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ABSTRACT

Using microdata from the 1994-6 International Adult Literacy Survey (IALS), we examine the role of cognitive skills in explaining higher wage inequality in the US. We find that while the greater dispersion of cognitive test scores in the US plays a part in explaining higher US wage inequality, higher labor market prices (i.e., higher returns to measured human capital and cognitive performance) and greater residual inequality still play important roles for both men and women. And we find that, on average, prices are quantitatively considerably more important than differences in the distribution of test scores in explaining the relatively high level of US wage inequality. This finding holds up when we examine natives only and when we correct for sample selection.

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I. Introduction

A growing body of comparative labor market research has attempted to explain why the United States has considerably higher levels of wage inequality and lower unemployment than other countries in the OECD. Joblessness, especially long term unemployment, is a major labor market conundrum facing Europe, while low pay for workers at the bottom is one of America's signature labor market problems. So, for example, workers at the bottom of the wage distribution earn much more absolutely and relative to the middle in much of Europe than in the US; however, unemployment on the Continent has averaged around 10-12% for several years now but has been at or below 5.5% in the US since June 1996.[1] Joblessness among the young and the less skilled in much of Europe has reached especially high levels (Blanchflower and Freeman, 2000; Kahn forthcoming).

Explanations for the diverging performance between the US and much of the rest of the OECD have included an emphasis on labor market institutions as well as on market factors and the characteristics of the labor force.[2] These institutions, including collective bargaining, unemployment insurance (UI), and job protection regulations, are hypothesized to compress wage differentials at the bottom of the distribution in the other OECD countries compared to the US. In turn, if wage setting institutions allow firms to be on their labor demand curves, this compression is expected to produce employment problems for the low skilled. A link in this explanatory chain is that labor market prices indeed be higher in the US than elsewhere. While this may be the case, economists have also recognized that differences in population heterogeneity across countries can produce varying levels of wage inequality. For example, the level and quality of schooling may be more dispersed across individuals in one country than in another, or there may be differing distributions of labor market experience.

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[1] See Freeman (1994), OECD (1994) and the USBLS website. Interestingly, in the early 1970s, the US had higher unemployment than the average in Europe (e.g., Freeman 1988).

[2] For discussions of the evidence on these issues, see, e.g., Blau and Kahn (1999) or Bertola (1999).

Most previous attempts to disentangle the effects of population heterogeneity and labor market prices on wage inequality have used micro-data that allowed controls for levels of schooling and age or actual labor market experience (e.g., Blau and Kahn 1996; Kahn forthcoming), generally concluding that both prices and population heterogeneity play a role. However, labor market skills may differ even among workers with the same years of schooling and age or experience. In particular, it is believed that school systems in Continental Europe produce a more uniform level of cognitive ability than the highly decentralized United States system. Supporting this view are the results of international comparisons of performance on the same tests, which show much lower relative and absolute performance in the United States among those with little education than in the rest of the OECD (OECD 1998; Nickell and Bell 1996; Nickell and Layard 1999). If these tests measure skills that are useful in the labor market, the evidence on test scores could provide an alternative to the institutional explanation for high US wage differentials. Nickell and Layard (1999) in fact make such an argument by using aggregate data from six countries to show that wage differentials by education groups are positively related to test score differentials across the same education groups.

In this paper, we use microdata from the 1994-6 International Adult Literacy Survey (IALS) to identify the precise role of cognitive performance in explaining international differences in wage inequality. In addition to the traditional human capital measures of schooling and age, the IALS contains the results of comparable cognitive tests administered in a number of countries in the areas of mathematics, prose literacy, and document-reading ability. Although the US has relatively high wage and test score differentials, it is not apparent without further analysis how much of the higher US wage dispersion is explained by the distribution of cognitive ability. Using a full-distributional accounting method devised by Juhn, Murphy and Pierce (1993), we find that while cognitive performance on these tests plays a part in explaining higher US wage inequality, labor market prices (i.e. returns to measured human capital and cognitive performance) and residual inequality still play important roles for both men and women. Thus, the US labor market does appear to have higher prices for skills even when we for control for cognitive performance. And we find that, on average, these prices are quantitatively more important than differences in the distribution of test scores in explaining the relatively high levels of US wage inequality.

II. Previous Findings on the Impact of Pay-Setting Mechanisms on Relative Wages

Unions are a key labor market institution potentially influencing both wage distributions and employment outcomes. A large body of research has found that unions raise the wages of those with low measured skills by more than those of other workers (Freeman 1980; Freeman 1982; Blanchflower and Freeman 1992; Blau and Kahn 1996; Kahn forthcoming). In addition, some studies have found higher residual inequality among nonunion than union workers or larger union wage effects for workers lower in the distribution of wages conditional on human capital and job characteristics (Freeman 1980; Chamberlain 1991; Blau and Kahn 1996; Kahn 1998). Both sets of findings suggest that unions compress the distribution of wages.

Recent research on union wage compression has attempted to take into account the process by which workers are selected into scarce union jobs (Card 1996; Lemieux 1998; Hirsch and Schumacher 1998). If unions raise the wages of the low skilled, this will produce a queue from which employers will choose the best candidates. Workers covered by unions are thus likely to have better skills, both measured and unmeasured, than nonunion workers. It is even possible that, on net, unions do not compress wages but merely cause a reallocation of skilled workers into union jobs. Taking this selection process into account, Card (1996) and Lemieux (1998) found that unions still compressed wages in the US and Canada, while Hirsch and Schumacher (1998) found no union compression effects for the US. Kahn (forthcoming) found that across 15 OECD countries, higher union coverage was associated with lower overall wage inequality, other things equal. This suggests a true union compression effect, since, if all unions did was reallocate skilled workers to the union sector within a country, there would be no effect on overall wage inequality.

The research considered thus far does not take account of cognitive skills in analyzing wages or employment. Yet, a voluminous literature, primarily from the United States, documents the strong impact of cognitive ability, as measured by standardized test scores, on wages, even after controlling for education and age-related proxies for experience.[3] It is possible that, in more highly unionized economies, the less educated have better cognitive skills relative to the middle than in less unionized economies. This may even be an intuitively plausible outcome to the extent that governments in highly unionized countries push for extensive, uniform national systems of education.[4] If this is the case, union wage-setting may not be directly responsible for wage compression, although unions may have influenced the government's education policies.

As noted above, Nickell and Layard (1999), using aggregate data from the IALS and the OECD, presented evidence of a positive correlation between wage differentials and test score differentials across education categories. In particular, the US had the highest wage and test score differentials by education. While this suggests that cognitive skills play a role in explaining higher US wage inequality, in the absence of the type of detailed analyses we perform here, it is not possible to know how important this role is. In addition, Freeman and Schettkat (2000a) report that the OECD found that the return to education, controlling for test score, and the return to test score, controlling for education, were higher in the US than Germany. Again, while these results suggest that labor market prices are higher in the US, they do not tell us the relative importance of prices vs. cognitive skill distributions in explaining higher US wage inequality.

Two recent studies using the IALS microdata both shed light on the importance of cognitive skills in explaining high US wage inequality. First, Leuven, Oosterbeek and van Ophem (1998) note that the wage differentials between men with low- and middle-level scores

[3] See, for example, Cawley, Coneely, Heckman, and Vytlacil (1996), Neal and Johnson (1996), Bishop (1991), Murnane, Willett and Levy (1995), and Leuven, Oosterbeek and van Ophem (1998).

[4] Summers, Gruber and Vergara (1993), for example, argue that in heavily unionized, "corporatist" societies (i.e. where unions, management and government play an important role in coordinating wage-setting at the national level), social spending is likely to be higher than in less unionized countries.

on cognitive tests was substantially higher in the US than in more unionized countries such as Sweden, Switzerland, Canada, Germany and the Netherlands. They pose supply and demand as a possible explanation for this disparity, since the United States has a relatively large supply of men with low test scores. Second, Freeman and Schettkat (2000b) studied the determinants of individuals' after tax personal incomes and found that the US has higher returns to education and test scores than Germany, as well as higher residual income inequality. They suggest that union-induced wage compression was an important factor explaining their results.

Our own study extends this work to examine the impact of cognitive skills in a more comprehensive fashion. In contrast to this earlier work, we provide a full accounting of the impact of cognitive skills, other human capital characteristics and labor market prices on wage inequality in the United States compared to other countries. Our use of a full-distributional accounting method allows us to decompose differences in wage inequality at any point of the distribution. This is a potentially important analysis in light of the presence of wage floors that mainly impact the bottom of the wage distribution. In contrast to Freeman and Schettkat (2000b), we examine several countries other than the US and study the wage determination process and the impact of cognitive test scores on wages in each country in considerable detail. By focusing on the weekly labor earnings of full-time workers, we are able to approximate a wage rate and thus shed light more directly on the wage structure. In addition, in contrast to Leuven, et. al (1998), we include women in our analysis; and, unlike Freeman and Schettkat (2000b), we estimate separate wage structures for men and women.

III. Empirical Analysis

A. Data

The International Adult Literacy Survey (IALS) is the result of an international cooperative effort, conducted over the 1994-6 period, to devise an instrument to compare the cognitive skills of adults across a number of countries.[5] The sampling frame was similar across countries, with the target population being those 16 years and older who were not in institutions or the military.[6] In addition to test scores, data are available on gender, employment status, schooling, age, full-/part-time status, weeks worked in the past year, industry, occupation, and, for a subset of countries, earnings. We analyze earnings which are available for Canada, Switzerland, the Netherlands, Sweden, and the United States.[7]

Of unique interest in the IALS is its measurement of cognitive skills. This was accomplished through three tests that were administered to all respondents in their respective home languages.[8] These tests were designed to measure:

"a) Prose literacy—the knowledge and skills needed to understand and use information from texts including editorials, news stories, poems and fiction;

b) Document literacy—the knowledge and skills required to locate and use information contained in various formats, including job applications, payroll forms, transportation schedules, maps, tables, and graphics; and

c) Quantitative literacy—the knowledge and skills required to apply arithmetic operations, either alone or sequentially, to numbers embedded in printed materials, such as balancing a checkbook, calculating a tip, completing an order form, or determining the amount of interest on a loan from an advertisement" (*IALS Guide CD-ROM*, page 9).

[5] For further description of the IALS, see OECD (1998) and USDOE, NCES (1998).

[6] There were some geographic exclusions in some cases, but these were 3% or less of the target population, except for Switzerland, where the exclusion of Italian and Rhaeto-Romantic regions, persons in institutions and persons without telephones accounted for 11% of the total potential sample. In all cases, the IALS supplied a set of sampling weights, which we used in all of our analyses. See the IALS documentation file, available from Statistics Canada.

[7] We obtained the IALS data from Statistics Canada. Data on earnings were provided to us after we received permission from each country's study director. Data on earnings were also available in the IALS for Germany and Poland, but these countries were not included in our study. We excluded Germany because, in our version of the IALS data, the sample size was extremely small for cases in which earnings data were available, East and West Germany were not distinguished, and the earnings distributions we obtained were not comparable to other sources. We excluded Poland because of its status as a transition economy. There were several other countries included in the IALS—Belgium, Britain, Ireland, and New Zealand. Unfortunately, wage data were not available in these instances.

[8] The average total duration of the tests was 69 minutes, with a range among the countries we studied from 60 for Switzerland/German to 73 for Canada/French (Jones 1998).

Proficiency in each of the three test areas was scored on a scale of 0-500, after the tests were read by several graders from the respondent's own country. The IALS provides five alternative estimates of proficiency for each test, which were computed from the raw test performance information using a multiple imputation procedure developed by Rubin (1987). These alternative estimates are in fact highly correlated. We found that within each of the three types of test, the five estimates of the score were correlated at .90.[9] Further, to ensure comparability of grading across countries, an average of 9.4% of the tests for each country were regraded by personnel from another country; inter-rater agreement with respect to these regrades was 94-99%.

Although, in principle, interpreting prose or documents, and using mathematics may each require different skills, we found that these skills, as measured by the IALS, are in fact highly correlated. Forming a score for each of the three tests (i.e., quantitative, prose, and document literacy) based on the average of the five available estimates, we found that these scores were correlated at between .91 and .94. Due to this high correlation, in the econometric work that follows, we report results based on a measure of cognitive skills which is an average of the three average test scores for each individual; however, we also estimated models with the three average test scores entered separately, with very similar results.

Response rates in the IALS were reasonably high for most countries: Canada (67.4%), Netherlands (44.8%), Sweden (60%), Switzerland (55%), and the United States (59.4%). The coordinators of the IALS were concerned about possible biases induced by the fact that response rates were less than 100% and were able to perform a detailed study of non-respondents in three countries: Canada, Sweden and the United States (Darcovich, Binkley, Cohen, Myberg and Persson 1998). The authors concluded that while there may have been some non-response biases, "the magnitude of bias introduced into the estimates appears to be small" (Darcovich, et.al 1998, p.71).

[9] All reported correlations are based on calculations using sampling weights and include the full set of countries with test score data except, for the reasons indicated above, Germany and Poland.

B. Decomposition of International Differences in Wage Inequality

1. Decomposition Method

To shed light on the issue of labor market prices, we apply a full distributional accounting scheme developed by Juhn, Murphy and Pierce (1993) to study intertemporal changes in US wage inequality and employed by us in previous work to analyze the sources of international differences in wage inequality (Blau and Kahn 1996). Using this approach, international differences in wage inequality may be attributed to three effects: a measured characteristics effect due to differences in the distribution of measured characteristics of workers; a wage coefficients effect due to differences in the rewards to measured characteristics; and a wage equation residual effect which is unexplained and potentially reflects the impact of unmeasured prices but which may also be due to differences in the distribution of unmeasured productivity characteristics and measurement errors. We take the wage coefficients effect and perhaps some portion of the wage equation residual effect as measures of the importance of labor market prices in explaining international differences in wage inequality.

To implement this decomposition, we begin with the following wage equations for individual i in country j (j = 0, 1), estimated separately by sex among full-time workers:

(1a) $$Y_{i0} = B_0 X_{i0} + e_{i0} \equiv B_0 X_{i0} + F_0^{-1} (\theta_{i0} \mid X_{i0})$$

and

(1b) $$Y_{i1} = B_1 X_{i1} + e_{i1} \equiv B_1 X_{i1} + F_1^{-1} (\theta_{i1} \mid X_{i1})$$

where Y is the natural log of weekly earnings, X is a vector of explanatory variables to be discussed below, B is a vector of coefficients, e is a disturbance term, θ is the individual's percentile in the distribution of wage residuals, and $F^{-1}(\cdot \mid X)$ is the inverse cumulative distribution of log wage residuals. In order to produce a wage measure that is as close as possible to an hourly earnings concept (i.e., price), we restrict the wage analysis to full-time workers; further, in order to produce a homogeneous sample of those with strong labor force commitment, we included only those who were employed at least 26 weeks in the previous year. For two countries, earnings were topcoded (Switzerland and the Netherlands, at 100,000 francs and 200,000 guilders respectively, or about US$66,000 to US$105,000 as of 1993. We multiplied the top coded value by 1.2 in these cases, although our overall results were not sensitive to this. Finally, we excluded those with measured weekly earnings less than the equivalent of US$80 (or for full time workers, less than about $2.00/hr at a time when the US minimum wage was $4.25) or more than US$10,000.

We then create two hypothetical wage distributions. First, we construct for country 1 the set of wages that would emerge if we applied the estimated country 0 wage function (B_0) and inverse residual distribution function $F_0^{-1}(\theta|X)$ to each country 1 worker:

(2) $$Y(1)_{i1} = B_0 X_{i1} + F_0^{-1}(\theta_{i1} \mid X_{i1})$$

$Y(1)_{i1}$ is computed for each (full-time) worker i in country 1 by valuing his/her measured characteristics at the country 0 coefficient vector B_0 and position in his/her own country's distribution of wage residuals (e.g. the 35th percentile) at the corresponding position in the country 0 residual distribution. The difference between the distribution of Y for country 0 and of Y(1) for country 1 is attributed to differences between the two countries in the distribution of measured characteristics, including cognitive skills.[10]

[10] $Y(1)_{i1}$ also uses country 1's estimated values of θ, but these are standardized across countries and therefore do not directly contribute to differences in the distribution of wages. However, to the extent that θ is more strongly

The second hypothetical distribution for country 1 results from giving each person in the country 1 sample his/her own country's estimated wage coefficients but the country 0 wage residual corresponding to his/her position in the residual distribution:

(3) $$Y(2)_{i1} = B_1 X_{i1} + F_0^{-1} (\theta_{i1} \mid X_{i1})$$

The difference between the distributions of $Y(2)_{i1}$ and $Y(1)_{i1}$ is entirely due to the difference between the wage functions for country 1 and country 0. Finally, the impact of the distribution of wage residuals on country 1's wage distribution relative to that of country 0 is the difference between the distributions of Y_{i1} and $Y(2)_{i1}$.

In the decompositions reported in the text below, pair-wise comparisons between the US and each of the other countries were implemented using the US as the base for the personal characteristics distribution (country 1); however results were similar when we used the other country as the base in each pair-wise comparison with the US.

The explanatory variables in X include measures of educational attainment, age, average IALS test score, and, in some models, industry and occupation dummies. (Variable means and selected regression results are shown in appendix Tables A1-A2.)

Schooling is measured by number of years completed, and age is measured by a series of dummy variables for the following categories: 26-35, 36-45, 46-55, and 56-65, with age 16-25 being the omitted category. We adopted this age specification because the IALS age data for Canada were only available in categorical form.

Finally, in some of our analyses, we include a vector of one-digit industry and occupation dummies.[11] Including these variables might be considered desirable in that it controls for

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correlated with X in one country than another, the difference between the distribution of lnW_0 and $Y(1)_1$ will also reflect the effects of this difference in correlation. We discuss differences in unmeasured productivity characteristics below.

[11] The occupations were i) managers; ii) professional and technical workers; iii) clerical workers; and iv) sales and service workers, with craftworkers, operatives and laborers the omitted category. Industries were i) agriculture; ii) mining and manufacturing; iii) transportation, communications and utilities; iv) construction; and v) finance, insurance, real estate and business services, with community, social and personal services the omitted category.

differences across countries in occupational and industrial distributions in measuring the impact of labor market prices. However, explanatory variables such as test score and education may be expected to affect wages both directly, holding occupation and industry constant, and indirectly, through their effect on representation in higher-paying industries and occupations. Coefficients from regressions excluding industry and occupation variables thus shed light on the total effect of these variables. Moreover, if wage-setting institutions do in fact influence relative wages, the distribution of occupations and industries may also be affected (Edin and Topel 1997; Davis and Henrekson 1999). We thus focus on models excluding these variables.

2. Overview of International Differences

Before turning to the results of the decomposition, we first review the extent of international differences in wage inequality and cognitive test scores, as well as our findings for the effects of test score and education in the wage regressions estimated for each country. Figures 1 and 2 give summary information on male and female wage inequality across our sample of countries. In earlier work using male wage data for the 1980s, we found higher levels of wage inequality for the US overall, but a considerably larger difference between the US and other countries in the extent of wage inequality at the bottom than at the top of the wage distribution. In fact, at the top, the difference between the US and other countries was relatively small (Blau and Kahn 1996). However, since then, inequality at the top has grown sharply in the US relative to other countries (Topel 1997). The 1993 IALS earnings data in Figure 1 bear this out, showing considerably higher US wage inequality among men both at the bottom (50-10) and the top (90-50) of the wage distribution, with a similar difference between the US and the average for the other countries for both wage gaps. As may be seen in Figure 2, inequality is also relatively high for US women, and the female 50-10 gap is especially high in the US. Among women, however, Canada has greater inequality than the US, a pattern also seen in OECD (1996) data.

Table 1 provides evidence on the distribution of cognitive test scores for men and women in the population across the full set of nine countries with text score data (Panel A) and for the wage sample in the five for which this information is available (Panel B). The wage sample is comprised of full-time workers; further exclusions are detailed below. Looking first at the full population shown in Panel A, a striking pattern is the higher level of test score inequality for both men and women in the United States than elsewhere, particularly at the bottom of the distribution. Americans do substantially worse than the non-U.S. average at the bottom, about the same at the median, and somewhat better at the top. The US shortfall at the 10th percentile of the test score distribution is 15.5 points for women and 23.7 points for men, while the US advantage at the 90th percentile is 7.3 points for women and 8.3 for men. However, the 50-10 male test score gaps in Britain, Canada, and Ireland that are more comparable to those in the US than is the case for the other countries. Among women, the 50-10 gap is higher in the US than in every other country, with Belgium, Canada and New Zealand having the gaps closest to the US.

When test score differentials are computed for the subset of workers in the wage sample, roughly similar patterns are obtained (Panel B). However, it is notable that, for the five countries on which we have wage data, full-time employment tends to be selective of individuals with higher test scores. The mean of the wage sample is higher and the standard deviation of the wage sample is generally lower than for the full population, though the extent of these differences varies considerably across countries. We address the issue of sample selection below.

The test score patterns for the wage sample roughly mirror the differences between the US and other countries in wage distributions shown in Figure 1 and 2, at least in leading us to expect larger wage differentials between the middle and the bottom, and the middle and the top in the US. However, among men, test scores are likely to provide a better explanation for the larger US gap at the bottom than at the top, since the difference in dispersion of test scores between the US and other countries in the upper ranges is relatively small. Finally, we note that, in each country, and particularly in the US, the mean test score for both samples tends to be less than the median, reflecting the especially low values in the left tail of the distribution of test scores.

Figures 3 and 4 compare the level of test scores by education for the population across countries for men and women, standardizing for international differences in age composition. To obtain the age-adjusted test scores, we regressed test scores on dummy variables for education and age, estimating separate regressions for men and women in each country. Test scores by education level were evaluated at age 26-35.[12] In each country, additional years of schooling are associated with higher test scores, controlling for age. However, the relationship between test scores and education is steeper for the United States. For our first educational category, less than 9 years, individuals in the United States score worse than virtually all of the other countries; this gap is smaller at each successive year of schooling so that for higher levels of education (by the college level), US scores are fairly similar to those in other countries. In contrast to the US pattern, test scores in Sweden are higher than those in other countries at all education levels and the relationship between test scores and education is flatter. As a consequence, the difference between Sweden and other countries also tends to diminish at higher educational levels. While Figures 3 and 4 are for the full population, these patterns are similar when we restrict the samples to natives only (see Figures A1 and A2). These results are consistent with a higher estimated return to education in the US and a lower return in Sweden in standard wage regressions, not controlling for test scores.

An interpretation of the US pattern is that Americans arrive at high school less well prepared than their counterparts in other countries; however, those who continue their education into college are able to make up this shortfall. Alternatively, it may be that those who attend college in the US are more positively selected on cognitive skills than is the case elsewhere. Below, we present some further test score results for natives only, an analysis that may shed additional light on the quality of schooling.

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[12] The age dummies were those itemized above: 26-35; 36-45; 46-55; and 56-65, with 16-25 comprising the omitted category. The education categories may be seen in the figures; ed<9 was the omitted category.

We next consider differences across countries in the impact of measured cognitive skills and education on wages. In assessing the effect of cognitive skills on wages, it is useful to consider two extreme views of its possible impact. On the one hand, it is possible that cognitive ability is fully formed on the basis of heredity and socialization before one begins school. Schooling decisions are then made on the basis of expected costs and benefits, which in turn are likely to be affected by cognitive ability. Under this scenario, the full effects of cognitive ability can be estimated by excluding schooling from the wage regressions, allowing cognitive ability to have both direct and indirect (through schooling) effects on wages. And the effects of schooling are best estimated controlling for cognitive ability. On the other hand, suppose that cognitive ability is largely the result of schooling. Then the full effects of schooling can be estimated by excluding cognitive ability from wage equations, and the effects of cognitive ability should be assessed by controlling for schooling. While the strong positive association between additional education and test scores, even at very low levels of education where attendance is quite prevalent, suggests some causal role for education, we cannot choose between these two views on a priori grounds. We can, however, estimate the wage equations that they imply and at least place some bounds on the impact of education and cognitive ability on pay. An additional motivation for estimating the effect of education on wages both including and excluding test score is to ascertain the extent to which the higher US returns to education are accounted for by measured cognitive skills.

Table 2 shows the estimated effects of a one standard deviation increase in education or test score on log wages under alternative equation specifications (regression results for the specification in which both test score and education are included are presented in Appendix Table A2). These standard deviations are computed on the pooled male and female regression samples, where each country is given the same weight.[13] The effects of education and test scores are highly significant in almost every case, with 38 of the 40 coefficients statistically significant

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[13] That is, each individual is given a weight of $s/(Ns_a)$, where s is the individual's sampling weight; N is his/her country's sample size; and s_a is his/her country's average sampling weight.

at the 1% level or better on two-tailed tests; and the remaining two significant at the 5% level or better. These effects are economically as well as statistically significant. For example, consider the effects of test scores on wages. In the models excluding education, a one standard deviation increase in test scores raises wages by 10.0 to 24.2 percent for men and 7.7 to 25.3 percent for women.[14] These might be considered maximal effects of cognitive ability on the assumption that all schooling decisions occur on the basis of fully-formed cognitive ability. Including education lowers the estimated return to a one standard deviation increase in test score to 7.6 to 16.4 percent for men and 3.3 to 16.7 percent for women. Thus, for both sexes, an important part of the total impact of cognitive ability on wages is due to its association with education: for men, 32 percent in the US and an average of 25 percent in the other countries, and, for women, 46 percent in the US and an average of 33 percent in the other countries. The change in the coefficient on test score when education is added to the model is significant for both men and women in the US and a total of 2 out of 5 times for men and 3 out of 5 times for women.

Among men, the US has the highest returns to cognitive ability of the included countries; a one standard deviation increase in test scores is estimated to raise wages in the US by 16.4 percent (controlling for education) and 24.2 percent (not controlling for education) compared to non-US averages of 10.3 and 13.7 percent, respectively. This result is in line with higher rewards to skills in general in the US than elsewhere, and also with a larger supply in the US of individuals with especially low test scores. However, although the effects of test scores on US women's wages are higher than the other country average, this is a sizable difference only for the specification excluding education where the US effect of test scores is 22.1% versus an average effect elsewhere of 15.1%. Moreover, Canadian women have higher estimated returns than US women in both specifications and Dutch women have higher returns when education is included.

Table 2 also contains our findings for the return to education. The coefficients are of comparable magnitude to the test score effects, suggesting that education and cognitive skills are

[14] These statements about percentage effects are approximate, since they refer to the regression coefficients, which are in log units.

both important determinants of wages and roughly equally so. The coefficients on education are positive and significant in all cases, both including and excluding test score. This is strong evidence that, while cognitive ability is an important component of the impact of education, it does not fully capture all dimensions of the contribution of education to productivity. Analogous to our findings above, however, the control for test score does reduce the estimated return to education, suggesting that at least part of the measured return to years of education is due to its effect on (or association with) cognitive ability. This change in coefficients is again significant for both men and women in the US and a total of 3 out of 5 times for men and 2 out of 5 times for women. Among males, the inclusion of test score lowers the estimated return to education by 42.8 percent for the US and 40.1 percent, on average, for the other countries; for women the comparable figures are 27.0 percent for the US and 32.2 percent for the other countries.

Nonetheless, considerable variation in the estimated return to education remains, even when test score is included. Of particular interest is that the measured return to education in the United States remains considerably higher than elsewhere. After controlling for test score, a one standard deviation increase in schooling is estimated to raise the wages of US men by 16.6 percent and US women by 26.4 percent, compared to a non-US average of 6.4 percent for men and 10.3 percent for women. With the inclusion of test scores, the ratio of the average return to education among the other countries to the US return increases only slightly from 36.9 to 38.6 percent among men, and actually falls slightly from 41.9 to 38.9 percent among women.[15] Thus, the greater dispersion of test scores in the United States does little to account for its higher return to education. Among both men and women, education is considerably more highly rewarded in United States than elsewhere, even controlling for test score. Test scores do appear to play a larger role in explaining the lower returns to education in Sweden compared to the other European countries. With the inclusion of test scores, the ratio of the Swedish return to the

[15] This corresponds to log wage coefficients on education for the US of .0820 (males) and .1018 (females) excluding test score and .0469 (males) and .0744 (females) including test score. The non-US averages are .0303 (males) and .0427 (females) excluding test score and .0181 (males) and .0290 (females) including test score.

average for the other European countries rises from 71.9 to 90.8 percent among men and from 65.6 to 94.0 percent among women.[16]

Results are similar in specifications including industry and occupation (see Table A3). The inclusion of industry and occupation reduces the estimated effect of test score and education in both specifications indicating that some of the return to higher cognitive skills and additional education is reaped in greater access to jobs in higher-paying industries and occupations.

3. Decomposition Results

US Labor Market Prices

While the descriptive data on wages and test scores suggest that cognitive skill plays a part in explaining the higher level of wage inequality in the US, a more systematic analysis is needed to establish its precise importance. The decompositions shown in Table 3, which use US measured characteristics and other country coefficients and residuals as the base, enable us to assess the overall effect of differences in the distribution of characteristics, labor market prices and residual inequality, in explaining higher US wage inequality, when test score is included in the standard human capital specification (Appendix Table A4 shows results for the same model with the opposite base). We first discuss these results which are based on a model which includes both test scores and education, we then briefly consider alternative specifications and the marginal effect of the distribution of test scores in explaining higher US inequality.

Each entry in Table 3 should be read as a US-other country difference. Thus, for example, the first entry in column 1 indicates that the male 50-10 wage gap is .134 log points higher in the US than in Canada, and the entry for the row labeled "Non-US Average" indicates that this gap is .264 log points higher in the US than the unweighted average for the other countries. For males, results suggest that differences between the US and other countries in the

[16] This corresponds to log wage coefficients on education for Sweden of .0234 (males) and .0307 (females) excluding test score and .0168 (males) and .0277 (females) including test score. The non-US averages, excluding Sweden, are .0326 (males) and .0467 (females) excluding test score and .0185 (males) and .0294 (females) including test score.

distribution of schooling, age and test scores are important factors in explaining the higher level of US wage inequality between the middle and the bottom of the distribution, accounting for 47 percent of the higher US gap, on average. However, higher prices of measured characteristics in the US are also important, accounting for 29 percent, on average, while the greater US dispersion in the distribution of wage residuals accounts for 24 percent.

As in the case of males, the US distribution of measured characteristics also widens the female 50-10 wage gap, but its effect is smaller. The measured characteristics effect accounts for 15% of the higher US wage gap, while wage coefficients and wage residuals explain 31% and 54%, respectively, of the higher US gap, on average. The US-Canada comparison comprises an exception to the general pattern of results for the female 50-10 wage gap. In this case, as we saw above, wage inequality is greater in Canada. While the distribution of measured characteristics is more than sufficient to account for this difference, the wage coefficient effect is close to zero. Residual wage inequality is found to have a substantial a positive effect, however.

Similar to the results for the 50-10 gap, estimated wage coefficients and residual wage inequality are found to widen the US wage 90-50 gap relative to the non-US average. The wage coefficients effect is estimated to account for 48 to 66 percent of the US-other country difference, on average, while the residual effects account for 46 to 72% of the higher US 90-50 gap. However, in contrast to the results for 50-10 gap, the US distribution of characteristics is generally estimated to lower its 90-50 male and female wage gaps and hence does not help to explain the higher US gap.[17] As in the case of the 50-10 gap, female wage inequality is larger in Canada than in the US. In this case, however, not only is the measured characteristics effect more than sufficient to account for the difference, the wage coefficients effect is positive.

In interpreting the findings for the wage residual effect, it is important to bear in mind that the residuals contain the effect not only of higher US prices of unmeasured characteristics, but also of differences between the US and other countries in the dispersion of unmeasured

[17] Examination of our data reveals that for men, the US distribution of age and education is more compressed at the top than elsewhere; while for women, the negative measured characteristics effect primarily reflects the distribution of age.

characteristics, as well as measurement error. Bearing this qualification in mind, the findings are consistent with higher labor market prices, both measured and unmeasured, in the US after accounting for test scores. Even were we to conservatively estimate the impact of higher prices as corresponding only to the measured prices effect, we would still conclude that US prices account for 29 to 31 percent of higher US inequality between the middle and the bottom of the male and female distributions, and 48 to 66 percent of the larger US gap between the middle and the top.

Results are similar when we add controls for major industry and occupation to the wage regressions (Table A4). The wage coefficient and wage residual effects are large and positive. Comparing these results to those presented in Table 3 indicates that adding industry and occupation variables to the wage equation raises the average wage coefficients effect, implying that the returns to these variables are larger in the US than elsewhere. Taken together wage coefficients and residual effects are more than sufficient to account for the larger US gap between the middle and the top and from 65 to 85 percent of the greater gap between the middle and the bottom in the US.

Our conclusions are also similar when we use the opposite weights (i.e., US coefficients and residuals and other country measured characteristics) for decomposing the difference in wage inequality between the US and the other countries. The results for the human capital specification are presented in Table A5. The average wage coefficients and residual effects are all positive and, with one exception, comparable in magnitude to those in Table 3.[18] The average residual effect is always large and positive. Taken together the wage coefficients and residual effects account for 77 percent of the US-other country difference on average.

[18] The exception is the wage coefficients effect for the female 50-10 gap which explains only 5 percent of the US-country j difference, on average, in this case. This reflects a fairly sizable *negative* wage coefficient effect for the Netherlands. As we noted above, for women, the return to test scores is somewhat higher in the Netherlands than in the US and as may be seen in Table A2, two of the coefficients on the age dummy variables are also larger.

Alternative Specfications and The Marginal Effect of the Distribution of Cognitive Skills

Table 4 presents summary decomposition results (i.e., average effects) from a variety of alternative specifications of the wage equation where the explanatory variables include: i) age and test score; ii) age and education; iii) age, education and test score. This last specification repeats the summary results from Table 3 for comparison. Table 4 also includes an additional column (column 3) giving the marginal effect of test scores in explaining the higher level of US wage inequality. This effect is computed as the difference between the measured characteristics effect with and without test score in the model. We present these alternatives in light of our earlier discussion about the differing scenarios under which cognitive ability and education can affect wages.

As may be seen in Table 4, wage coefficient and residual effects are positive, on average, across all three specifications. Measured characteristics effects are positive for the 50-10 gap, and negative for the 90-50 gap. The marginal effects for test score are, with one exception, positive indicating that the inclusion of test scores in the wage equation generally raises the measured characteristics effect. Of particular interest is the impact of adding test score to the traditional human capital equation which includes controls for age and education: the inclusion of test score raises the average measured characteristics effects by .016 to .048 log points. Overall, excluding the case in which the marginal effect of test score is negative, the estimated contribution of test scores to explaining higher US inequality ranges from 5 to 15 percent of the US-other country differential, on average.

While the US distribution of test scores helps to explain the higher level of US wage inequality, Table 4 indicates that higher US prices are far more important, accounting for 27 to 66 percent of the difference in inequality between the US and other countries. The average wage coefficients effect is found to be substantially larger than the marginal effect of test scores under both specifications which include test score—ranging from .042 to .075 log points greater. And, the average coefficient and residual effects taken together exceed the marginal effect of test scores by .114 to .280 log points. These results suggest that labor market prices are quantitatively more important than the distribution of cognitive ability in explaining the higher level of wage inequality in the US.

Adjusting for Sample Selection

While the analysis so far suggests that labor market prices are higher in the United States than elsewhere, it is possible that these findings reflect sample selectivity. Specifically, employment-to-population ratios are usually higher in the US than in other countries (Blau and Kahn 1999). It is possible that US wage inequality appears to be higher because we observe a larger portion of the bottom of the queue of workers in the US than in other countries, in which a smaller percentage of the population is employed. Put differently, unmeasured characteristics of the employed could provide an alternative explanation of the differences across countries in overall wage inequality and in the wage equations and residuals as well.

To investigate these issues, we first calculated the fraction of each country's adult male or female population that was employed full-time and worked at least 26 weeks (i.e. that was potentially available for our wage sample). Among men, these percentages were: Canada 63.9%, Netherlands 66.1%, Sweden 63.0%, Switzerland 79.6%, and the United States 71.1%; the corresponding percentages for women were 36.1% for Canada, 21.4% for the Netherlands, 43.8% for Sweden, 39.0% for Switzerland, and 48.0% for the US. Under the assumption that inclusion in the sample is selective of those with better wage offers, one might conclude that US men in the wage sample were less positively selected than men in all of the countries except Switzerland, while US women would be less positively selected than women in all of the other countries. However, it is not necessarily the case that the wage sample is positively selected and our simple adjustment for sample selection does not require such an assumption.

To illustrate the adjustment, consider the comparison of US and Canadian men. We first compute a predicted probability of being in the wage sample for each US male in the population based on a probit model for US men in which the probability of being in the wage sample is a function of age dummies, education and test score. Since Canadian men are 10.1% less likely than American men to be in the wage sample,[19] we then exclude from the original US male wage sample the 10.1% with the lowest predicted probabilities of inclusion. Finally, we reestimate the US wage equations on this reduced sample and perform the Juhn, Murphy and Pierce (1993) decomposition for the selectivity-adjusted US sample and the original Canadian sample. This procedure provides some adjustment for selectivity bias both in our estimate of overall wage inequality and our estimation of the wage equation itself.[20] Since we would in this case exclude from the US sample those with the 10.1% lowest predicted probabilities of inclusion, we have made no a priori assumption about the wage offers the nonemployed receive in Canada. A similar adjustment is made for each pairwise (i.e., US-other country) comparison for men and for women.

The results are presented in Tables 5. Wage coefficients and residuals effects in these models are virtually always positive and are similar in magnitude to those from the uncorrected samples (Table 3). We thus conclude that labor market prices are higher in the United States even after correcting for the selectivity of wage samples. Further, it is interesting to note that, when we correct for selectivity, the estimated US-other country difference in wage inequality tends to be reduced and the measured characteristics effect usually becomes less positive or more negative. Since in all cases except one (Swiss men), the correction involves removing the portion of the United States sample with lowest predicted probabilities of sample inclusion, the compression of the measured characteristics effect is an intuitively plausible result. Yet price and residual effects continue to be as large and positive as they were not correcting for selectivity.

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[19] That is: (71.1-63.9)/71.1=.101.

[20] This correction is similar in spirit to that used by Hunt (forthcoming).

Immigrant Status, Race and Ethnicity

The results presented so far suggest that the United States has a more diverse population with respect to cognitive skills, as well as higher labor market prices than other countries. However it is possible that a given test score may not mean the same for an immigrant as it does for a native, given differences in language ability. If this is the case, our regression results may in part reflect the native-immigrant composition of the each country's wage samples. On the other hand, it is possible that the tests measure skills in a way that is equally valid for both immigrants and natives. Even in this case, however, it may be of interest to identify the role of immigrant-native composition in producing the observed results. Moreover, even if the test is equally valid for both natives and immigrants, there may be labor market discrimination against immigrants which could potentially affect the estimated wage coefficients. To address these concerns, we re-estimated our models for natives only; our results are shown in Table 6. We find that the estimated US-country j difference in wage inequality tends to be smaller when we compare natives in both countries, especially among women. However, the results of the decomposition are quite similar to those obtained for the full population: we estimate positive wage coefficient and residual effects in virtually every case that are, by and large, of similar magnitude to the full-sample results.

It is interesting to note that, while the US distribution of test scores remains more dispersed, the difference between the US and the other countries is considerably reduced, when we restrict the sample to natives in each country, especially for the 50-10 comparison. Among men, the 50-10 test score gap was 79.7 points in the US, compared to an average of 70.0 in the eight other countries studied here. In the full sample, the gap was 98.9 for the US and an average of 77.5 for the other countries (Table 1). Among women, the 50-10 gap in the US was virtually the same (70.6), as it was in the other countries (70.1) when the sample was restricted to natives, while among the population as a whole, the figures were 93.5 for the US and 76.0 for the other countries. The impact is smaller for the 90-50 gap. Among native men the gap was 8.2 points higher in the US, a slightly smaller difference than that for the whole population of 10.6; and for native women, the gap was 5.4 points higher in the US, virtually the same as the corresponding difference for the whole population (5.3).

These results shed light on the source of lower US test scores at the bottom of the test score distribution for the full population. While it might be tempting to conclude that poor quality education is responsible for low US test scores at the bottom, consideration of the native sample suggests that this argument applies only partially to men and perhaps not to at all women. Native US men at the 10th percentile scored only 7.9 points below those in other countries, in contrast to the overall population difference at the 10th percentile of 22.7 points. And, native US women at the 10th percentile actually outscored their counterparts in other countries by 4.5 points.

Given the well-known racial differentials in wages and employment in the US, particularly for men (e.g., Altonji and Blank 1999), another possible alternative explanation for our finding of higher skill prices in the US is that they are related to race. To see if race is driving our wage results, we re-estimated all of our models using a subsample of non-Hispanic whites from the US and the original samples from the other countries.[21] We found that the US still had higher wage differentials than other countries for the 50-10 and 90-50 wage gaps. The Juhn, Murphy and Pierce (1993) decomposition results based on white US subsamples were similar to those in Table 3, with measured prices and residuals both widening the 50-10 and 90-50 wage gaps in the US relative to the other countries.

Measurement Error and Functional Form

While, as noted, the IALS found that inter-rater reliability on test scores was very high (94-97%), it is still possible that measurement error affects our test proficiency measures and therefore the regression coefficients on which the inequality decompositions are based. We

[21] Information on race and ethnicity was not consistently available for the other countries.

attempted to deal with such possible errors in a variety of ways. First, rather than use the average of the quantitative, document and prose scores as the measure of literacy, we estimated models using the quantitative score only. We then used the prose and document scores as instruments for the quantitative score to account for measurement error. The results were very similar to the regression coefficients reported in Table A2. Second, rather than use the average of the five scores provided for quantitative, literacy and prose literacy, we used the first estimate of each score to construct an average of the three test scores (i.e., quantitative, literacy and prose literacy). We then used the second, third, fourth and fifth estimates (each averaged across quantitative, document and prose scores) as instruments for the first one. Again, we obtained very similar results.

Our functional forms, as reported in Table A2 are relatively simple, and we tested for the existence of interactions between education and test scores, as well as for quadratic terms for education and test scores. These alternative functional forms yielded no consistent patterns. For example, when we added a linear interaction between education and test score, with no quadratic terms, nine of the ten interactions (5 countries x 2 sexes) were insignificant, with 5 positive and 5 negative point estimates. When we included quadratic education and test score terms but no interactions, we obtained 5 positive and 5 negative education squared terms, with 3 significant and 7 positive and 3 negative test score squared terms, with 2 significant. Finally, in a model with full interactions between linear and quadratic education and test score terms, in 5 of ten cases, the quadratic and interaction terms were significant as a group and in the other 5 they were not. As was the case in the simple interaction and quadratic models, there was no particular pattern to these nonlinear terms. Further, when we used this quadratic-interaction model as a basis for Juhn, Murphy and Pierce (1993) decompositions, we obtained very similar results to those in Tables 3. Our basic conclusions about higher US labor market prices are thus robust with respect to alternative functional forms.

IV. Conclusion

This paper has used data from the International Adult Literacy Survey to examine the role of cognitive ability in explaining higher wage inequality in the US. Using a full-distributional accounting method devised by Juhn, Murphy and Pierce (1993), we find that while performance on cognitive tests plays a role in explaining greater US wage inequality, higher labor market prices (i.e. higher returns to measured human capital and cognitive performance) and greater residual inequality still play important roles for both men and women. And we find that, on average, prices are quantitatively considerably more important than differences in the distribution of test scores in explaining the relatively high levels of wage inequality in the US.

Even if the US does in fact have higher prices of labor market skills than other countries, the explanation for this difference could still rest either on institutions, such as collective bargaining, or on supply and demand. The US has much less coverage by collective bargaining than elsewhere in the OECD, but the US also has a greater abundance of low-skilled workers. Either feature of the US labor market, or a combination of both, could produce higher skill prices. There is evidence from international studies that changes in the relative supply of skilled workers and that changes or differences in wage-setting institutions can affect relative wages (Freeman and Katz 1995; Blau and Kahn 1999), suggesting that both types of explanation may be credible for the United States. But our study has shown that high wage inequality in the US is not in the main due to a more heterogenous population with respect to literacy skills, although this factor does play a role.

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Figure 1: 50-10 and 90-50 Log Wage Differentials for Men

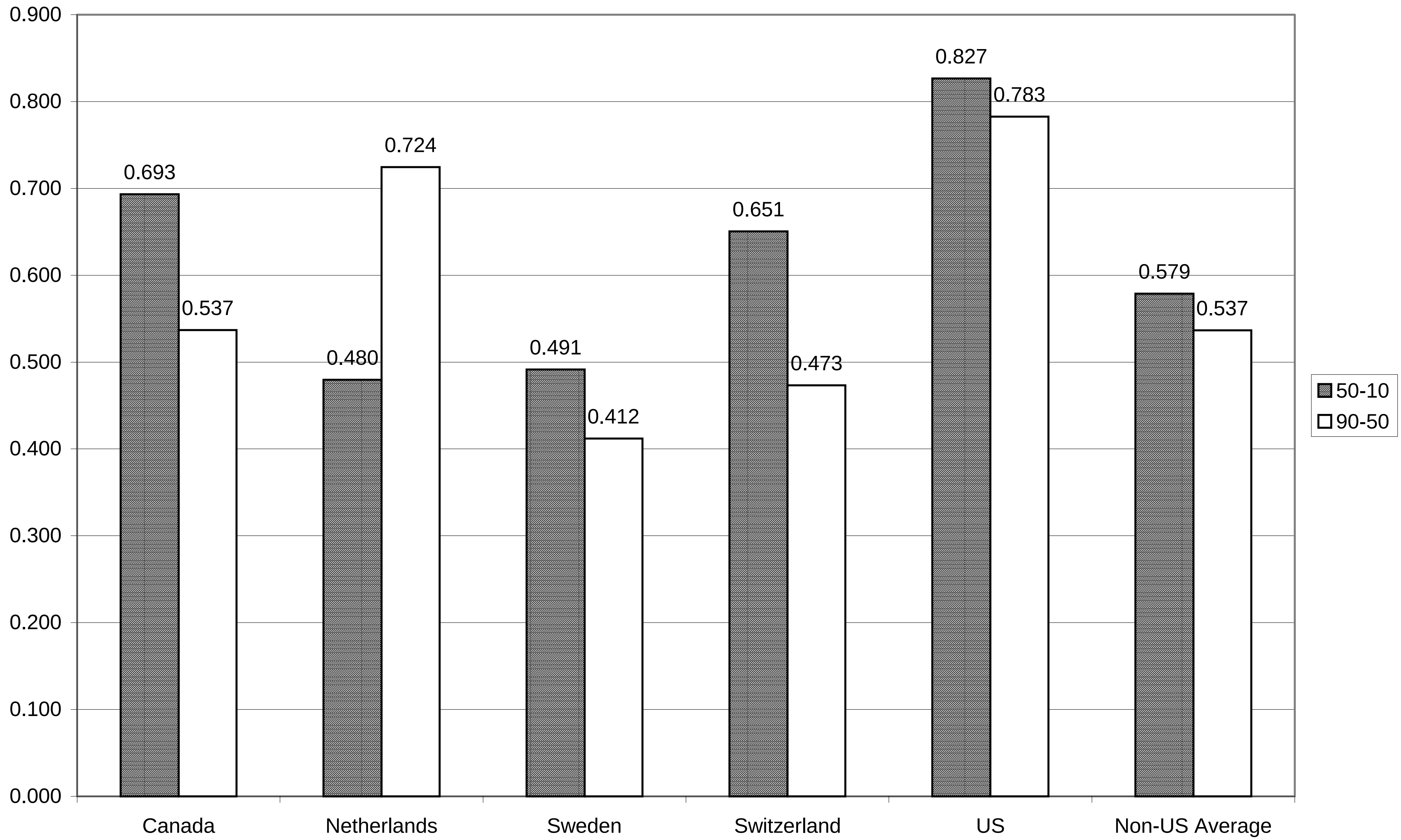

Figure 2: 50-10 and 90-50 Log Wage Differentials for Women

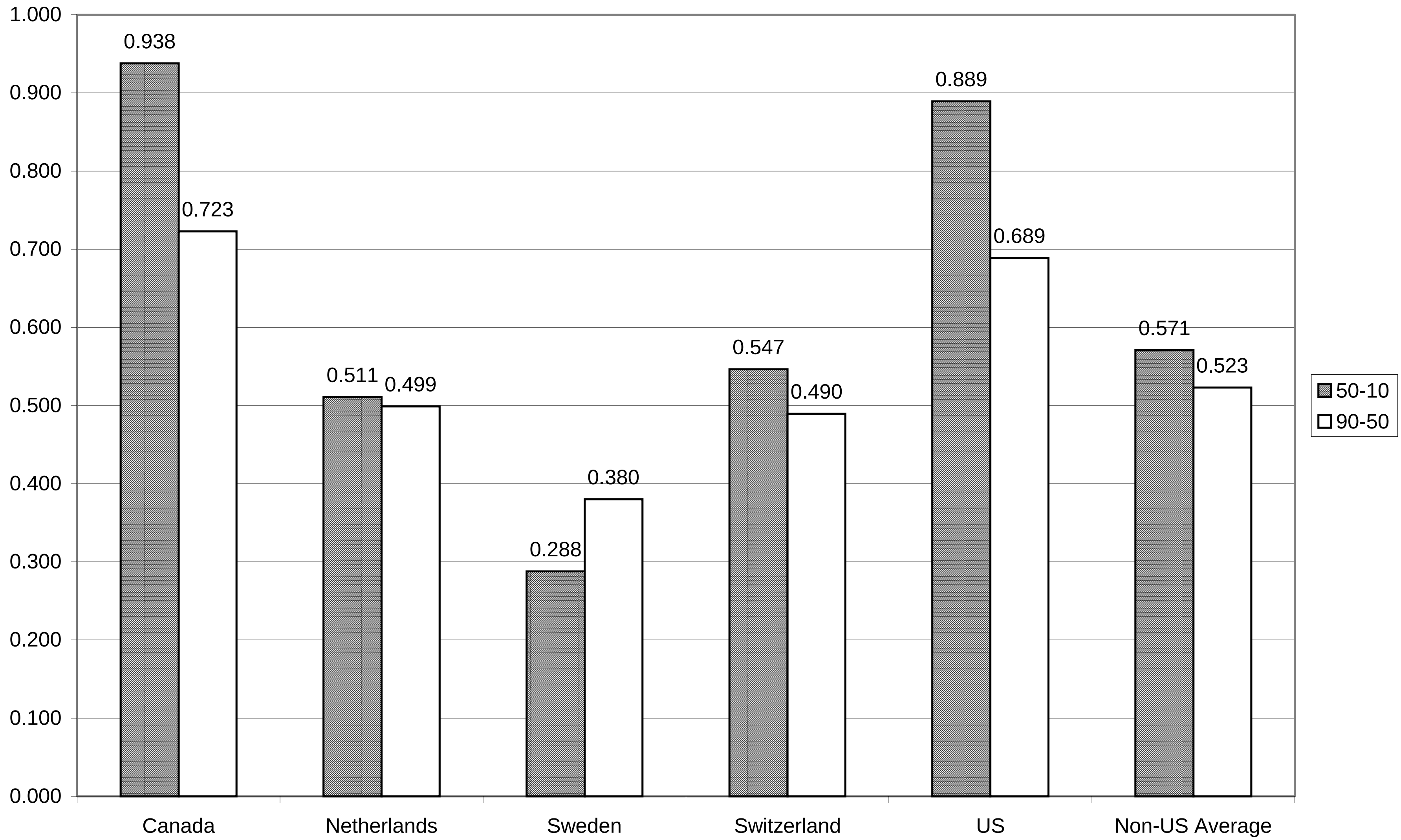

Figure 3: Age-Adjusted Test Score by Education Level, Men (Evaluated at Age 26-35)

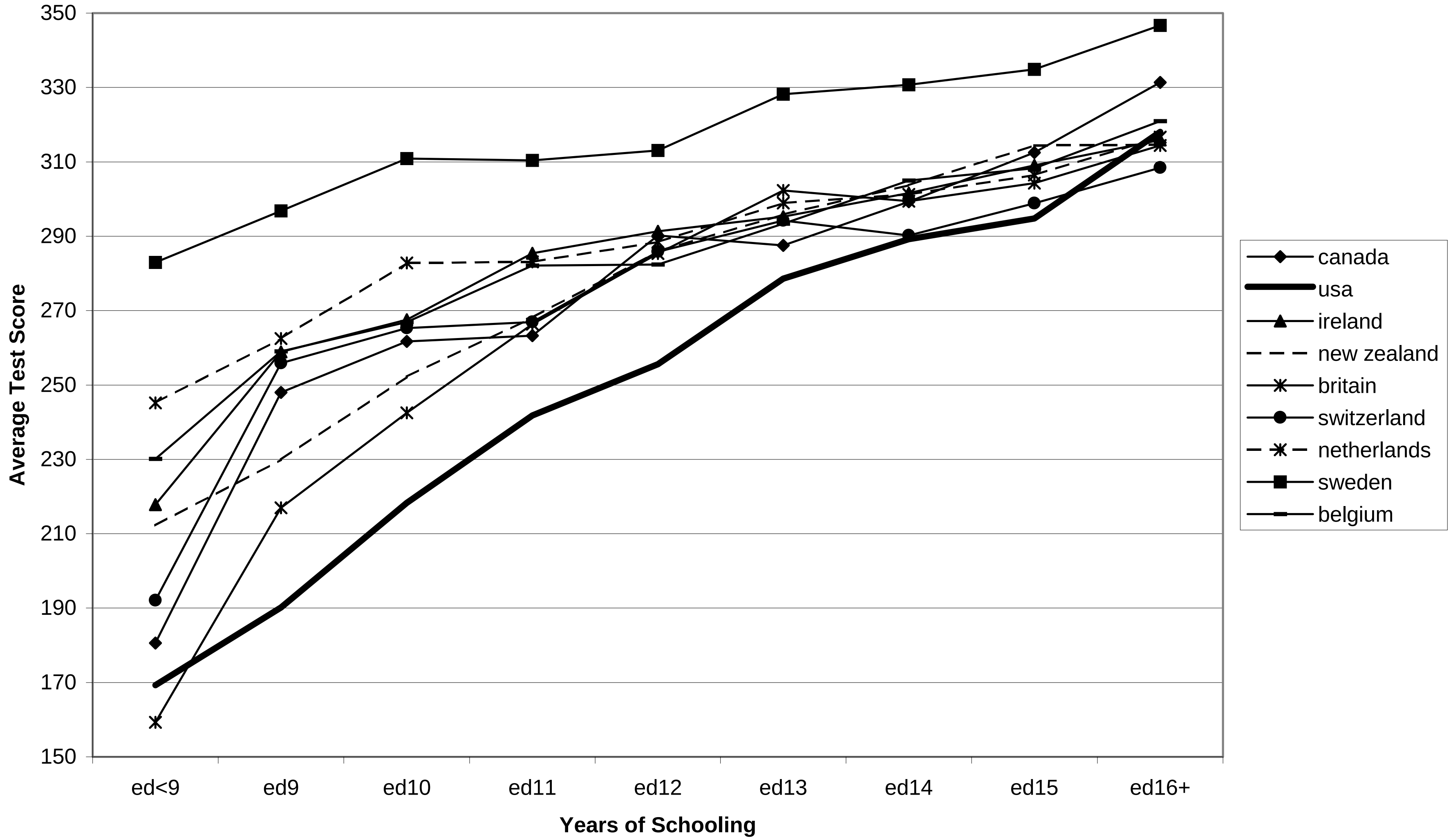

Figure 4: Age-Adjusted Test Scores by Education Level, Women (Evaluated at Age 26-35)

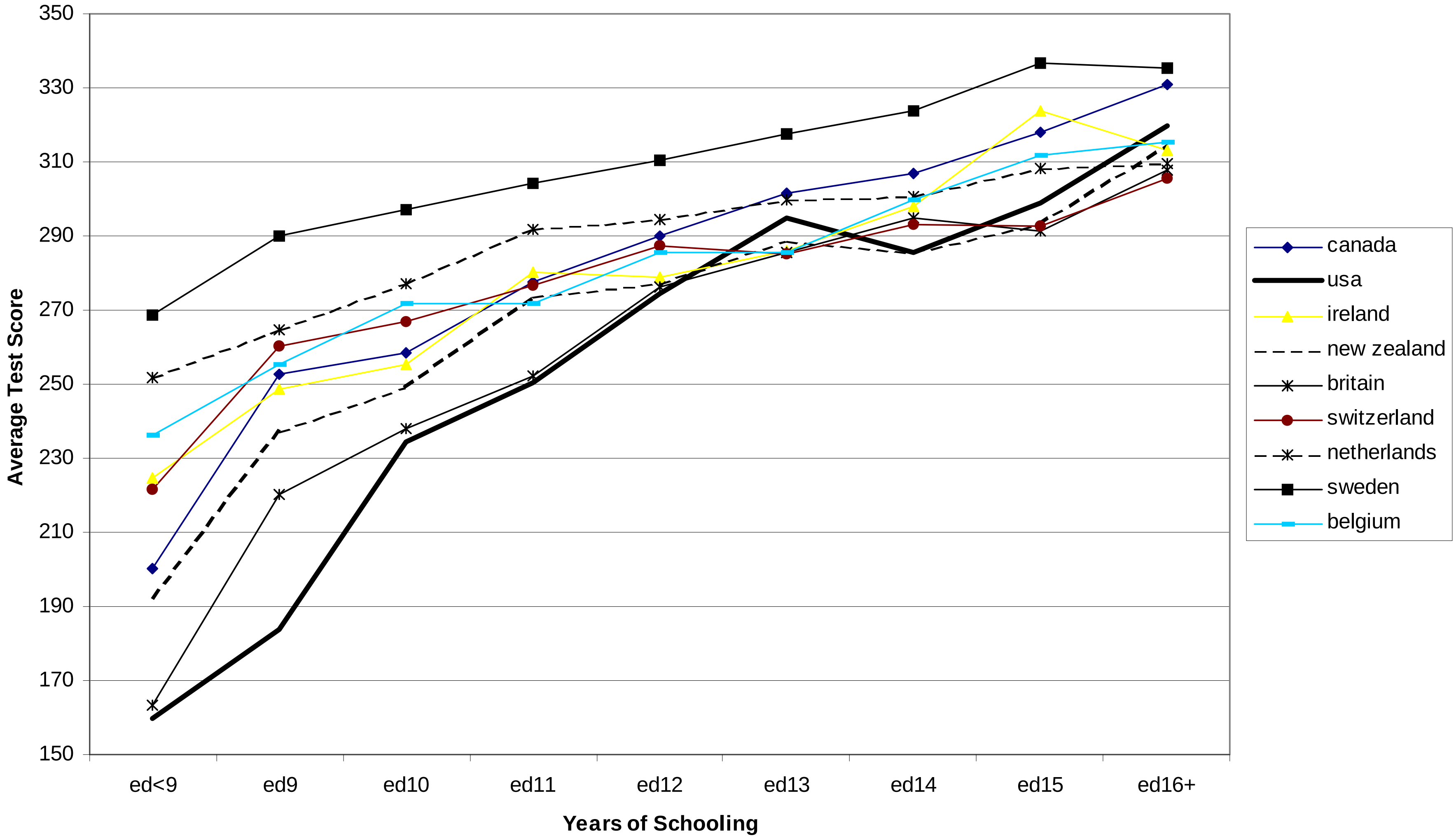

Table 1: Distribution of Individual Average Literacy Test Scores by Country and Gender

Country	Mean	Standard Deviation	Percentile 10	Percentile 50	Percentile 90	Differential 50-10	Differential 90-50
A. Population							
				Men			
Belgium	284.63	51.43	221.67	292.13	341.79	70.46	49.67
Britain	273.59	63.55	192.67	283.89	344.79	91.22	60.90
Canada	277.66	67.06	186.76	289.28	346.95	102.52	57.67
Ireland	264.47	59.47	185.76	273.26	329.88	87.50	56.62
Netherlands	289.13	43.97	231.60	295.47	338.00	63.87	42.53
New Zealand	273.12	57.00	200.09	279.71	340.49	79.61	60.78
Sweden	308.47	48.26	249.08	312.38	364.67	63.30	52.29
Switzerland	281.67	51.80	227.26	288.75	334.03	61.50	45.28
United States	275.60	65.54	188.13	287.05	350.89	98.92	63.85
Non-US average	281.59	55.32	211.86	289.36	342.58	77.50	53.22
				Women			
Belgium	270.46	57.02	194.14	282.25	334.63	88.11	52.38
Britain	261.81	58.33	187.80	267.18	329.75	79.38	62.58
Canada	281.88	60.16	204.25	288.78	349.56	84.53	60.77
Ireland	261.69	54.37	190.39	266.50	326.03	76.11	59.53
Netherlands	282.24	43.93	224.90	288.92	333.50	64.02	44.57
New Zealand	271.04	56.11	194.45	278.89	335.14	84.43	56.25
Sweden	300.17	48.70	238.98	304.97	356.93	66.00	51.95
Switzerland	271.12	50.81	212.72	278.34	324.78	65.63	46.44
United States	274.80	62.87	190.45	283.96	343.57	93.51	59.61
Non-US average	275.05	53.68	205.95	281.98	336.29	76.03	54.31
B. Wage Sample							
				Men			
Canada	295.96	52.40	233.95	296.76	362.29	62.81	65.53
Netherlands	294.07	40.43	241.92	297.80	338.92	55.88	41.12
Sweden	311.60	46.37	256.31	313.94	365.97	57.63	52.03
Switzerland	283.79	51.32	227.65	291.01	334.86	63.36	43.85
United States	288.97	61.43	216.49	297.16	357.13	80.67	59.98
Non-US average	296.35	47.63	239.96	299.88	350.51	59.92	50.63
				Women			
Canada	299.11	56.19	225.92	307.46	365.08	81.53	57.62
Netherlands	300.53	34.17	251.05	303.85	340.39	52.80	36.54
Sweden	308.54	43.08	259.48	310.49	361.42	51.02	50.93
Switzerland	278.74	47.51	230.62	284.72	326.95	54.10	42.23
United States	289.56	58.79	221.53	294.54	352.88	73.01	58.34
Non-US average	296.73	45.24	241.77	301.63	348.46	59.86	46.83

Note: Individual scores are the average of quantitative, document and prose test scores. Non-US average is the unweighted average of the figures in the Table. Wage sample described below.

Source: International Adult Literacy Survey.

Table 2: Log Wage Effects of a 1 Standard Deviation Increase in Test Score or Education

	Education		Test Score	
	Control for test score?		Control for education?	
	No	Yes	No	Yes
Men				
Canada	0.1421	0.0875	0.1381	0.0928
	(0.0163)	(0.0192)	(0.0152)	(0.0180)
Netherlands	0.0950	0.0471	0.1965	0.1628
	(0.0115)	(0.0124)	(0.0174)	(0.0194)
Sweden	0.0831	0.0598	0.1004	0.0757
	(0.0145)	(0.0154)	(0.0168)	(0.0178)
Switzerland	0.1095	0.0628	0.1111	0.0809
	(0.0209)	(0.0244)	(0.0190)	(0.0223)
United States	0.2909	0.1664	0.2421	0.1636
	(0.0213)	(0.0254)	(0.0165)	(0.0200)
Non-US Average	0.1074	0.0643	0.1365	0.1031
Women				
Canada	0.2793	0.1483	0.2528	0.1665
	(0.0205)	(0.0268)	(0.0174)	(0.0231)
Netherlands	0.1143	0.0969	0.1578	0.1248
	(0.0213)	(0.0214)	(0.0337)	(0.0335)
Sweden	0.1088	0.0981	0.0773	0.0331
	(0.0133)	(0.0143)	(0.0163)	(0.0169)
Switzerland	0.1034	0.0677	0.1175	0.0927
	(0.0272)	(0.0289)	(0.0263)	(0.0282)
United States	0.3612	0.2638	0.2213	0.1187
	(0.0267)	(0.0315)	(0.0190)	(0.0217)
Non-US Average	0.1515	0.1027	0.1513	0.1043

Notes: Regressions include controls for age; standard errors are in parentheses. A one standard deviation increase in education is 3.5467 years; a one standard deviation increase in test scores is 51.0599 points. Standard deviations are calculated on the pooled weighted male and female wage samples giving each country the same weight.

Table 3

Decomposition of US-Country J Differences in Wage Inequality

	US Differential - Country j Differential	Measured Characteristics Effect	Wage Coefficients Effect	Wage Equation Residual Effect
		Men		
50-10 Log Wage Differential				
Canada	0.134	0.029	0.024	0.081
Netherlands	0.347	0.182	0.036	0.129
Sweden	0.327	0.084	0.164	0.079
Switzerland	0.250	0.205	0.081	-0.036
Non-US Average	0.264	0.125	0.076	0.063
Share of total	1.000	0.472	0.289	0.239
90-50 Log Wage Differential				
Canada	0.246	0.021	0.098	0.127
Netherlands	0.067	-0.144	0.083	0.129
Sweden	0.371	0.064	0.118	0.188
Switzerland	0.127	-0.105	0.093	0.139
Non-US Average	0.203	-0.041	0.098	0.146
Share of total	1.000	-0.203	0.484	0.718
		Women		
50-10 Log Wage Differential				
Canada	-0.049	-0.122	-0.003	0.076
Netherlands	0.378	0.098	0.092	0.188
Sweden	0.601	0.115	0.194	0.293
Switzerland	0.343	0.104	0.110	0.128
Non-US Average	0.318	0.049	0.098	0.171
Share of total	1.000	0.153	0.309	0.538
90-50 Log Wage Differential				
Canada	-0.071	-0.088	0.049	-0.032
Netherlands	0.186	0.066	0.053	0.067
Sweden	0.272	-0.045	0.175	0.142
Switzerland	0.163	0.002	0.085	0.076
Non-US Average	0.138	-0.016	0.091	0.063
Share of total	1.000	-0.119	0.658	0.461

Notes: The dependent variable is ln wages; regressions include controls for age, education and test score. Base: US measured characteristics; other country coefficients and residuals.

Table 4: Decomposition of US-Country J Differences in Wage Inequality: Average Effects for Alternative Specifications

Wage Equation Specification	US Differential - Country j Differential	Measured Characteristics Effect	Marginal Effect of Test Scores	Wage Coefficients Effect	Wage Equation Residual Effect
A. Men: 50-10 Log Wage Differential					
Age and Test Score	0.264	0.113	0.012	0.076	0.076
Age and Education	0.264	0.100	---	0.068	0.097
Age, Education, and Test Score	0.264	0.125	0.025	0.076	0.063
B. Men: 90-50 Log Wage Differential					
Age and Test Score	0.203	-0.031	0.022	0.064	0.170
Age and Education	0.203	-0.068	---	0.154	0.116
Age, Education, and Test Score	0.203	-0.041	0.027	0.098	0.146
C. Women: 50-10 Log Wage Differential					
Age and Test Score	0.318	0.019	0.020	0.085	0.215
Age and Education	0.318	0.000	---	0.129	0.189
Age, Education, and Test Score	0.318	0.049	0.048	0.098	0.171
D. Women: 90-50 Log Wage Differential					
Age and Test Score	0.138	-0.009	-0.002	0.046	0.100
Age and Education	0.138	-0.032	---	0.140	0.030
Age, Education, and Test Score	0.138	-0.016	0.016	0.091	0.063

Notes: The dependent variable is ln wages; regressions include controls for indicated variables. Base: US measured characteristics; other country coefficients and residuals. The marginal effect of test score is the difference between the measured characteristics effect with and without test score in the model.

Table 5

Decomposition of US-Country J Differences in Wage Inequality: Samples Adjusted for Selectivity

	US Differential - Country j Differential	Measured Characteristics Effect	Wage Coefficients Effect	Wage Equation Residual Effect
		Men		
50-10 Log Wage Differential				
Canada	0.031	-0.079	0.062	0.047
Netherlands	0.244	0.110	0.027	0.107
Sweden	0.254	-0.019	0.183	0.089
Switzerland	0.316	0.229	0.015	0.072
Non-US Average	0.211	0.061	0.072	0.079
Share of total	1.000	0.287	0.340	0.373
90-50 Log Wage Differential				
Canada	0.284	0.002	0.106	0.176
Netherlands	0.064	-0.149	0.093	0.121
Sweden	0.379	0.034	0.133	0.212
Switzerland	0.130	-0.120	0.091	0.159
Non-US Average	0.215	-0.058	0.106	0.167
Share of total	1.000	-0.272	0.494	0.778
		Women		
50-10 Log Wage Differential				
Canada	-0.165	-0.143	-0.116	0.094
Netherlands	0.278	-0.036	0.116	0.198
Sweden	0.446	0.065	0.190	0.191
Switzerland	0.227	0.000	0.119	0.107
Non-US Average	0.197	-0.028	0.078	0.147
Share of total	1.000	-0.144	0.394	0.750
90-50 Log Wage Differential				
Canada	-0.069	-0.133	0.107	-0.043
Netherlands	0.070	-0.013	0.050	0.032
Sweden	0.313	-0.040	0.195	0.159
Switzerland	0.164	-0.072	0.177	0.059
Non-US Average	0.120	-0.065	0.132	0.052
Share of total	1.000	-0.540	1.107	0.434

Notes: The dependent variable is ln wages; regressions include controls for age, education and test score. Base: US measured characteristics; other country coefficients and residuals. See the text for a description of the selectivity adjustment.

Table 6

Decomposition of US-Country J Differences in Wage Inequality: Natives Only

	US Differential - Country j Differential	Measured Characteristics Effect	Wage Coefficients Effect	Wage Equation Residual Effect
		Men		
50-10 Log Wage Differential				
Canada	0.020	-0.014	0.023	0.011
Netherlands	0.244	0.056	0.071	0.117
Sweden	0.239	0.084	0.113	0.042
Switzerland	0.144	0.272	-0.136	0.008
Non-US Average	0.162	0.100	0.018	0.044
Share of total	1.000	0.616	0.111	0.274
90-50 Log Wage Differential				
Canada	0.172	0.030	0.061	0.081
Netherlands	-0.010	-0.190	0.096	0.084
Sweden	0.297	0.007	0.140	0.150
Switzerland	0.100	-0.104	0.113	0.090
Non-US Average	0.140	-0.064	0.103	0.101
Share of total	1.000	-0.458	0.735	0.723
		Women		
50-10 Log Wage Differential				
Canada	0.000	-0.049	0.011	0.038
Netherlands	0.310	0.122	0.049	0.139
Sweden	0.533	0.121	0.168	0.244
Switzerland	0.274	0.175	0.077	0.022
Non-US Average	0.279	0.092	0.076	0.111
Share of total	1.000	0.330	0.273	0.397
90-50 Log Wage Differential				
Canada	0.087	0.002	0.083	0.002
Netherlands	0.186	0.008	0.119	0.058
Sweden	0.272	-0.055	0.227	0.100
Switzerland	0.163	-0.001	0.077	0.086
Non-US Average	0.177	-0.011	0.127	0.062
Share of total	1.000	-0.065	0.716	0.348

Notes: The dependent variable is ln wages; regressions include controls for age, education and test score. Base: US measured characteristics; other country coefficients and residuals.

Figure A1: Age- Adjusted Test Scores by Education for Natives Only, Men (Evaluated at Age 26-35)

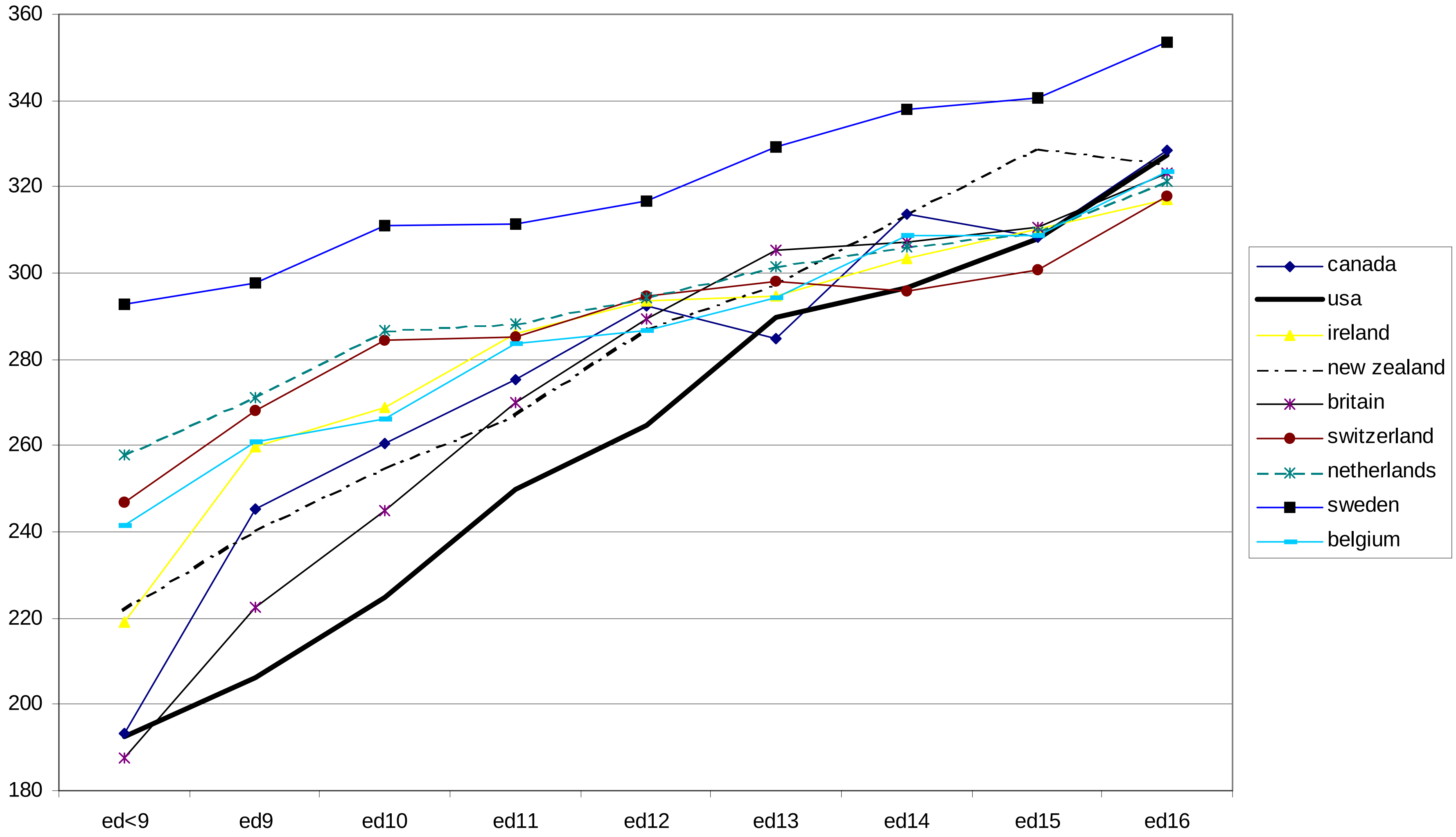

Figure A2: Age- Adjusted Test Scores by Education for Natives Only, Women (Evaluated at Age 26-35)

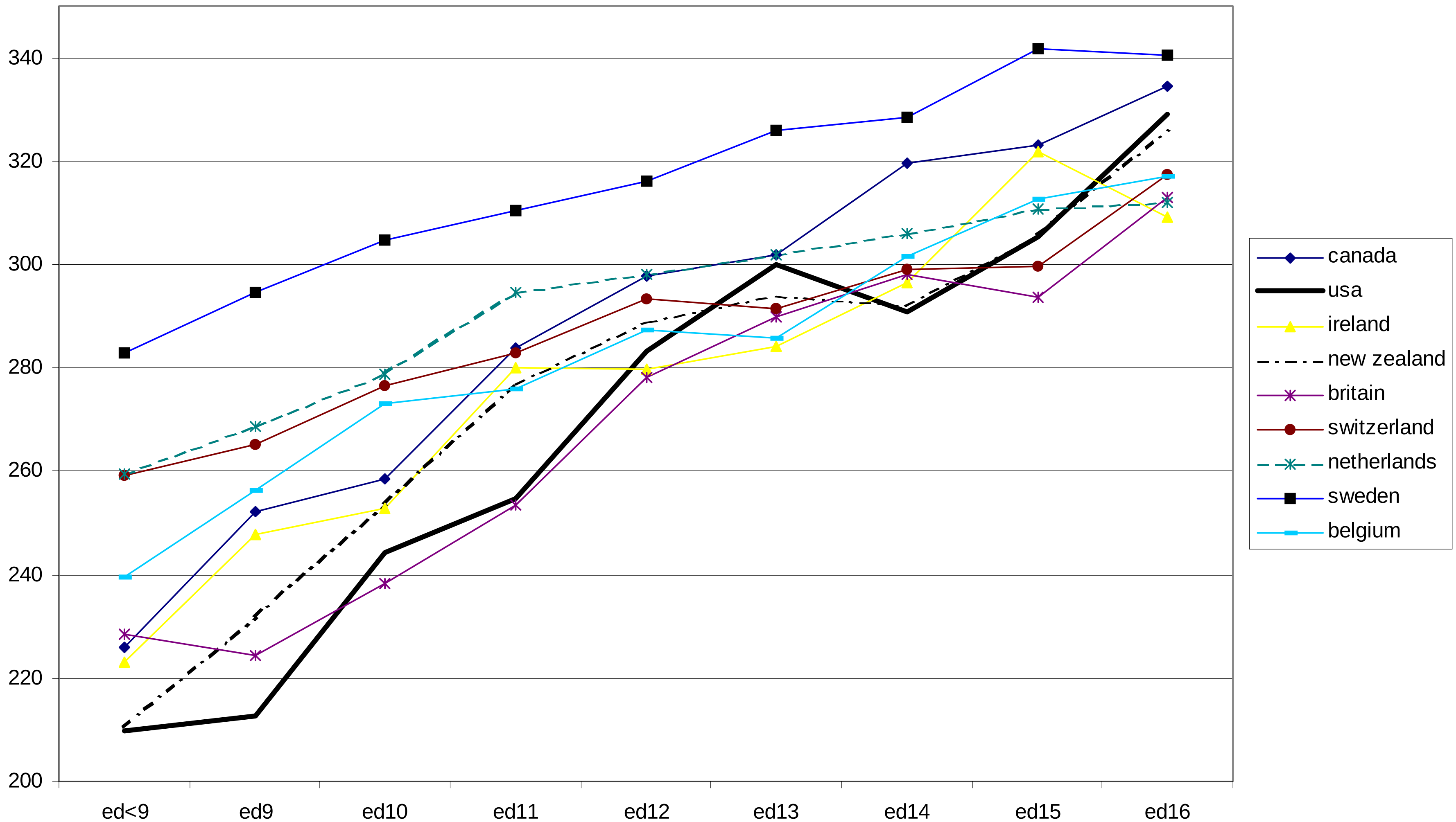

Table A1

Means of Explanatory Variables in the Wage Regressions by Country

Variable	Canada	Netherlands	Sweden	Switzerland	US
		Men			
Education (years)	13.281	13.439	11.838	13.011	14.084
Age 26-35	0.339	0.314	0.236	0.307	0.286
Age 36-45	0.306	0.305	0.322	0.228	0.336
Age 46-55	0.206	0.229	0.256	0.203	0.200
Age 56-65	0.058	0.055	0.116	0.113	0.092
Test score	295.962	294.065	311.601	283.788	288.966
No. of observations	827	867	686	647	717
		Women			
Education (years)	13.640	13.815	12.142	12.323	13.843
Age 26-35	0.319	0.348	0.206	0.364	0.267
Age 36-45	0.319	0.176	0.290	0.206	0.294
Age 46-55	0.205	0.186	0.282	0.178	0.248
Age 56-65	0.031	0.021	0.121	0.046	0.111
Test score	299.113	300.534	308.541	278.738	289.558
No. of observations	628	327	507	340	554

Table A2

Selected Wage Regression Results by Country

	Men				Women			
Variable	coeff	std err	coeff	std err	coeff	std err	coeff	std err
				Canada				
Education	0.0401	0.0046	0.0247	0.0054	0.0788	0.0058	0.0418	0.0076
Age 26-35	0.5885	0.0576	0.5783	0.0568	0.5574	0.0631	0.4796	0.0616
Age 36-45	0.6866	0.0584	0.6832	0.0575	0.3224	0.0645	0.2727	0.0624
Age 46-55	0.8353	0.0614	0.8516	0.0606	0.5844	0.0686	0.5823	0.0659
Age 56-65	0.6200	0.0818	0.6510	0.0808	0.3479	0.1201	0.3875	0.1155
Test score	----	----	0.0018	0.0004	----	----	0.0033	0.0005
N	827		827		628		628	
R squared	0.2468		0.2704		0.3427		0.3936	
				Netherlands				
Education	0.0268	0.0032	0.0133	0.0035	0.0322	0.0060	0.0273	0.0060
Age 26-35	0.3621	0.0514	0.3534	0.0495	0.3165	0.0523	0.3003	0.0514
Age 36-45	0.5538	0.0516	0.5644	0.0496	0.3566	0.0625	0.3635	0.0613
Age 46-55	0.6286	0.0535	0.6630	0.0517	0.4730	0.0622	0.5432	0.0638
Age 56-65	0.5166	0.0745	0.5607	0.0718	0.6266	0.1460	0.6498	0.1433
Test score	----	----	0.0032	0.0004	----	----	0.0024	0.0007
N	867		867		327		327	
R squared	0.2134		0.2730		0.2358		0.2675	
				Sweden				
Education	0.0234	0.0041	0.0168	0.0043	0.0307	0.0037	0.0277	0.0040
Age 26-35	0.4006	0.0652	0.3743	0.0647	0.1579	0.0494	0.1531	0.0493
Age 36-45	0.5079	0.0634	0.4979	0.0627	0.2184	0.0470	0.2190	0.0468
Age 46-55	0.6422	0.0645	0.6227	0.0638	0.2684	0.0471	0.2719	0.0470
Age 56-65	0.5195	0.0723	0.5155	0.0714	0.2268	0.0547	0.2413	0.0551
Test score	----	----	0.0015	0.0003	----	----	0.0006	0.0003
N	686		686		507		507	
R squared	0.1739		0.1954		0.1716		0.1779	

Table A2 (ctd)

Selected Wage Regression Results by Country

	Men				Women			
Variable	coeff	std err	coeff	std err	coeff	std err	coeff	std err
				Switzerland				
Education	0.0309	0.0059	0.0177	0.0069	0.0292	0.0077	0.0191	0.0081
Age 26-35	0.5169	0.0602	0.5240	0.0597	0.3910	0.0667	0.4189	0.0663
Age 36-45	0.7277	0.0634	0.7423	0.0629	0.4764	0.0756	0.5202	0.0757
Age 46-55	0.8020	0.0649	0.8142	0.0644	0.4675	0.0782	0.5188	0.0787
Age 56-65	0.6480	0.0750	0.6750	0.0747	0.2555	0.1255	0.2766	0.1238
Test score	----	----	0.0016	0.0004	----	----	0.0018	0.0006
N	647		647		340		340	
R squared	0.2434		0.2587		0.1806		0.2064	
				United States				
Education	0.0820	0.0060	0.0469	0.0072	0.1018	0.0075	0.0744	0.0089
Age 26-35	0.4095	0.0779	0.4146	0.0745	0.3866	0.0841	0.3534	0.0822
Age 36-45	0.6072	0.0767	0.5936	0.0734	0.4079	0.0832	0.3878	0.0812
Age 46-55	0.6555	0.0819	0.6365	0.0784	0.5283	0.0848	0.5217	0.0826
Age 56-65	0.6461	0.0952	0.6519	0.0910	0.5360	0.0969	0.5371	0.0944
Test score	----	----	0.0032	0.0004	----	----	0.0023	0.0004
N	717		717		554		554	
R squared	0.2988		0.3592		0.2882		0.3251	

Table A3: Log Wage Effects of a 1 Standard Deviation Increase in Test Score or Education, Including Controls for Age, Industry and Occupation

	Education		Test Score	
	Control for test score?		Control for education?	
	No	Yes	No	Yes
		Men		
Canada	0.1025	0.0675	0.0973	0.0746
	(0.0197)	(0.0212)	(0.0166)	(0.0179)
Netherlands	0.0643	0.0376	0.1384	0.1171
	(0.0120)	(0.0126)	(0.0187)	(0.0199)
Sweden	0.0646	0.0507	0.0729	0.0579
	(0.0153)	(0.0158)	(0.0170)	(0.0175)
Switzerland	0.0808	0.0545	0.0800	0.0577
	(0.0223)	(0.0246)	(0.0211)	(0.0233)
United States	0.2434	0.1431	0.2017	0.1511
	(0.0251)	(0.0277)	(0.0180)	(0.0202)
Non-US Average	0.0781	0.0525	0.0972	0.0768
		Women		
Canada	0.2088	0.1199	0.1717	0.1227
	(0.0250)	(0.0291)	(0.0186)	(0.0219)
Netherlands	0.1114	0.0974	0.1389	0.1098
	(0.0220)	(0.0221)	(0.0342)	(0.0339)
Sweden	0.0935	0.0861	0.0578	0.0258
	(0.0137)	(0.0145)	(0.0162)	(0.0165)
Switzerland	0.0625	0.0478	0.0634	0.0497
	(0.0279)	(0.0290)	(0.0275)	(0.0287)
United States	0.2522	0.2143	0.1199	0.0612
	(0.0297)	(0.0324)	(0.0204)	(0.0215)
Non-US Average	0.1190	0.0878	0.1080	0.0770

Notes: Regressions include controls for age, occupation and industry; standard errors are in parentheses. A one standard deviation increase in education is 3.5467 years; a one standard deviation increase in test scores is 51.0599 points. Standard deviations are calculated on the pooled weighted male and female wage samples giving each country the same weight.

Table A4

Decomposition of the US-Country J Differences in Wage Inequality, Including Industry and Occupation Controls

	US Differential - Country j Differential	Measured Characteristics Effect	Wage Coefficients Effect	Wage Equation Residual Effect
		Men		
50-10 Log Wage Differential				
Canada	0.134	0.029	0.008	0.097
Netherlands	0.347	0.128	0.110	0.108
Sweden	0.327	0.075	0.192	0.059
Switzerland	0.250	0.137	0.123	-0.010
Non-US Average	0.264	0.092	0.109	0.064
Share of total	1.000	0.349	0.410	0.241
90-50 Log Wage Differential				
Canada	0.246	0.068	0.100	0.078
Netherlands	0.067	-0.152	0.090	0.129
Sweden	0.371	0.080	0.127	0.163
Switzerland	0.127	-0.092	0.100	0.119
Non-US Average	0.203	-0.024	0.104	0.122
Share of total	1.000	-0.118	0.515	0.603
		Women		
50-10 Log Wage Differential				
Canada	-0.049	-0.131	-0.019	0.102
Netherlands	0.378	0.117	0.121	0.141
Sweden	0.601	0.115	0.271	0.215
Switzerland	0.343	0.095	0.162	0.086
Non-US Average	0.318	0.049	0.134	0.136
Share of total	1.000	0.153	0.420	0.427
90-50 Log Wage Differential				
Canada	-0.071	-0.084	0.056	-0.042
Netherlands	0.186	0.016	0.124	0.045
Sweden	0.272	0.023	0.138	0.111
Switzerland	0.163	-0.024	0.130	0.057
Non-US Average	0.138	-0.017	0.112	0.043
Share of total	1.000	-0.125	0.814	0.311

Notes: The dependent variable is ln wages; regressions include controls for age, education test score; industry and occupation. Base: US measured characteristics; other country coefficients and residuals.

Table A5

Decomposition of the US-Country J Differences in Wage Inequality, Alternative Base

	US Differential - Country j Differential	Measured Characteristics Effect	Wage Coefficients Effect	Wage Equation Residual Effect
		Men		
50-10 Log Wage Differential				
Canada	0.134	0.043	0.017	0.073
Netherlands	0.347	0.032	0.071	0.243
Sweden	0.327	0.118	0.091	0.118
Switzerland	0.250	0.100	0.148	0.003
Non-US Average	0.264	0.073	0.082	0.109
Share of total	1.000	0.277	0.309	0.413
90-50 Log Wage Differential				
Canada	0.246	0.097	0.019	0.130
Netherlands	0.067	-0.032	0.040	0.058
Sweden	0.371	-0.013	0.132	0.252
Switzerland	0.127	-0.043	0.019	0.151
Non-US Average	0.203	0.002	0.053	0.148
Share of total	1.000	0.012	0.260	0.728
		Women		
50-10 Log Wage Differential				
Canada	-0.049	-0.191	0.035	0.107
Netherlands	0.378	0.251	-0.080	0.207
Sweden	0.601	0.220	0.041	0.341
Switzerland	0.343	0.088	0.062	0.193
Non-US Average	0.318	0.092	0.015	0.212
Share of total	1.000	0.289	0.046	0.665
90-50 Log Wage Differential				
Canada	-0.071	-0.106	0.110	-0.075
Netherlands	0.186	-0.013	0.091	0.107
Sweden	0.272	-0.061	0.136	0.197
Switzerland	0.163	-0.031	0.156	0.038
Non-US Average	0.138	-0.053	0.123	0.067
Share of total	1.000	-0.382	0.895	0.487

Notes: The dependent variable is ln wages; regressions include controls for age, education and test score. Base: other country measured characteristics; US coefficients and residuals.