This is to look at the dispersion of pay among workers in narrow skill categories in the EU and US. Assume that the dispersion of skills was the primary factor behind US-EU differences in the distribution of earnings. Then if we look at groups of workers within increasingly narrow skill bands in the US and EU, we should find increasingly small differences in the dispersion of earnings. In the extreme, workers with exactly the same scores should have roughly the same distributions of earnings.

Table 9 records standard deviations of ln earnings in the US, Germany, Netherlands, and Sweden for groups of workers that are roughly comparable in skills. Panel A focuses on workers in the same quintile of the earnings distribution within each country. 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. In some cases, such as in the second quntile, the dispersion of ln earnings is greater than it is overall. Panel B examines dispersion of pay for workers in narrowly defined skill bands, rather than in similar percentiles in the score distribution. It focuses on persons with scores in the middle portions of the score distribution because we necessarily have more observations there than at the tails to estimate the dispersion of pay. The figures show higher dispersion of earnings in the US than in EU countries, with the largest differences occurring among lower skilled workers.

But perhaps part of the reason for the widely dispersed earnings within the quintile groups or in specified score groups in the US is that Americans within those groups have more dispersed skills than Europeans. Quintiles and 20 point bands of scores may be too coarse-grained measures to uncover the true effect of skill dispersion on the dispersion of earnings. What happens to the dispersion of ln earnings if we increasingly narrow the range of measured skills for a group?

The easiest way to answer this question is to estimate a linear regression model in which the dependent variable is the ln of earnings and the principal independent variables are sets of 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 ($d_1 \ldots d_S$) for the percentile group of the individual in the distribution of scores. For instance, if s=2, the vector would simply 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 residual variance from these regressions measures the average variance of pay within the groups, while the mean square error from the regression gives the dispersion in standard deviation terms. Narrowing the range of scores covered by a group will, of course, also reduce the average dispersion of scores for that group. 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 3 summarizes the results of this analysis for the US in the NALS, where we have a sufficiently large sample to allow us to create a large number of groups of workers and for the US and the three EU countries in the IALS files. 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. Each point on the graph shows, in addition, the number of groups into which we classified the sample. Narrowing the range of scores included in a group reduces dispersion noticeably in the US, but only up to a point. In the NALS, the dispersion of earnings falls as we increase the number of groups to 20 to 50 and then asymptotes at about 0.78. In the IALS, the dispersion asymptotes at about 0.85 in the US with roughly 20 to 50 groups as well. 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.

The figure shows that at any given level of dispersion of scores, the dispersion of ln earnings is much higher in the US than in the EU. More striking, it also shows that the asymptote for the dispersion of earnings in the US exceeds the level of dispersion for the *entire* work force in the EU countries, even with the NALS data where dispersion of wages is lower than in the IALS. Put differently, the dispersion of earnings among Americans with essentially identical skills obtained by dividing the work force into over 3100 groups is greater than the dispersion of earnings among Europeans with differing skills obtained for the whole working population!

Figure 4 drives this point home in another way. It records the dispersion of earnings among Americans with "precisely" the same test score for a number of scores where we have a reasonably large sample in the NALS. Because of the way the NALS constructs its test scores using a logistic item response model, "precisely" does not mean that persons have exactly the same score. We have taken a narrow band of 4 points on the scale, centered around the reported number, to represent the same score. 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 for all workers in Germany, the Netherlands, and Sweden. Americans with effectively the same literacy score are paid more disparately than are all workers in those countries.

5. Micro vs. Macro Evidence

That the micro data on the relation between test scores and earnings rejects the claim based on macro data that the dispersion of skills is the primary determinant of the dispersion of earnings across countries will come as no surprise to anyone who has estimated micro earnings equations. What explains the divergent set of results?

One natural reading of the cross-country relation between dispersion of scores and dispersion of earnings in figure 1 is that it is spurious – an ecological correlation due to some omitted variable, such as the difference between EU institutional wage-setting and US market wage-setting (Blau and Kahn 2000), or English-speaking. Indeed, the correlation in the figure can be decomposed into two parts: an essentially flat curve for the continental European and non-English speaking countries and another curve for the English-speaking countries. The steep upward relation among the English-speaking countries, moreover, also seems spurious, for if we look only at the standard deviation of the scores of natives, the US moves substantially toward the vertical axis while the earnings ratio does not change.

But perhaps this is too harsh a conclusion. There are economic patterns that are strong at the macro level but not at the micro level for good reason. For instance, wages are highly related to capital/labor ratios across countries, but wages are only weakly related to capital/labor ratios associated with working in different sectors within a country, where mobility will tend to produce similar wages. We would be loathe to conclude from a regression of wages on capital labor ratios within the US that the greater capital intensity of the US does not explain a large part of the US wage advantage over a third world country. Perhaps the observed country pattern evinced in figure 1 reflects some comparable phenomenon (sorting, perhaps?) that the micro data cannot reveal.

To see if the difference between our micro analysis and the observed macro relation is due to the level of aggregation, we calculated the standard deviation of scores and the standard deviation of ln earnings for US states with sufficiently large numbers of observations in the NALS to give reliable estimates. This gave us 15 states, all of whom had over 200 observations. Figure 5 graphs the standard deviation of ln earnings and the standard deviation of scores/100 in those states. The two variables are positively related, so that the regression of the standard deviation of ln earnings on the standard deviation of scores across the states gives a coefficient of 0.25 (*t*-stat = 1.58) with an R^2 of 0.16. Thus, even in the US, where the relationship between skills and earnings appears to be strongest, the regional pattern is not terribly striking, and seems consistent with the micro regressions reported in section 3. By contrast, a regression of the standard deviation of ln earnings on the standard deviation of scores across countries gave a coefficient of 0.79 with an R^2 of 0.54. This cross-country relationship seems very strong, and more difficult to reconcile with the micro evidence. The failure of the US states to reveal a strong relationship appears to be further evidence that the strong macro-level correlation is largely spurious.

6. Conclusion: If Not Measured Skills, What?

Our analysis rejects the claim that differences in the dispersion of skills between the US and 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 less than 10% of the greater dispersion of earnings among workers in the US than in those countries. A much higher proportion of the observed difference in the dispersion of earnings -- around a quarter -- is due to the higher coefficients on earnings determining factors in the US, though as we note some part of this may reflect differences in the dispersion of skills. Most of the differences in dispersion occurs among workers identical by measured skill and other characteristics.

What might explain these “residual differences”? There are four possible explanations for the higher within-group dispersion of pay in the US than in EU countries.

1. Unobserved heterogeneity of skills is greater in the US than in the EU. 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 two of our findings cast doubt on this “extrapolation”: the fact that the dispersion of measured skills in the US is “exaggerated” by inclusion of immigrants whose low test scores do not reflect their skills; and the finding that the disperson of pay among Americans with the same literacy scores exceeds the dispersion of pay among all workers in EU countries. It is difficult to believe that Americans with the same observed skills have greater dispersion in unobserved skills than Europeans have in both unobserved and observed skills. Accordingly, we reject this possible explanation as a major factor accounting for the greater residual variance of earnings in the US.

2. Unobserved heterogeneity in workplaces is greater in the US than in the EU, generating greater compensating differentials. Since the EU has a more regulated labor market, US workplaces probably vary more in their non-wage characteristics than EU workplaces. But many of the differences in workplaces are likely to exacerbate rather than reduce the observed difference in dispersion. In particular, EU countries have national health insurance, while health benefits vary with place of employment in the US. Employer-related pension plans are also less important in the EU than in the US. To the extent that these and other valuable non-wage aspects of work are positively related to wages, the dispersion of earnings understates rather than overstates the "true" difference in the dispersion of economic rewards among workers in the US and EU countries.

3. The US has a greater premium on unobserved skills than EU countries. This is consistent with our regression analysis and the findings of others that earnings determining factors almost always have higher coefficients in earnings equations in the US than in EU countries. It also fits well with the fact that EU wage-setting institutions explicitly seek to reduce the dispersion of pay among "similar" workers and in some situations among workers with varying observed levels of skills, as well. We regard this as a plausible hypothesis, but doubt that it can account for all of the residual difference save in a tautological way. Our finding that the dispersion of earnings among American workers with the same test scores exceeds the dispersion of earnings among all workers in low inequality EU countries suggests that however we group people, there will be higher variance of earnings among "otherwise identical persons" in the US than in the EU.

4. The US wage-setting system pays "otherwise identical persons" more variably than do EU wage-setting systems, conditional on outcomes beyond their control. This explanation is mindful of Jencks' emphasis on the role of chance or luck in earrnings determination. To make it more precise and testable, we link it to specific features of the wage-setting system.[5] Consider two identical workers in the US: Joe and Clone. Each faces the same opportunity set: taking a job with Megabucks.com or with Bigbucks.com. The offers from Mega and Big are identical: $50,000 and promises of bonuses, promotions, and stock options valued at $50,000. Objectively these offers are the same. No one knows whether Mega or Big will succeed or fail. The market has equalized the *ex ante* earnings for these two jobs. Joe goes for Mega. Clone chooses Big. Five years later, Mega hits the jackpot, replacing Windows with Doors. Joe gets his $50k in bonuses, promotions, options. Clone does not. Ex post there is a huge dispersion of earnings between identical workers. EU wage-setting systems give market outcomes much 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 unifying principle behind explanations 3 and 4 is that they postulate that the same wage-determining factor has a higher impact on earnings in the US than in the EU. Explanation 3 makes the key factor unobserved skills, which pay off more in the US than in the EU. Explanation 4 makes the key factor unanticipated economic shocks, which payoff more in the US than in the EU. The explanations differ in whether the factor lies within the person or in the employment situation in which she finds herself.

How might we get a handle on these two explanations?

Longitudinal data on wages in the US and EU could help measure the posited differential role of shocks on earnings of persons with similar unobserved skills. Consider the path of wages for a given person over some time period in the US and EU. Skills, observed or unobserved, will be the same over the period for that individual, and so too should the return to those skills. Then, conditional on life cycle changes in earnings, economy-wide shocks and so forth, explanation 4 predicts that the dispersion of pay for the individual will vary more in the US than in the EU. Individual variation in earnings will be higher in the US than in the EU.

Data on the wages of a set of immigrants from the EU to the US (or the reverse) could similarly help assess the importance of differences in the rewards to unobserved skills on the dispersion of pay. Assume that people who work first in the EU and then in the US (and conversely) have the same individual skills. The residual from an earnings equation based on their experience in one setting would give a measure of their unobserved characteristics. Explanation 3 would then predict that this residual would obtain a higher coefficient in a US wage equation than in the EU equation, thus contributing to greater variance of residuals in the US. The key assumption here is that the US values unobserved characteristics similarly to EU countries, but scales those unobservables more highly.

While explanations 3 and 4 differ in important ways, they both stress differences in wage-setting systems as the prime reason for the greater earnings inequality in the US than in the EU; and thus lead in a very different direction for research than if differences in the distribution of skills were the main factor behind differences in earnings inequality. They direct attention at the ways in which different methods of pay produce different levels of dispersion among otherwise similar people in similar situations and ultimately at the rationale and benefits and costs of these different pay-setting systems.

Endnotes

1. This is true in crude statistics that make little or no adjustment for differences in the nature of school systems but also in more refined estimates that take account of, say, apprenticeship and related programs. 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 Holland, and 0.30 for Sweden.

2. (For a reference on IRT, see F. M. Lord, "Applications of Item Response Theory to Practical Testing Problems" (Hillsdale, NJ: Eribaum, 1980).)

3. Poland, which we have not included in the table, has higher inequality than the US. Poland also has an extremely low mean score in adult literacy.

4. The exact results are given in the following tables.

Table A1. Probit: Factors Predicting Low-Score Quintile

	Age	Educ	Immigrnt	Nonwhite	R2	N
IALS	0.0017	-0.048	0.22	0.21		
	(0.0004)	(0.003)	(0.03)	(0.02)	0.35	2855
	3.99	-18.25	9.18	12.67		
NALS	0.0049	-0.046	0.18	0.23		
	(0.0001)	(0.001)	(0.01)	(0.01)	0.36	24876
	46.32	-52.42	21.08	37.26		

Table A2. Probit: Factors Predicting Low Earnings Quintile

	Age	Age^2	Sex	Educ	Imm	Non-white	R^2	N
IALS	-0.06	0.00	0.16	-0.02	0.03	-0.10		
	(0.01)	(0.00)	(0.02)	(0.00)	(0.03)	(0.03)	0.19	1529
	-10.67	9.74	7.79	-5.62	1.02	-4.11		
	-0.04	0.00	0.13	-0.03	0.07	0.03		
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	0.14	11386
NALS	-19.26	16.21	17.26	-18.75	5.31	2.97		

5. The ideas in this section owe much to discussions with Michael Schwarz.

Table 1. Summary of Adult Literacy Test Scores, for All Adults and for Employed Workers

	All Adults				*Employed Workers*			
Country	N	Mean	Std Dev	CoV	N	Mean	Std Dev	CoV
Holland	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 (ials)	3045	272	65	**0.24**	2047	283	60	**0.21**
US (nals)	24944	270	64	**0.24**	12366	288	58	**0.20**

Source: International Adult Literacy Survey (OECD and Statistics Canada). The second source of US data is the National Adult Literacy Survey.

Table 2A. Average Score, by Within-Country Score Quintile – *All Adults*

Score Quintile	1	2	3	4	5
Holland	209	264	289	308	337
Germany	223	265	285	308	342
Sweden	210	272	299	325	361
Belgium	191	258	287	309	342
New Zealand	188	252	278	302	338
Switzerland	180	256	282	304	334
Great Britain	173	241	275	305	342
Ireland	176	239	270	297	334
N. Ireland	170	240	273	302	340
Canada	163	248	282	310	351
US (ials)	169	248	283	311	350
US (nals)	171	246	279	308	347

Table 2B. Average Score, by Within-Country Score Quintile – *Workers Only*

Score Quintile	1	2	3	4	5
Holland	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 (ials)	191	261	291	318	355
US (nals)	199	267	295	321	356

Table 3. Proportion of Persons in Lower Within-Country Quintile Compared to Proportion of Persons in Population, by Characteristic

	Germany	Holland	Sweden	US (ials)	US (nals)
Immigrant					
Lowest q	0.09	0.12	0.12	0.33	0.27
Total pop	0.05	0.05	0.07	0.13	0.10
Ratio	1.56	2.20	1.76	2.54	2.75
Low educ					
Lowest q	0.40	0.53	0.48	0.70	0.83
Total pop	0.26	0.23	0.23	0.39	0.47
Ratio	1.54	2.33	2.06	1.82	1.77
Minority					
Lowest q				0.57	0.54
Total pop				0.26	0.22
Ratio				2.19	2.42

Note: “low educ”includes people in the bottom education quintile in each country. Minority includes all non-whites; data on race were only available for the US.

Table 4. Distribution of Literacy Scores and Earnings, by Demographic Group

	SD Scores			*Q3/Q1 Score Ratio*		
	All	Native	Native and White	All	Native	Native And White
Germany	0.41	0.39		1.25	1.24	
Holland	0.40	0.38		1.28	1.26	
Sweden	0.45	0.42		1.28	1.25	
US (ials)	0.59	0.50	0.46	1.50	1.38	1.34
US (nals)	0.58	0.50	0.45	1.47	1.38	1.34
	SD Log Earnings			*Q3/Q1 Earnings Ratio*		
	All	Native	Native and White	All	Native	Native And White
Germany	0.68	0.68		2.62	2.64	
Holland	0.68	0.69		3.05	3.08	
Sweden	0.67	0.68		2.59	2.60	
US (ials)	0.93	0.93	0.88	4.10	4.11	4.02
US (nals)	0.86	0.85	0.84	3.02	3.01	2.98

Table 5. Dispersion of, and Correlations Among, Earnings, Education and Test Scores

	Coefficient of Variation			*Correlations*		
	Earnings	Educ	Score	Earnings -Educ	Earnings-Score	Educ-Score
Germany	0.66	0.28	0.14	0.26	0.17	0.35
Holland	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 (ials)	0.87	0.22	0.20	0.39	0.33	0.56
US (nals)	0.85	0.17	0.20	0.40	0.32	0.60

Table 6. Mean Score by Income Quintile

Income Quintile	Germany	Holland	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

Table 7. Regression Estimates of Log Earnings on Score and/or Education

	Score	Educ	Score and Educ	
Germany	0.16	0.03	0.07	0.03
	(0.05)	(0.01)	(0.05)	(0.01)
	3.41	5.87	1.49	5.02
Holland	0.32	0.03	0.23	0.02
	(0.04)	(0.00)	(0.04)	(0.00)
	9.26	9.30	5.98	5.91
Sweden	0.13	0.02	0.07	0.02
	(0.04)	(0.00)	(0.04)	(0.00)
	3.70	5.12	1.85	3.99
US (ials)	0.48	0.08	0.32	0.05
	(0.04)	(0.01)	(0.04)	(0.01)
	13.70	13.20	7.57	6.87
US (nals)	0.51	0.12	0.3	0.08
	(0.01)	(0.00)	(0.02)	(0.00)
	39.13	40.52	18.68	21.20

Notes: controls for sex, immigrant status, and (quadratic) age. Sample size ranges from 918 to 1660; R^2 ranges from 0.21 to 0.39.

Table 8. Predicted Change in Standard Deviation of Log Earnings in the US, under Alternative Scenarios

Average Difference in Standard Deviation Log Earnings $s(\ln w_{US})$ - $s(\ln w_{EU})$:		0.256
Predicted Change in Standard Deviation of Log earnings…		
If the US had US earnings equation, but	EU distribution of scores[1]	-0.017
	EU distribution of education[2]	+0.024
	EU distribution of all factors[3]	-0.019
If the US had US score distribution, but	EU coefficient on scores[4]	-0.034
	EU coefficient on education[5]	-0.044
	EU coefficients on all factors[6]	-0.088

1. Distribution of scores: regress ln earnings on scores only; replace s^{US}_{score} with s^{EU}_{score}.
2. Distribution of education regress ln earnings on educ only: replace s^{US}_{educ} with s^{EU}_{educ}.
3. Distribution of all factors: regress ln earnings on score and educ, sex, immigrant status and (quadratic) age; predict ln earnings using EU sample and US coefficients.
4. Coefficient on scores: regress ln earnings on scores only; replace b^{US}_{score} with b^{EU}_{score}.
5. Coefficient on education: regress ln earnings on educ only; replace b^{US}_{educ} with b^{EU}_{educ}.
6. Distribution of all factors: regress ln earnings on score and educ, sex, immigrant status and (quadratic) age; predict ln earnings using US sample and EU coefficients.

Table 9A. 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
Holland	0.63	0.62	0.69	0.68	0.76
Sweden	0.50	0.63	0.73	0.72	0.75
US (ials)	0.82	0.95	0.83	0.96	0.86
US (nals)	0.83	0.80	0.75	0.86	0.84

Table 9B. 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
Holland	0.67	0.59	0.68	0.69	0.76
Sweden	0.59	0.58	0.63	0.81	0.71
US (ials)	0.83	1.01	0.92	0.92	0.87
US (nals)	0.83	0.78	0.73	0.90	0.90

Table 10: Distribution of Log Earnings for Very Narrow Score Groups

	Std Dev (ln earnings)	Observations
Germany	0.68	924
Holland	0.68	1660
Sweden	0.67	1537
US (NALS)	0.86	11419
NALS Score Group:		
260	0.80	239
270	0.58	275
280	0.74	361
290	0.82	322
300	0.73	382
310	0.77	363
320	0.84	345
330	0.79	330
340	0.84	291
350	0.97	237
360	0.76	167
370	0.85	128
Mean for narrow groups:	0.79	286

Regression of Log Earnings on Score, Natives Only

	Germany	Holland	Sweden	USA
	0.17	0.31	0.16	0.52
	(0.05)	(0.04)	(0.04)	(0.04)
	3.34	8.31	4.25	12.38
R^2	0.36	0.42	0.28	0.42
N	871	1578	1430	1255

Note: controls for sex and a vector of age dummies.

Regression of Earnings on Score, *omitting* Lowest Quintile in Each Country

	Germany	Holland	Sweden	USA
	0.11	0.25	0.11	0.50
	(0.08)	(0.06)	(0.05)	(0.07)
	1.43	4.59	2.23	6.92
R^2	0.36	0.42	0.28	0.40
N	744	1441	1362	1086

Note: controls for sex, immigrant status, and a vector of age dummies.

Regression of Earnings on Score, *omitting* Lowest Overall Quintile

	Germany	Holland	Sweden	USA
	0.11	0.25	0.11	0.41
	(0.08)	(0.06)	(0.06)	(0.06)
	1.41	4.21	1.89	6.66
R^2	0.36	0.43	0.29	0.39
N	731	1373	1230	1202

Note: controls for sex, immigrant status, and a vector of age dummies.

Regression of Earnings Rank on Score Rank

	Germany	Holland	Sweden	USA
	0.14	0.20	0.17	0.37
	(0.03)	(0.02)	(0.02)	(0.02)
	5.06	9.96	7.73	16.32
R^2	0.38	0.43	0.31	0.40
N	924	1660	1537	1561

Note: controls for sex, immigrant status, and a vector of age dummies.

Table A1. Probit: Factors Predicting Low Score Quintile

	Age	Educ	Immigrant	Nonwhite	R^2	N
IALS	0.0017 (0.0004) 3.99	-0.048 (0.003) -18.25	0.22 (0.03) 9.18	0.21 (0.02) 12.67	0.35	2855
NALS	0.0049 (0.0001) 46.32	-0.046 (0.001) -52.42	0.18 (0.01) 21.08	0.23 (0.01) 37.26	0.36	24876

Table A2. Probit: Factors Predicting Low Earnings Quintile

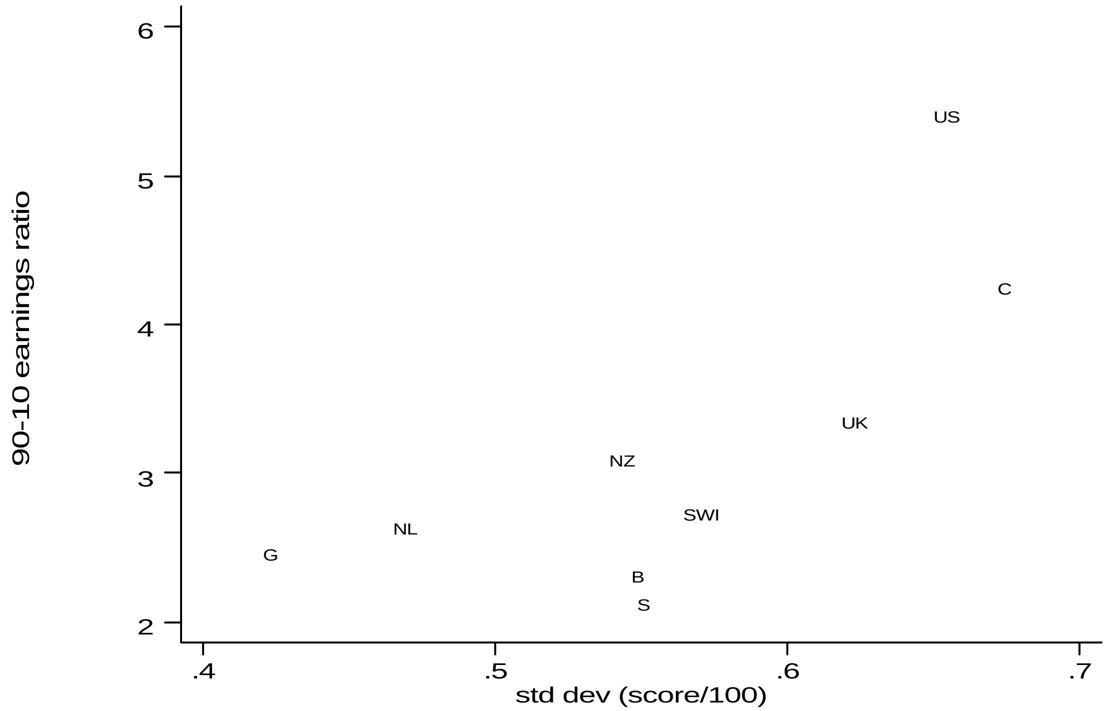
	Age	Age^2	Sex	Educ	Imm	Non-white	R^2	N
IALS	-0.06 (0.01) -10.67	0.00 (0.00) 9.74	0.16 (0.02) 7.79	-0.02 (0.00) -5.62	0.03 (0.03) 1.02	0.10 (0.03) 4.11	0.19	1529
NALS	-0.04 (0.00) -19.26	0.00 (0.00) 16.21	0.13 (0.01) 17.26	-0.03 (0.00) -18.75	0.07 (0.01) 5.31	0.03 (0.01) 2.97	0.14	11386

Table A3. Immigrant Earnings Premium under Different Specifications

	(See notes)	Controlling for education	Controlling for score	Controlling for educ and score
IALS	-0.24 (0.06) -3.94	-0.15 (0.06) -2.54	0.08 (0.06) 1.25	0.03 (0.06) 0.47
NALS	-0.24 (0.02) -9.84	-0.18 (0.02) -7.92	0.12 (0.02) 4.71	0.01 (0.03) 0.22

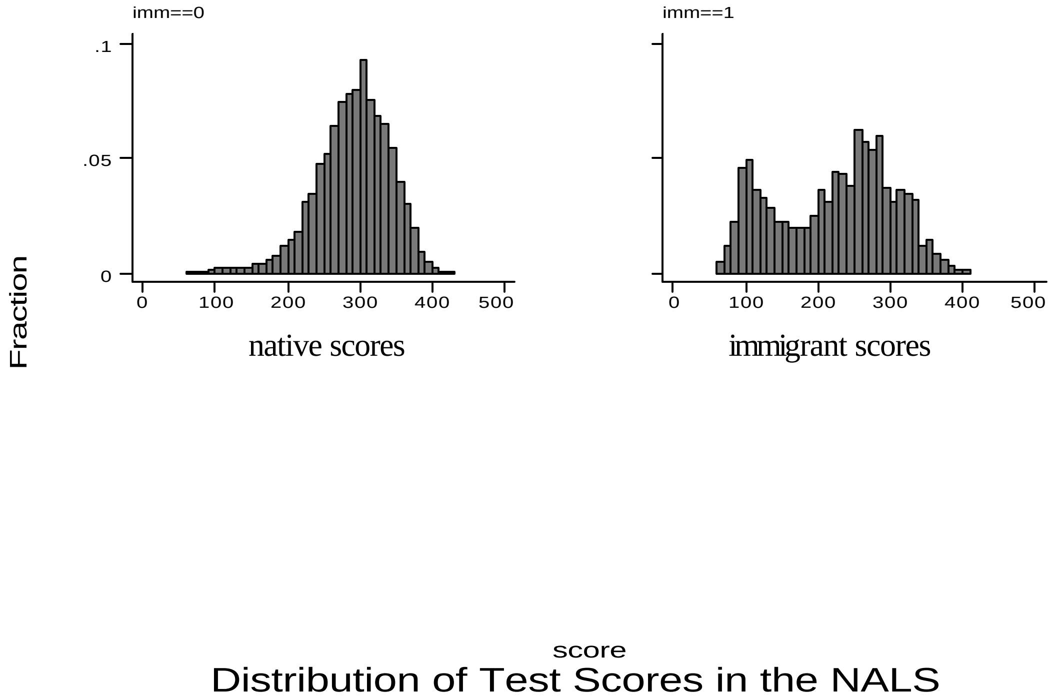
Notes: all regressions also control for sex and (quadratic) age.

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



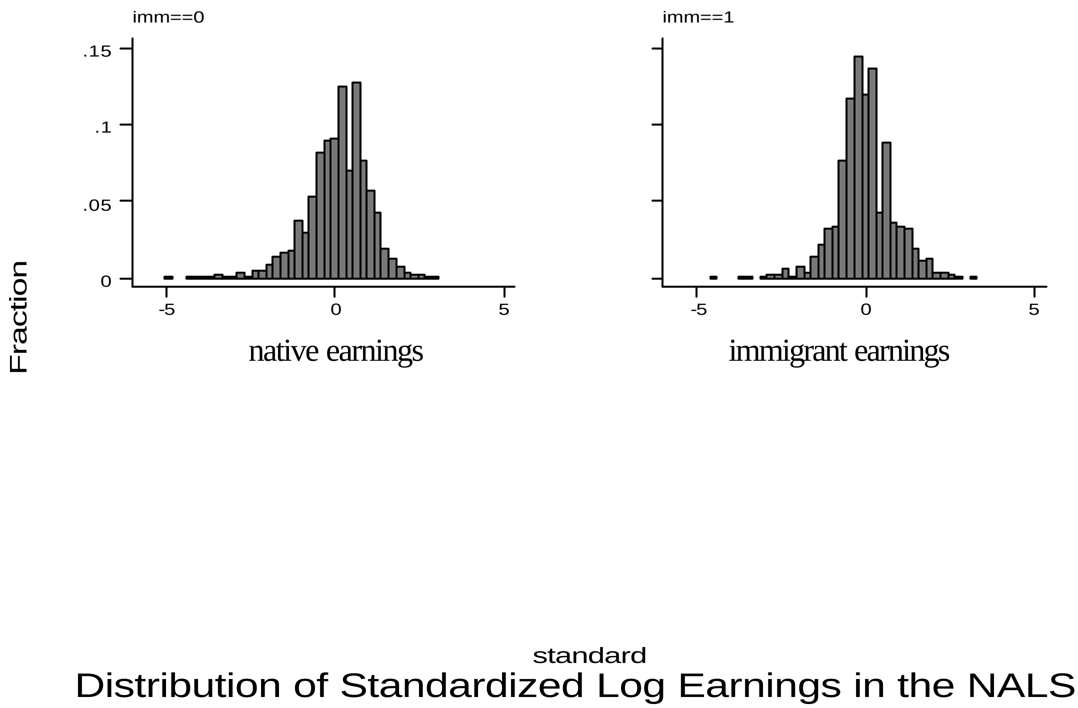
Notes: Standard deviation of score/100 (*stdscore*) for workers in the IALS, and 90-10 earnings ratio as reported by the OECD (1996).

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



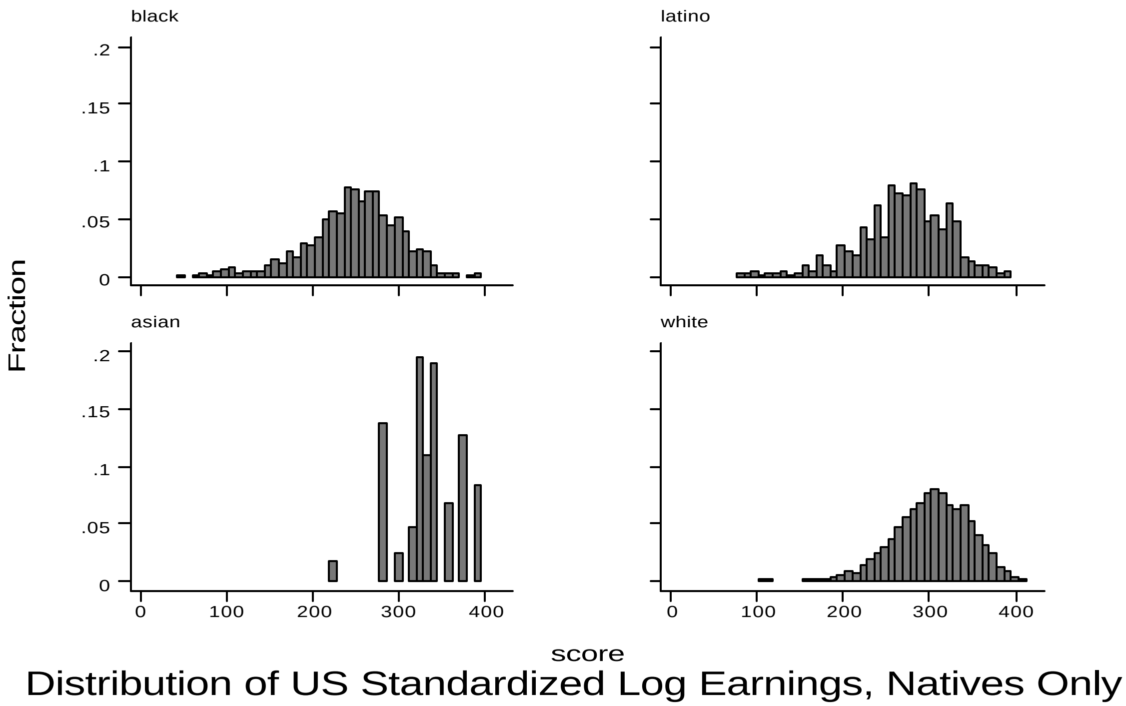
Note: The same patterns are found in the IALS, though with fewer observations.

Figure 2B: Standardized Log Earnings in the US, by Immigrant Status



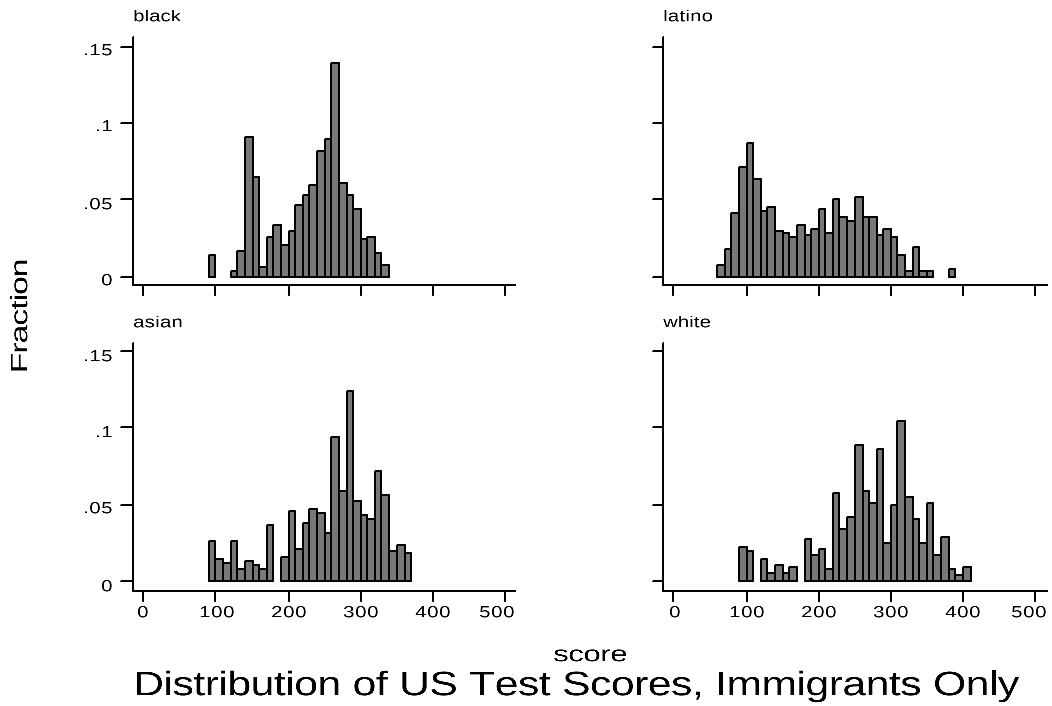
Note: The same patterns are found in the IALS, though with fewer observations.

Figure 2C: Test Scores in the US, by Race – Natives Only



Note: *Native Americans, Pacific Islanders, and others omitted; too few observations.*

Figure 2D: Test Scores in the US, by Race – Immigrants Only



Note: Native Americans, Pacific Islanders, and others omitted; too few observations.

Figure 3: The Dispersion of Ln Earnings and the Dispersion of Literacy Scores, by Country

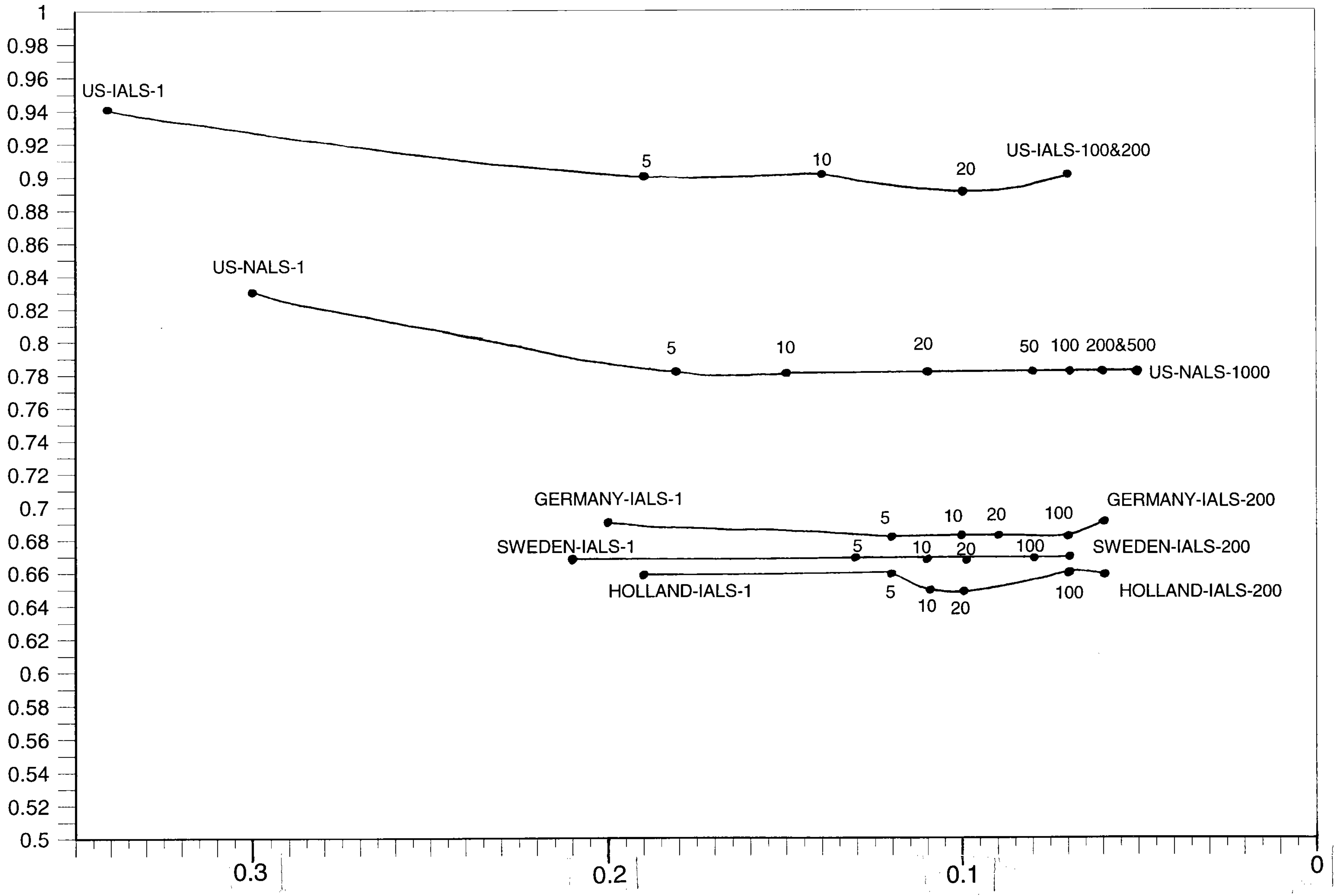


Figure 4: Distribution of Log Earnings for Very Narrow Score Groups

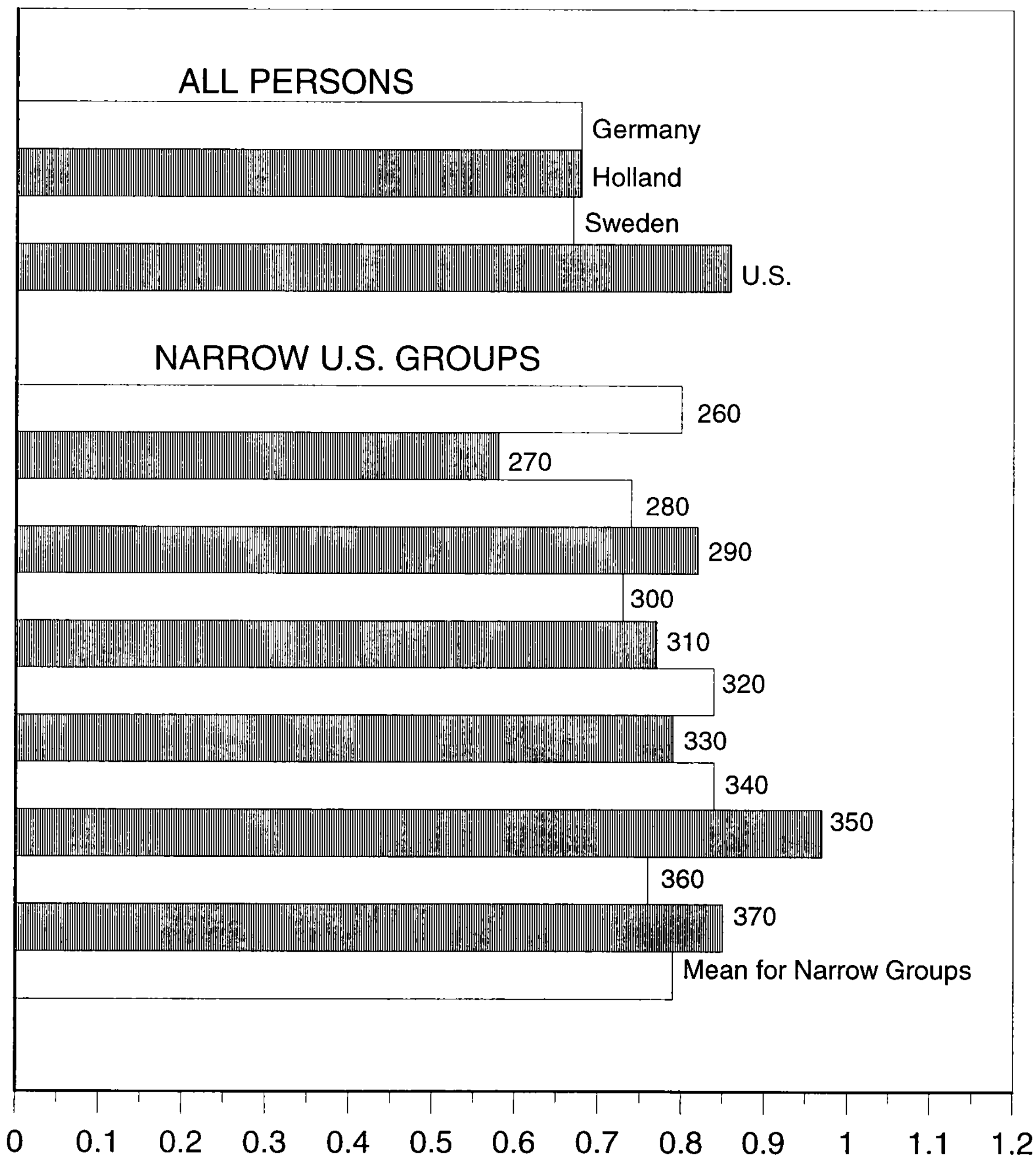
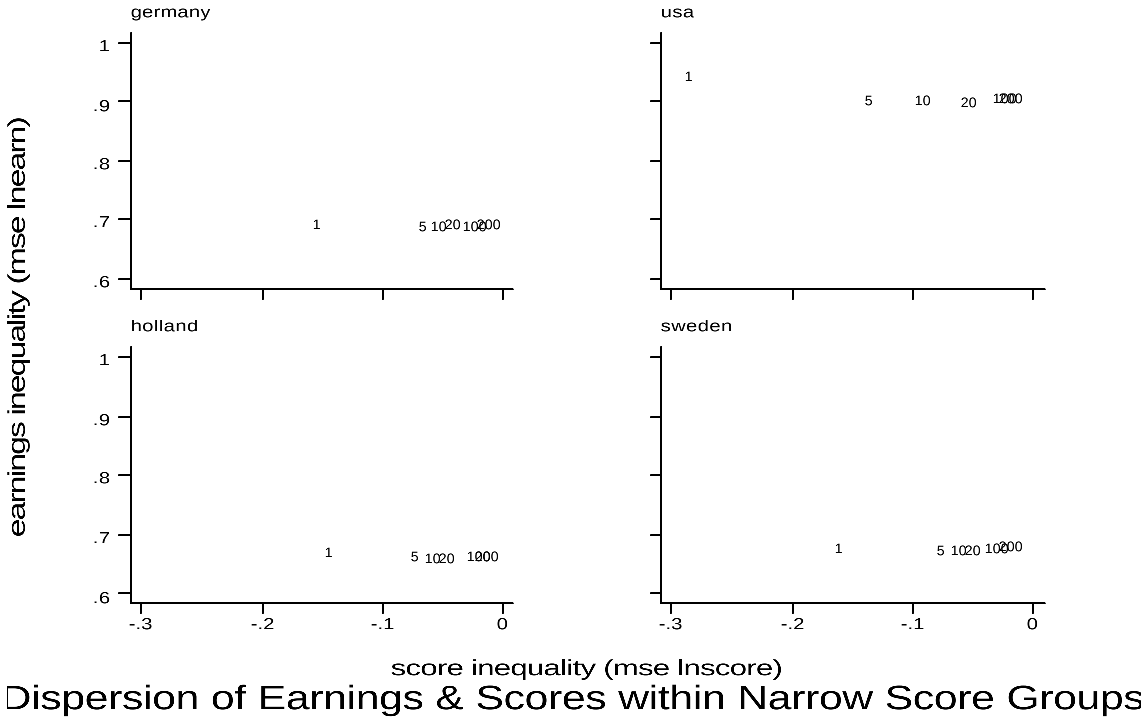
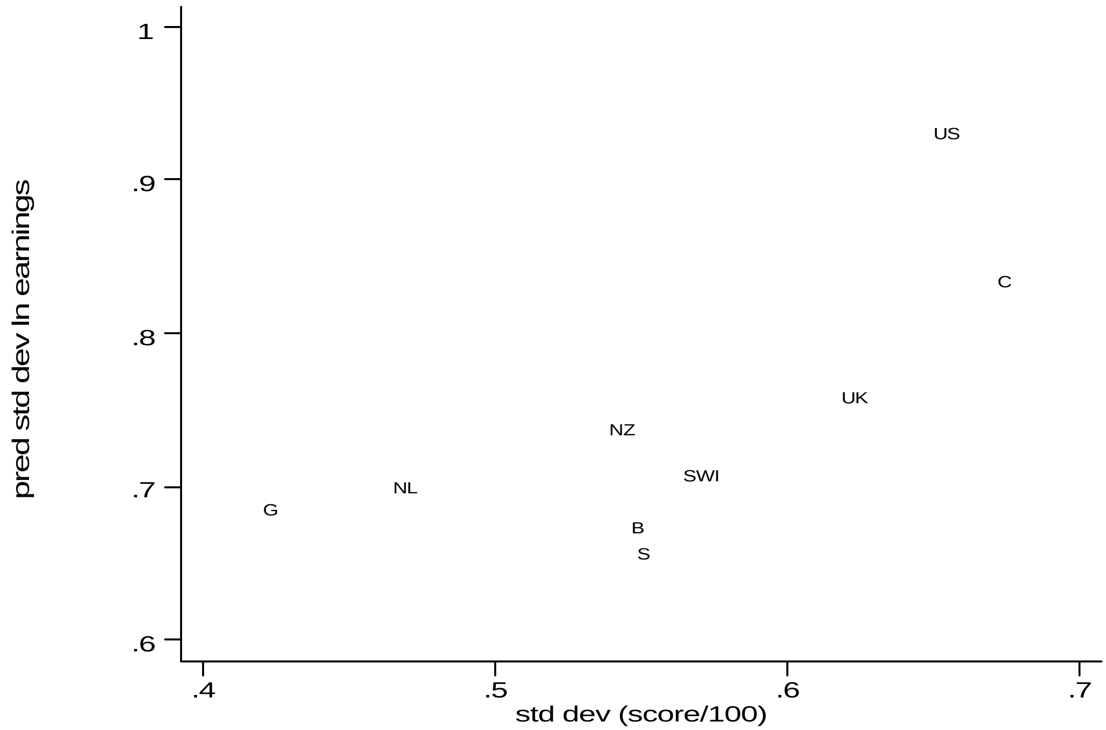


Figure 5. Score and Earnings Dispersion within Narrow Score Groups (IALS)



country	5	10	20	100	200
	intervals				
germany	185	92	47	9	5
usa	305	153	76	15	8
holland	332	160	84	17	8
sweden	307	153	77	15	8

Figure A: Earnings Inequality vs. IALS Test Score Dispersion for selected OECD countries, 1994



Notes: Standard deviation of score/100 (*stdscore*) and predicted standard deviation of log earnings (*pstdlnern*) for full-time employed workers in the IALS. The two are correlated r=.73, and fit the model psdlnearn = .30 + .79 sdscore with $R^2 = 0.54$.

[Note: To predict *pstdlnearn*, we regress *stdlnearn* on the 90-10 earnings ratio as reported by the OECD (1996) for the four countries for which we observe *stdlnearn*. We obtain *stdlnearn* = .2 + 3.4(90-10), with t-stat = 5.3 and $R^2 = .93$. We then use OECD data on the 90-10 ratio to predict *stdlnearn* for the other countries.]