WEB APPENDIX
"Firms and Skills: The Evolution of Worker Sorting"

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Appendix A: Description of data

A.1 Imputing enlistment data for women

Since women in general have not gone through the Swedish enlistment procedure, data on cognitive and non-cognitive abilities are lacking for half of the population. To get an idea if the patterns found for men are also applicable to women, we impute values for women using the conscription records of their close relatives. We judge this to be a reasonable approach as previous research has found the ability correlations between close family members to be substantial: After correcting for measurement error, Grönqvist et al (2017) find that the father-son ability correlations fall between 0.4 and 0.5 for non-cognitive and cognitive abilities. The same study also reports sibling correlations of 0.45 for cognitive and 0.3 for non-cognitive abilities, without adjusting for measurement error. The reliability ratios they report suggest that the true sibling correlations are approximately 0.6 for both types of abilities. Assortative mating is also substantial; Boschini et al (2011) find the correlation in educational attainment between Swedish spouses to be around 0.5.

To find close relatives, we make use of the Multi Generation Register (Flergenerationsregistret), which contains information on ties between parents and their children for all individuals who have ever resided in Sweden since 1961 and who are born after 1932. When we impute values for a woman, we give priority to the evaluation results for her oldest brother with a conscription record. If such a record is not available, we use her fathers' record and if that is missing, we turn to her sons (in age order). If none of these records can be found, we impute values using the woman's spouse, defined as the father of her first born child. Using this algorithm, 40 percent of values are imputed using brothers, 14 percent using fathers, 29 percent using sons, and 16 percent using spouses.

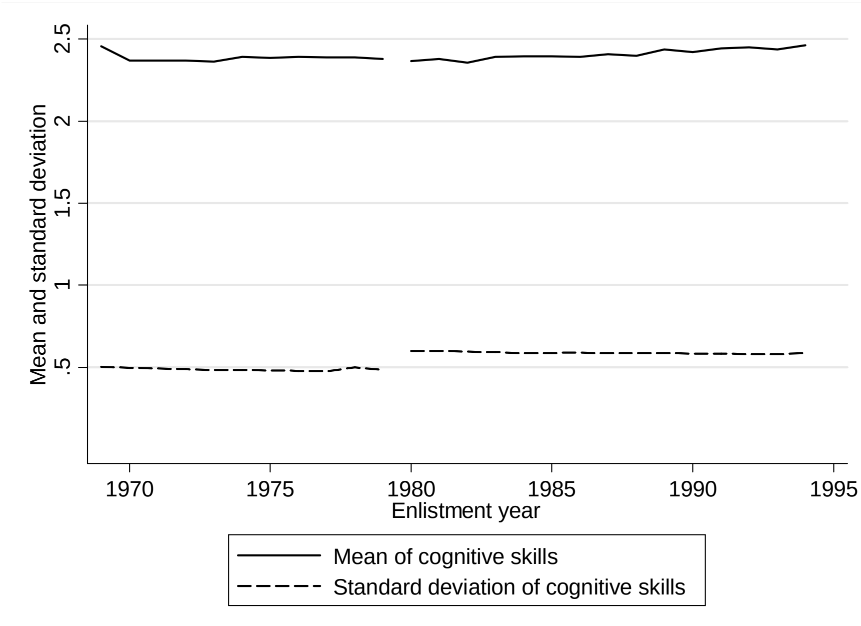
A.2 Trends in cognitive abilities

The analysis in this paper makes use of skill measures that are standardized by enlistment year. Standardization ensures that individuals at the same position in the overall skill distribution are compared over time, but may hide changes in the underlying distribution of skills. In this Appendix, we analyze if such changes are likely to be a concern for cognitive skills. This is possible since raw test scores are available for a subset of the years analyzed. For non-cognitive skills, no such raw scores are available and a similar analysis is thus not possible to undertake.

Between the enlistment years 1969 and 1994, the cognitive ability test consisted of four parts, testing verbal, logical, spatial and technical ability. The raw scores on these tests are transformed by the enlistment agency to a 1 to 9 "stanine" scale for each subtest. The resulting four stanine scores are then transformed into the aggregate 1 to 9 scales used for the main analysis of cognitive skills in this paper. In this Appendix, we instead make use of the raw scores. For some individuals, data on raw subscores are missing and we then only have data on the 1 to 9 scale for each subtest. In such cases, we impute the average raw score for those with the same subtest score on the 1 to 9 scale. In order to account for differences in maximum scores between subtests and test periods, we divide the raw scores by the maximum score possible for each subtest. The sum of the score on the four subtests is our measure of raw cognitive ability.

Figure A1 depicts the mean and standard deviation of raw cognitive abilities by enlistment year. In 1980 the test underwent minor revisions and apart from a jump in the standard deviation in connection to this, the dispersion of skills is stable throughout the time period. There is, however, a slight increase in mean cognitive skills. Taking the average of skills during the first four years and comparing it to the last four years, this increase amounts to 13 percent of a standard deviation.[1] We conclude from this exercise that standardization is unlikely to have any substantive impact on the analysis in this paper.

Figure A1. Trends in raw ability scores



Note: The figure shows the mean and standard deviation by enlistment year for the raw cognitive score. The raw score is the sum of four different subtests where the score from each subtest is equal to the proportion correct answers. The raw score thus ranges between 0 and 4. The break between 1979 and 1980 is due to a change in the test in 1980, making a direct comparison of the scores impossible.

A.3 Imputation of wages

Table A1 provides the basic statistics for actual and imputed wages. The Structural Wage statistics (SWS) data from which we pull directly observed monthly wages covers all workers in the public sector and in private firms above 500 workers. Information for smaller firms comes from a stratified random sample by industry. Coverage is increasing over time. Because of the sampling procedure, many workers for whom we do not observe wages in a given year may have a reported wage in an adjacent year. Our first step in imputing wages for a given worker i in year t is therefore to check whether worker i has a reported wage in year $t-1$, $t+1$, $t-2$ or $t+2$ (in that order) from the same employer. We then adjust these wages by the wage drift in each industry.

[1] The mean over the years 1969-72 is 2.37 and over 1991-94 2.45.

For worker-years where we are not able to directly observe or impute a wage from the SWS, we use monthly wage earnings. For each worker, we observe total annual wage earnings from every employer and the number of months worked, thus allowing us to calculate monthly earnings. We use monthly earnings only from the employer from which the worker received the highest earnings in each year. We trim monthly earnings at the 99.75th percentile and set wages to missing in case monthly earnings fall below the minimum wage. Because monthly earnings may exceed or fall below the monthly full-time wage for workers who work part-time or overtime, we use the sample of workers with SWS wages (directly observed or imputed using observations from adjacent years) to estimate a mapping from monthly earnings to full-time equivalent wages. Specifically, we regress the wage on a fifth-order polynomial in monthly earnings and dummies for two-digit industry, interacting all these variables with gender. We then plug in monthly earnings, industry, and gender into the model to derive predicted wages for workers for whom we only observe monthly earnings.

Table A1 shows summary statistics for directly observed SWS-wages, imputed SWS-wages, and wages imputed using earnings, for the full sample as well as for high- and low-skilled employees. High- and low-skilled refers to above/below mean level of educational attainment by cohort of birth. The higher monthly earnings of workers with SWS wages likely reflects the oversampling of workers in large firms in the SWS. The distributions of wages, monthly earnings, and wages imputed from monthly earnings are quite similar and consistent between groups with different educational attainment.

A.4 The final samples

The upper left panel of Figure A2 shows the evolution of the number of workers in our sample between 1986 and 2008. The solid line shows how the number of employed 30-35 year-old men with complete enlistment records changes over time. This is the group of men who could potentially be part of the final sample. Notably, the number of workers with a complete enlistment record falls in 1990 and increases in 1996. The reason is that the enlistment cohort of 1978 (men born in 1960) only consists of about 15,000 men compared to around 50,000 for the adjacent years (with the exception of 1979 where the enlistment records have data for 40,000 men). The Swedish War Archive has not been able to explain the reason behind the missing data. Since men who were born in 1960 enter our sample in 1990 (when they turn 30) and leave it in 1996 (when they turn 36), the size of our sample falls in 1990 and increases in 1996.

The three different dashed lines show the effect of our three main sample restrictions. First, we restrict the sample to men in private firms, thereby excluding about 20 percent of the sample. The second dashed line shows the number of men (with a complete enlistment record) who worked in private sector firms with at least 10 employees. This share of workers increases during our study period, from 50 to 60 percent, reflecting a lower employment share in small firms. The final dashed lines shows that adding the restriction that at least two workers be observed at each firm has a very small effect on the share observed workers.

The middle and lower panel of Figure A2 shows the mean values and variances for the different samples. The average skills of employed men increases by about 0.05 standard deviations during the first half of the 1990's, probably because low-skilled men had a harder time finding jobs during and after the crisis of 1991-1993 (see Appendix E). The middle panel

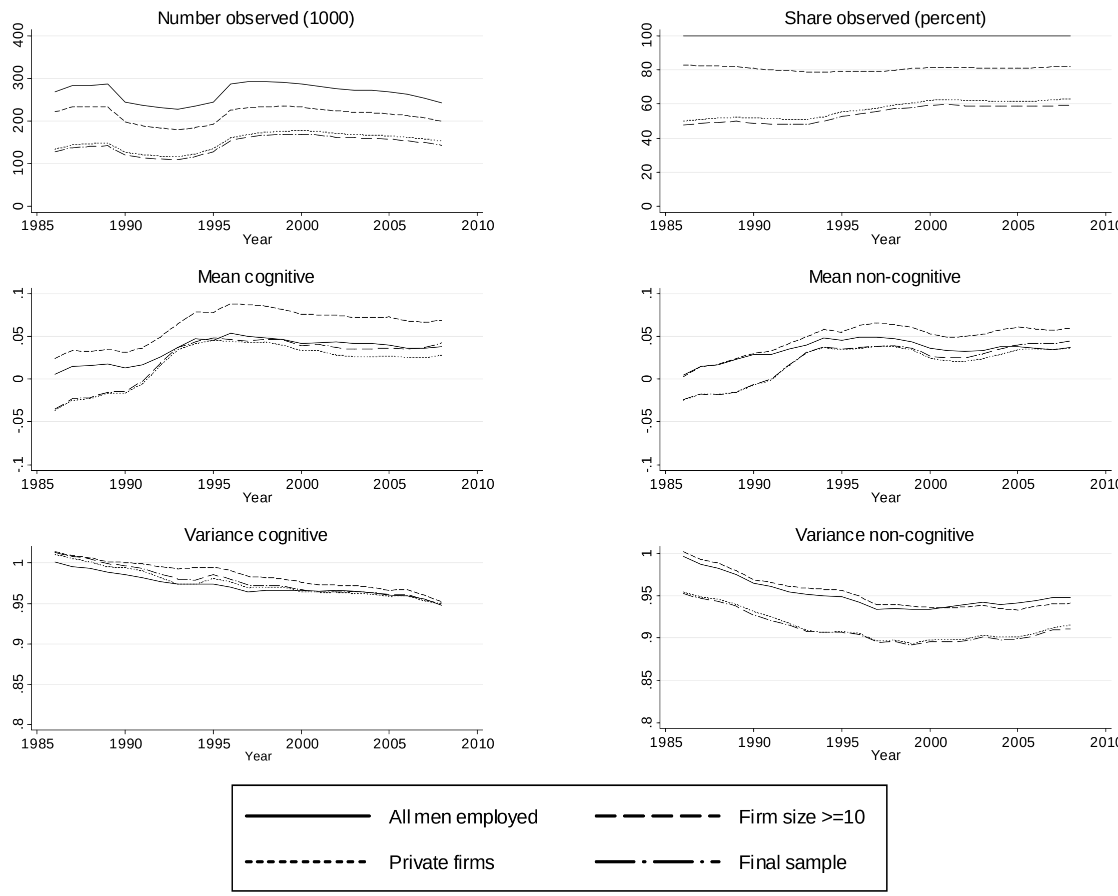
Table A1. Summary statistics for different types of imputation of wages (men 30-35)

				Wages and labor earnings for different samples						
		Observable earnings		All			High-skilled		Low-skilled	
Method	*N*	Wages	Earnings	Mean wages	Mean earnings	Predicted	Mean wages	Mean earnings	Mean wages	Mean earnings
Directly observed	1,786,721	10.10	10.12	10.09	10.11	10.10	10.20	10.23	10.00	10.03
		(0.28)	(0.30)	(0.29)	(0.30)	(0.26)	(0.31)	(0.32)	(0.24)	(0.25)
Imputed (within firm)	854,779	10.03	10.06	10.01	10.06	10.04	10.13	10.19	9.95	9.98
		(0.28)	(0.32)	(0.28)	(0.32)	(0.25)	(0.32)	(0.35)	(0.23)	(0.27)
Imputed (earnings)	3,391,926	10.00	9.97	10.00	9.97		10.09	10.08	9.94	9.90
		(0.24)	(0.31)	(0.24)	(0.31)		(0.28)	(0.35)	(0.20)	(0.26)

Summary statistics for observed directly wages from SWS, wages imputed with firm using SWS, and wages imputed using earnings from tax records. High- and low-skilled employees refers to employees above and below mean educational attainment in their respective cohort of birth. See text for details.

also shows that the trend toward higher average skills is present in all four samples and not an artefact of restricting the main sample to private firms with at least 10 employees. The lower panel shows that the sample variance fell throughout our study period, from slightly above 1 to about 0.95 for cognitive skill, and from 0.95 to 0.90 for non-cognitive skill. The reason is again selection into employment, not selection into different types of firms conditional on being employed, and the most likely explanation is that men from the low end of the skill distribution have found it harder to find employment.

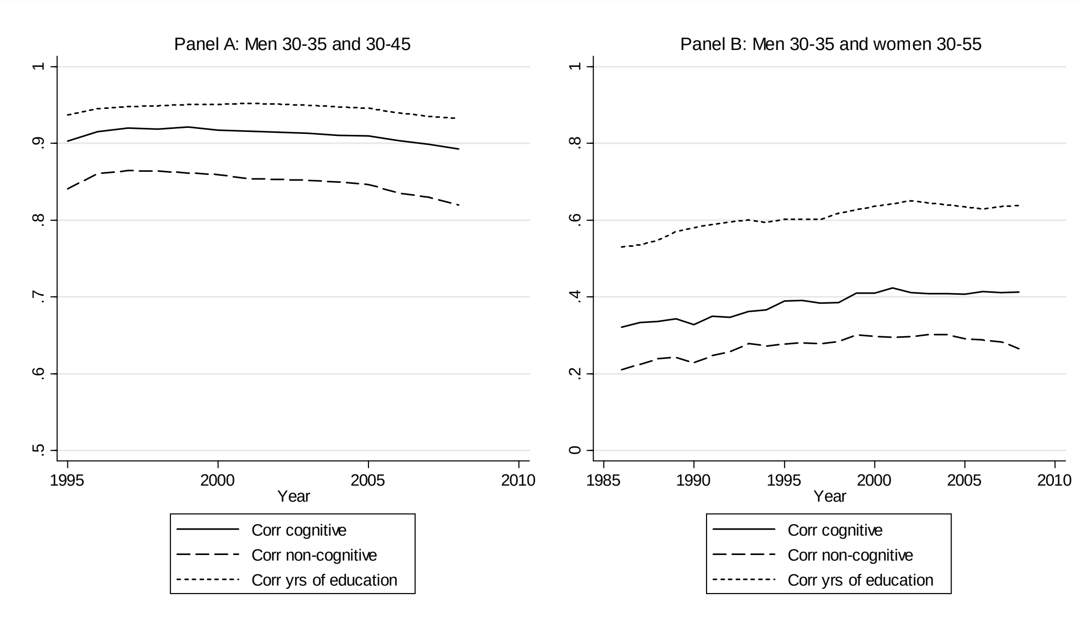
Figure A2. Sample descriptives and selection



Note: Sample size and skill moments from different sample restrictions. The sample "all men employed" includes all employed men with a complete draft record; the sample "private firms" includes the men in "all men" employed in a private firms; the sample "Firm size>=10" includes the men in "private firms" employed in firms with at least 10 employees; the "Final sample" includes all men with enlistment records in the sample "Firm size>=10".

Since the main analysis is based on 30-35 year old men, it is important to know the extent to which this sub-sample of employees is representative of the full workforce. In Figure A3, we therefore plot the correlations between firm level average skills based on different samples. For the period 1995 to 2008, Panel A depicts the correlations for average skills among 30-35 and 30-45 year old men. The correlations are very high, although the slight decline indicates that our sample grows slightly less representative over time. On the other hand, Panel B shows that the correlation between skills based on 30-35 year old men and the imputed skills for 30-35 year old women increases slightly over time.

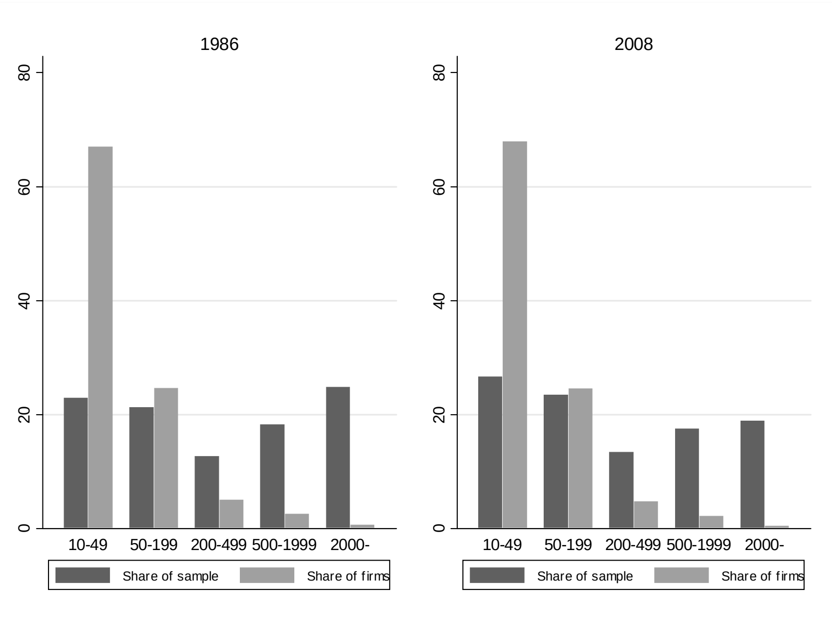
Figure A3. Correlations in firm-level average skills



Note: Correlation between firm-level average skills for men age 30-35 and men age 30-45 (Panel A). Correlation between firm-level average skills for men age 30-35 and women age 30-35 (Panel B).

Figure A4 shows the share of the main sample (men between 30 and 35 who work in firms with at least 10 employees) employed in firms of different size, measured as the number of employees. As shown in the figure, the share of workers employed in relatively small firms has increased while the share employed in large firms has decreased.

Figure A4. Share workers by firm size



Note: The figure shows the share of the sample (men aged 30-35) employed in firms of different size (total number of employees) in 1986 and 2008.

Appendix B: Measuring Sorting

B.1 Sample size corrections

The fact that we do not observe all workers in all firms implies that we need to adjust the variance decomposition. First, we show how we get from the unadjusted variance decomposition in (1) to the adjusted variance. When we have a sample of n_j workers from firm j with N_j workers in total, then an unbiased estimator of the within-firm variance of firm j is

$$\left(\frac{N_j - 1}{N_j}\right)\left(\frac{1}{n_j - 1}\right)\sum_i (C_{ij} - C_j)^2$$

For every firm in the sample, we know N_j (the number of employees) and n_j (the number of employees for which we observe skill).[2] In order to estimate the true between-firm variance, we need to tease out the share of the between-firm variance which is due to measurement error in the mean skill at the firm level. This measurement error variance amounts to

$$\frac{N-n}{Nn}S^2 = \frac{N_j - n_j}{N_j n_j}\left(\frac{1}{n_j - 1}\right)\sum_i (C_{ij} - C_j)^2$$

Using this expression and dividing each term by $n = \sum_j n_j$ (total number of observations in the sample) gives the decomposed variances

$$\underbrace{\frac{1}{n}\sum_j n_j \left(\frac{N_j - 1}{N_j}\right)\left(\frac{1}{n_j - 1}\right)\sum_i (C_{ij} - C_j)^2}_{\text{within-firm variance}} \tag{B1}$$
$$+\underbrace{\frac{1}{n}\sum_j n_j \left[(C_j - \overline{C})^2 - \frac{N_j - n_j}{N_j n_j}\left(\frac{1}{n_j - 1}\right)\sum_i (C_{ij} - C_j)^2\right]}_{\text{between-firm variance}}.$$

We now turn to the further decomposition of the between-firm variance. By analogy of the between-firm component, the between-industry variance VAR_{BI} is

$$\frac{1}{n}\sum_k n_k \left[(C_k - \overline{C})^2 - \frac{N_k - n_k}{N_k n_k}\left(\frac{1}{n_k - 1}\right)\sum_i (C_{ijk} - C_k)^2\right].$$

The between-firm variance within industries VAR_{BFWI} is just the difference between the between-firm and the between-industry variance, i.e.,

$$VAR_{BFWI} = VAR_{BF} - VAR_{BI}.$$

[2] In principle, the n_j workers whose skills we observe need to be a random sample of all the N_j workers in the firm for us to make an inference about the within-firm variance of firm j. This is not the case for us, since we focus on men between the age of 30 and 35 for the most part.

B.1.1 Correcting the between-firm return to skill

As described above, the fact that we only only observe a subet of all workers in each firm gives rise to measurement error in the measurement error in the firm-mean of skill. This measurement error in turn biases the estimated between-firm gradient between wages and skill in regression (3) of the paper. Assuming this measurement error is classical, we derive a correction for this error. Let the observed average (composite) skill level in firm j at time t be denoted by

$$s_{jt} = s_{jt}^{*} + e_{jt}$$

where s_{jt}^{*} is the true skill level and e_{jt} is a measurement error due to the fact that the skill level of all workers are not observed. Further, let β_{bt} denote the true firm-level skill gradient and β_{wt} the true within-firm return to skill. Then the estimated between-firm gradient is given by

$$\widehat{\beta}_{bt} = \frac{\beta_{bt} Var\left(s_{jt}^{*}\right) + \beta_{wt} Var\left(e_{jt}\right)}{Var\left(s_{jt}\right)}.$$

Using the sample-size adjustments from above, we get $Var\left(s_{jt}\right)$, $Var\left(s_{jt}^{*}\right)$, and $Var\left(e_{jt}\right)$. Further, ignoring individual-level measurement error in skills for simplicity, $\widehat{\beta}_{wt}$ from regression (6) is a consistent estimate of β_{wt}.

B.2 Measurement error correction

We derive the measurement error correction for cognitive skill, but the procedure is exactly the same for non-cognitive skill. Suppose observed cognitive skill (C) is a function of true skill (C^{*}) and measurement error (ε), so that

$$C_i = C_i^{*} + \varepsilon_{C,i}.$$

We assume that the measurement error is orthogonal to true skill and that both true skill and the error term are normally distributed. The total error variance equals

$$\frac{1}{n}\sum_j \sum_i \left(\varepsilon_{C,ij} - \overline{\varepsilon}\right)^2.$$

As for the skill measures, the error variance can be decomposed into between- and within-firm components. Let VI_{WF} denote the within-firm error variance and VI_{BF} the between-firm error variance. We get

$$VI_{WF,CS} = \frac{1}{n}\sum_j \sum_i \varepsilon_{C,ij}^{2} - \frac{1}{n}\sum_j \left(\varepsilon_{C,j} - \overline{\varepsilon}\right)^2$$

and

$$VI_{BF,CS} = \frac{1}{n}\sum_j \left(\varepsilon_{C,j} - \overline{\varepsilon}\right)^2.$$

Since the expected covariance between true skill and the measurement error is zero, VI_{WF} and VI_{BF} equal the expected inflation of the within- and between-firm variance in cognitive skill which is due to measurement error. To quantify the effect of the measurement error, we do a simulation where $\varepsilon_{C,ij}$ is drawn randomly for each individual from the distribution $N\left(0, \sigma^2_{\varepsilon_C}\right)$. Using the simulated data, we then calculate VI_{WF} and VI_{BF}. We use the estimated measurement error variances based on twin data reported by Lindqvist and Vestman (2011) in these simulations. Lindqvist and Vestman find that the error term variance is substantially higher for non-cognitive$\left(\sigma^2_{\varepsilon_N} = 0.297\right)$ than for cognitive skill $\left(\sigma^2_{\varepsilon_C} = 0.1325\right)$. Subtracting the simulated inflated variances from the between- and within firm variances in (1) gives us an unbiased estimate of the variance in true skill. However, since our skill measures have no natural metric, the statement that "measurement error inflates the between- and within firm variances" is misleading. To get an estimate which is comparable to the standard decomposition (under the assumption of no measurement error in skill), we normalize the measurement-adjusted variances so that the total adjusted sample variance equals the total unadjusted sample variance. Thus, only the relative size of the between- and within-firm components change.

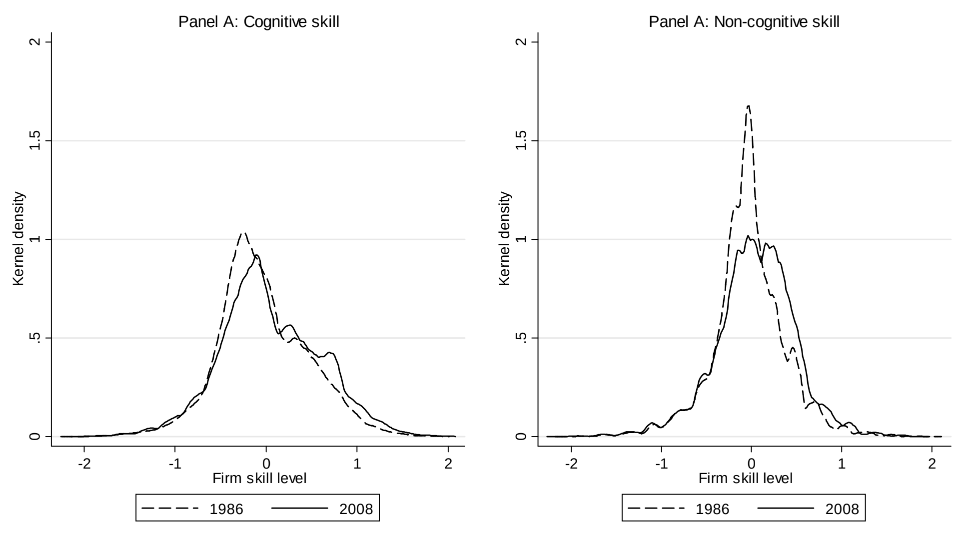
The adjusted components are:

$$
\begin{aligned}
BF\_VAR\_CS_{ADJ,t} &= \frac{BF\_VAR\_CS_{UNADJ,t} - VI_{BF,CS}}{1 - 0.1325/TOT\_VAR\_CS_{UNADJ,t}} \\
WF\_VAR\_CS_{ADJ,t} &= \frac{WF\_VAR\_CS_{UNADJ,t} - VI_{WF,CS}}{1 - 0.1325/TOT\_VAR\_CS_{UNADJ,t}} \\
BF\_VAR\_NCS_{ADJ,t} &= \frac{BF\_VAR\_NCS_{UNADJ,t} - VI_{BF,NCS}}{1 - 0.297/TOT\_VAR\_NCS_{UNADJ,t}} \\
WF\_VAR\_NCS_{ADJ,t} &= \frac{BF\_VAR\_NCS_{UNADJ,t} - VI_{BF,NCS}}{1 - 0.297/TOT\_VAR\_NCS_{UNADJ,t}}
\end{aligned}
$$

Note that the error term corrections should be adjusted for the same firm-sample-size multiplicator as used when deriving the unadjusted between- and within-firm variances, even though the these terms are not included in the expressions above. Since we randomize the error terms, the results come out slightly different in different simulations. Therefore, we use the median adjusted between- and within-firm variances based on 100.

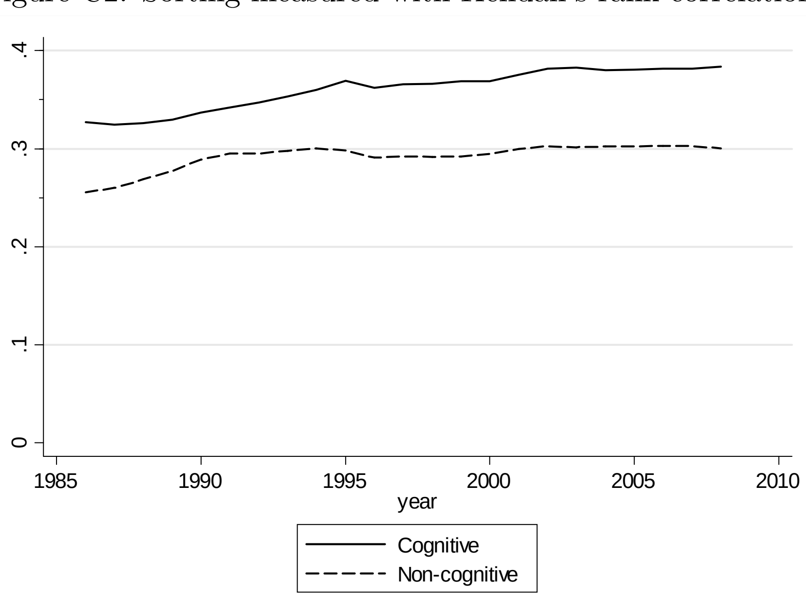
Appendix C: Additional results

Figure C1. Distribution of firm average skill



Note: Kernel density plots for average firm level skills, weighted by the number of observed workers at each firm. The sample includes 30-35 year-old men employed at firms with at least 10 employees. Bandwidths are .0618 for cognitive skills and .0412 for non-cognitive skills.

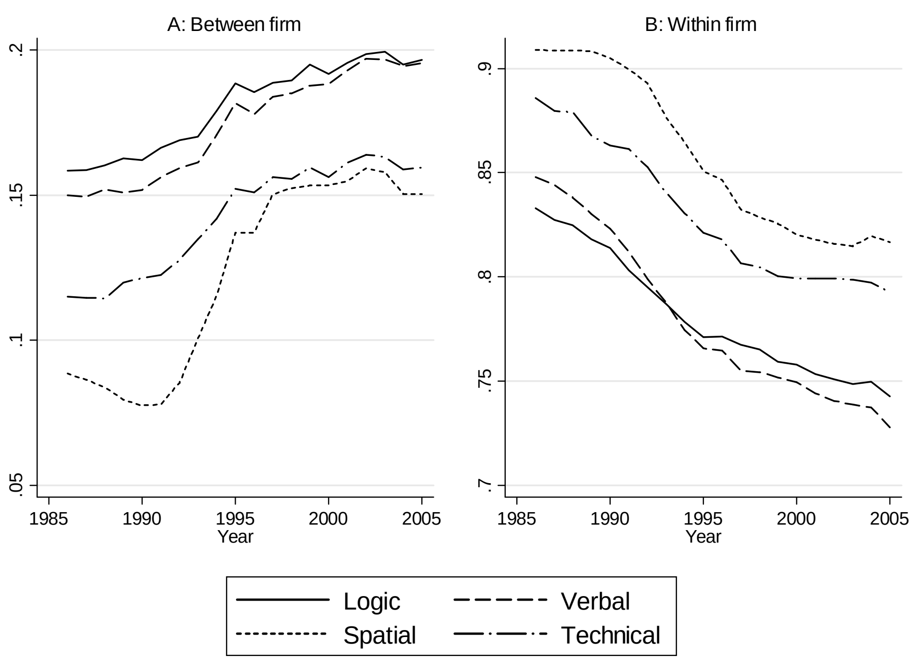
Figure C2. Sorting measured with Kendall's rank correlation



Note: The figure reports Kendall's rank correlation (tau-b) between each firm's rank in terms of average (cognitive or non-cognitive) skill, and rank of each worker's skill. The sample includes 30-35 year-old men employed at firms with at least 10 employees.

Figure C3 displays trends in sorting for sub-measures of cognitive skills. The measures for logical, verbal, spatial, and technical skills are standardized by enlistment year. For more details on these sub-measures, see Mood et al (2012).

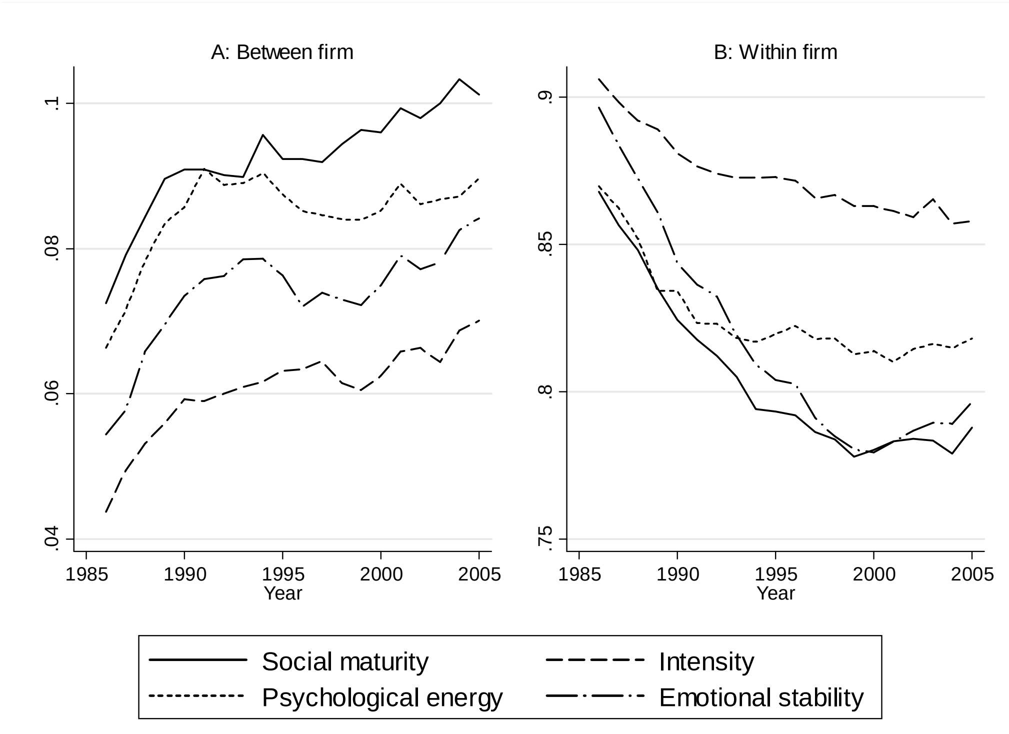
Figure C3. Sorting by cognitive sub-measures



Note: The sample includes 30-35 year-old men employed at private firms with at least 10 employees. Variance components are corrected for sample size according to the procedure in Appendix B1.

Figure C4 displays trends in sorting for sub-measures of non-cognitive skills. The measures for social maturity, intensity, psychological energy, and emotional stability are standardized by enlistment year. For more details on these sub-measures, see Mood et al (2012).

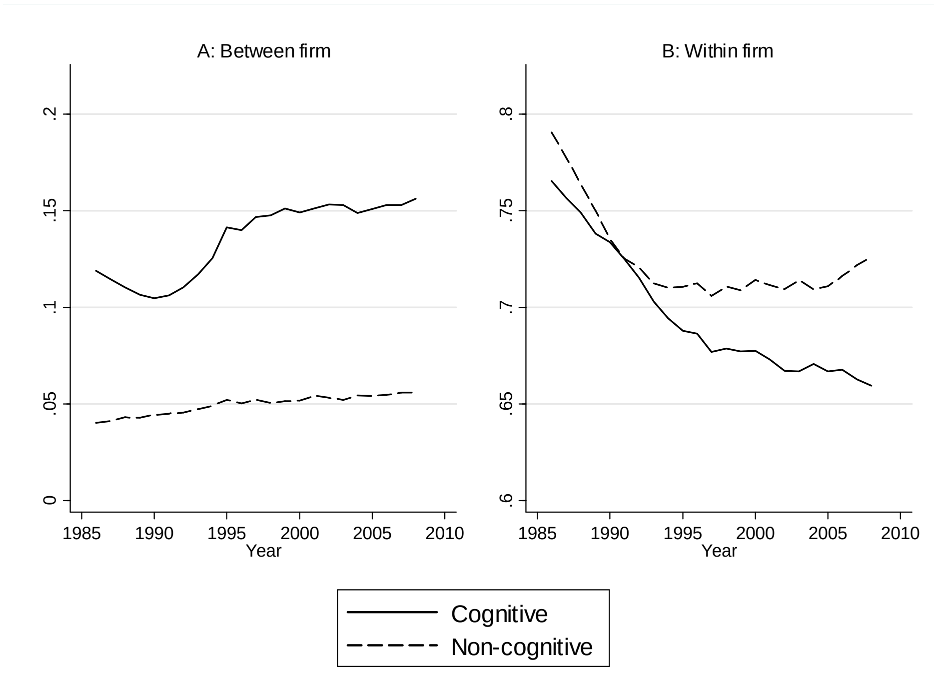
Figure C4. Sorting by non-cognitive sub-measures



Note: The sample includes 30-35 year-old men employed at private firms with at least 10 employees. Variance components are corrected for sample size according to the procedure in Appendix B1.

Figure C5 displays trends in sorting for residualized cognitive and non-cognitive skills. Cognitive skills are residualized by running a linear regression on non-cognitive skills and vice versa.

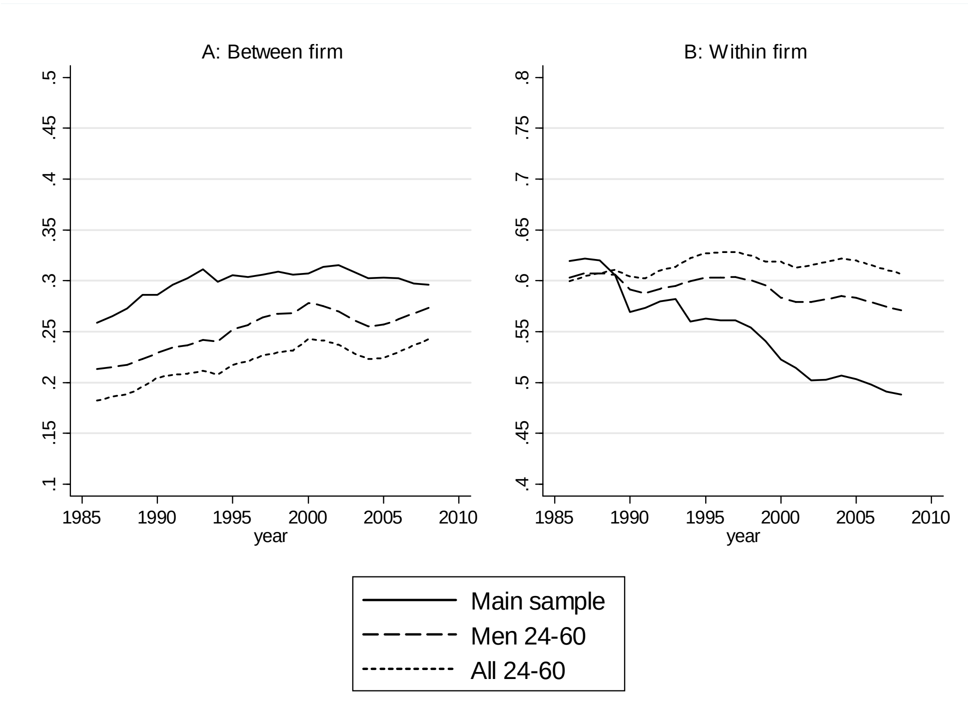
Figure C5. Sorting by residualized skills



Note: The sample includes 30-35 year-old men employed at private firms with at least 10 employees. Variance components are corrected for sample size according to the procedure in Appendix B1.

Figure C6 displays trends in sorting for standardized years of education for the main sample, for men age 24-60, and for all employees age 24-60.

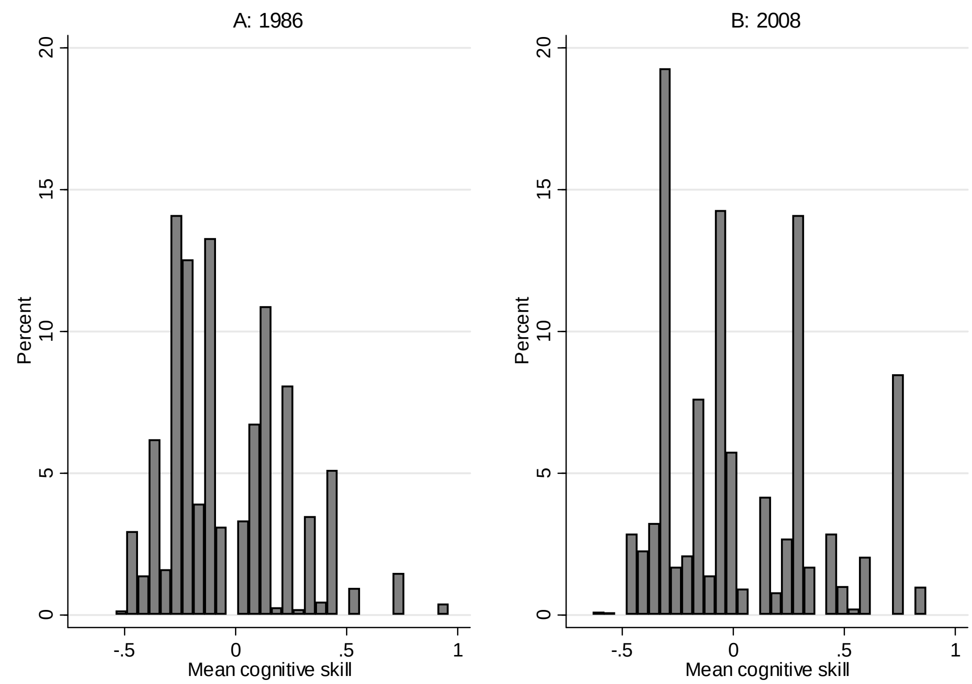
Figure C6. Sorting by educational attainment for different samples



Note: Employees at private firms with at least 10 employees. Variance components are corrected for sample size according to the procedure in Appendix B1.

Figure C7 shows the distribution of industry means in cognitive skill for 1986 and 2008. Each bin is weighted by its employment share.

Figure C7. Histogram of industry-level mean cognitive skill



Note: Each industry is weighted by its employment share. Bin width is 0.05.

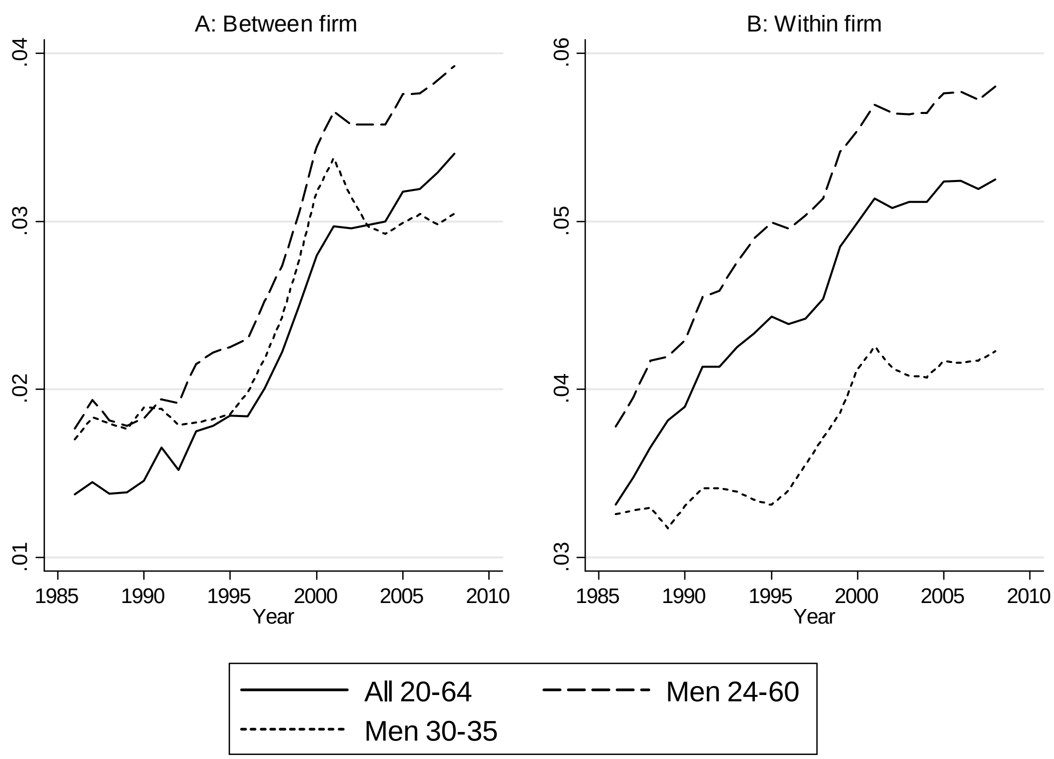
Figure C8 displays the share of employees in the ICT sector (NACE 32 and 72) for men and women respectively.

Figure C8. Share workers in the ICT sector

Note: Share workers in the IT (NACE 72) and telecom (32) industries.

Figure C9 displays trends in between and within firm wage variance for the main sample of 30-35 year old men, men age 24-60, and all employees age 24-60.

Figure C9. Evolution of the wage variance for various groups



Note: Employees at private firms with at least 10 employees. Variance components are corrected for sample size according to the procedure in Appendix B1.

C.1 Simulating random sorting

Table C1 contrasts the between- and within-firm variances in the sample with the corresponding simulated variances. The simulations are based on the assumption that workers are randomly assigned to firms. Table C1 shows the 1st, 50th and 99th percentiles and standard deviation of the simulated variances from 1,000 draws. Table C2 shows the share of employers who work in firms with average skills below or above a certain level. This table thus relies on the same data as Figure C1.

C.2 Decomposing the within-firm variance

In order to assess which factor is most important, we decompose the change in the within-firm variance in three parts

$$\underbrace{\sum_k \alpha_{k,86}\Delta\sigma_k^2}_{\text{Change in WF variance}} + \underbrace{\sum_k \Delta\alpha_k \sigma_{k,86}^2}_{\text{Change in shares}} + \underbrace{\sum_k \Delta\alpha_k \Delta\sigma_k^2}_{\text{Interaction term}}, \tag{C1}$$

where $\alpha_{k,t} = n_{k,t}/n_t$ denotes the share of the sample employed in industry k in year t, $\sigma_{k,t}^2$ is the average within-firm variance (weighted by firm size) in industry k in year t, $\Delta\sigma_k^2 = \sigma_{k,08}^2 - \sigma_{k,86}^2$ and $\Delta\alpha_k = \alpha_{k,08} - \alpha_{k,86}$. The first term in (C1) is the change in within-firm variance holding each industry's share of total employment fixed at its 1986 level. The second term is the change in within-firm variance due to changes in the relative size of industries. The third term is the covariance between changes in the relative size of industries and changes in within-firm variance.

Table C3 shows decomposition (C1) for each of our skill measures. The fall in the within-firm variance is mostly due to a fall in the within-firm variance for fixed industry shares. Industries with a low initial within-firm variance of cognitive skill did increase in size relative to other industries, but this effect can only explain a small share of the overall trend.

Table C1. Actual and simulated variance components

	Sample	P1	P50	P99
Cognitive skills 1986				
Within-firm	0.840	0.996	0.999	1.003
Between-firm	0.173	0.011	0.013	0.018
Non-cognitive skills 1986				
Within-firm	0.872	0.935	0.939	0.942
Between-firm	0.081	0.010	0.013	0.017
Cognitive skills 2008				
Within-firm	0.721	0.931	0.935	0.938
Between-firm	0.229	0.012	0.015	0.019
Non-cognitive skills 2008				
Within-firm	0.801	0.893	0.896	0.899
Between-firm	0.110	0.011	0.015	0.018

The leftmost column shows the variance components in the sample. The three rightmost columns shows the 1st, 50th and 99th percentile from 1,000 simulations assuming that workers are randomly assigned to firms.

Table C2. Distribution of firm-average skills

	Cognitive		Non-cognitive	
	1986	2008	1986	2008
Mean	-0.035	0.042	-0.024	0.045
Above 1.25 std	0.008	0.016	0.006	0.006
Above 1 std	0.023	0.048	0.015	0.017
Above .75 std	0.067	0.106	0.031	0.047
Above .5 std	0.155	0.215	0.083	0.125
Below -.5 std	0.137	0.145	0.093	0.101
Below -0.75 std	0.055	0.065	0.041	0.044
Below -1 std	0.023	0.029	0.016	0.019
Below -1.25 std	0.001	0.011	0.007	0.008

The table shows the share of firms with average skills below or above certain cutoffs. The sample includes all firms with at least 10 employees and two workers with observed skills.

Table C3. Decomposing the change in WF variance

	Cognitive	Non-cognitive
Change within-firm variance	-0.098	-0.066
Change in industry size	-0.019	0.025
Covariance	0.017	-0.007

Components in the decomposition of the change of the within-firm variance, described in Appendix C2.

Appendix D: Estimating the AKM model

We estimate AKM model using a rolling nine-year window with "middle years" from 1989 to 2005, thus using data from 1985 to 2009 and 17 different estimation samples in total. We restrict the estimation sample to men in the private sector who were between 24 and 60 years in the "middle" year for each estimation, implying workers are between 20 and 64 in each estimation sample. We include firms with at least 5 employees (including women and men outside of our age restriction for the estimation sample). The largest connected set varies between 98.9% and 99.4% of all workers in the estimation sample. For each estimation sample, we estimate the following parsimonious version of the AKM model:

$$\widetilde{w}_{it} = \alpha_i + \psi_{J(it,t)} + \mathbf{I}\boldsymbol{\delta} + r_{it}$$

where $\widetilde{w}_{it}$ is the residualized wage of worker i in year t, α_i is the worker effect, $\psi_{J(it,t)}$ is the firm effect worker i is employed by in year t, $\mathbf{I}$ is a vector of year-dummies and r_{it} is the error term.

A few comments on this model is in order. First, instead of controlling for age, we residualize wages with respect to age (using a dummy for each age) in each year. The reason is the high collinearity between age and cohort implies the estimation of the wage-age profiles is unstable across estimation samples. For the years where we estimated a flat wage-age profile, we see big differences between the average worker effects for different cohorts, with older cohorts having higher worker effects. In the cases where we estimate a steep wage-age profile, the between-cohort differences in worker effects are much smaller. The upshot is that, if we control for age in the estimating equation, the standard deviation of worker effects varies substantially across years, in a way not in congruence with actual changes in the distribution of wages. Residualizing wages with respect to age prior to estimation takes care of this problem. Second, we refrain from controlling for education. The reason is partly that education changes little for the individuals in our sample over time, implying it is strongly collinear with the worker effects, and so including it makes the estimation more demanding. But another reason is that we want the worker effects to come as close as possible to capture worker skills.

Before decomposing the worker effects, we standardize them by cohort and estimation year, thus making sure the standard deviation is by construction unchanged over time. We then decompose the variance of worker effects into between- and within-firm components using the exact same procedure as for our enlistment skill measures.

Figure D1-D3 shows some results from the AKM model not shown in the paper. Figure D1 shows the results from regressing worker effects on the corresponding workers' cognitive and non-cognitive skills. Figure D2 shows the standard deviation of unstandardized worker and firm effects increases over time, reflecting the general increase in wage inequality. Figure D3 shows the correlation between worker and firm effects go from slightly negative to 0.10-0.15 (depending on the sample) at the end of our study period.

Figure D1. Loading of cognitive and non-cognitive skills

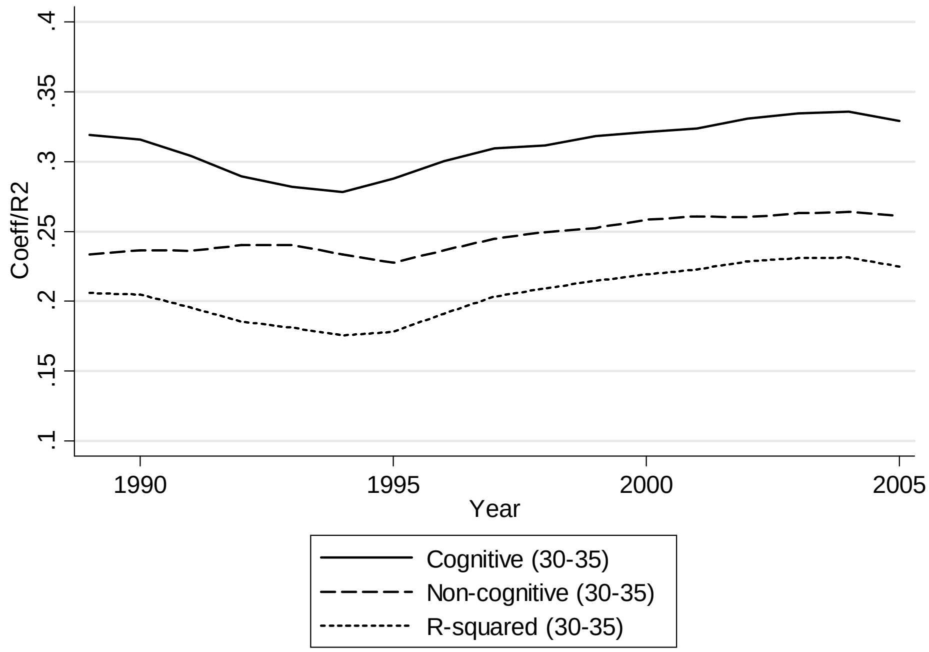


Figure D2. Standard deviation of unstandardized person- and firm fixed effects

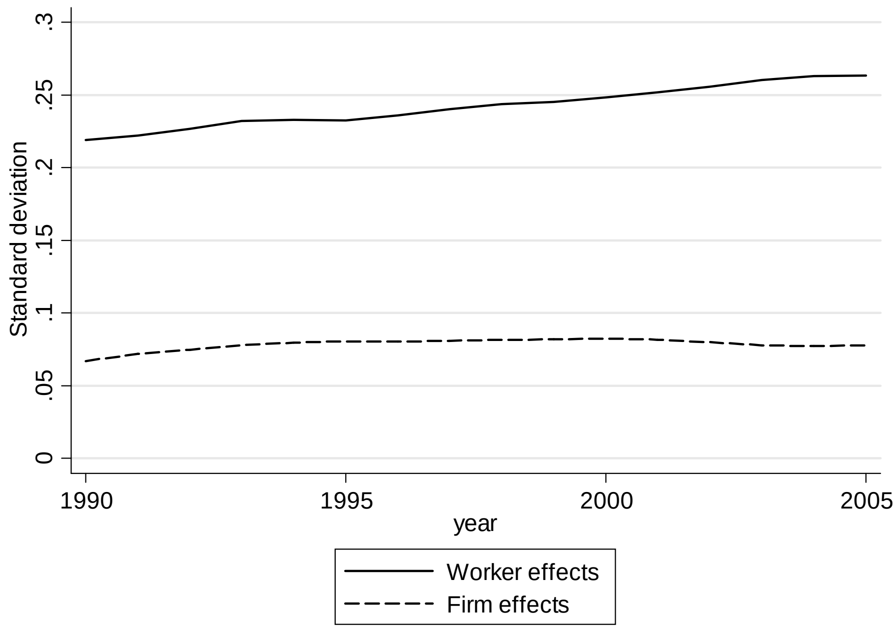
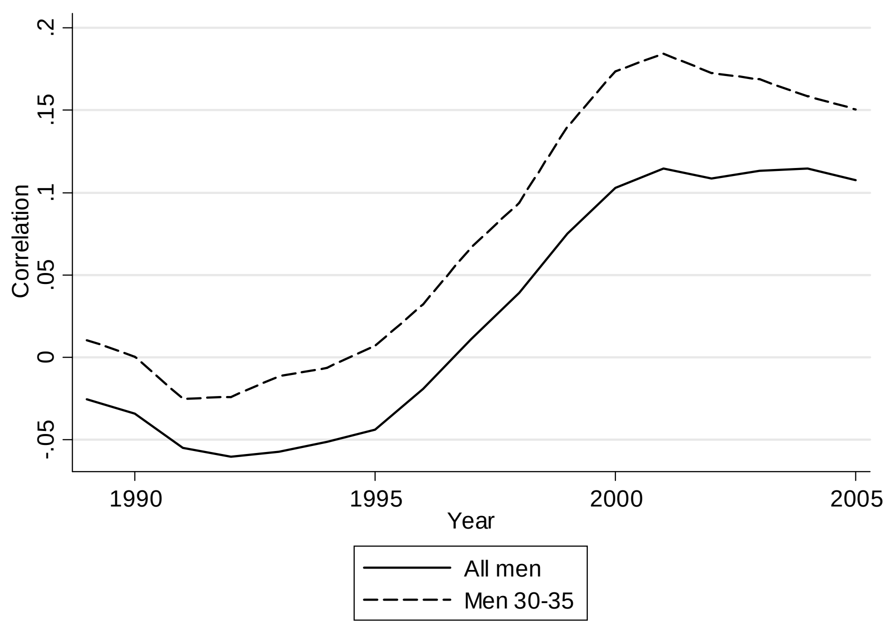


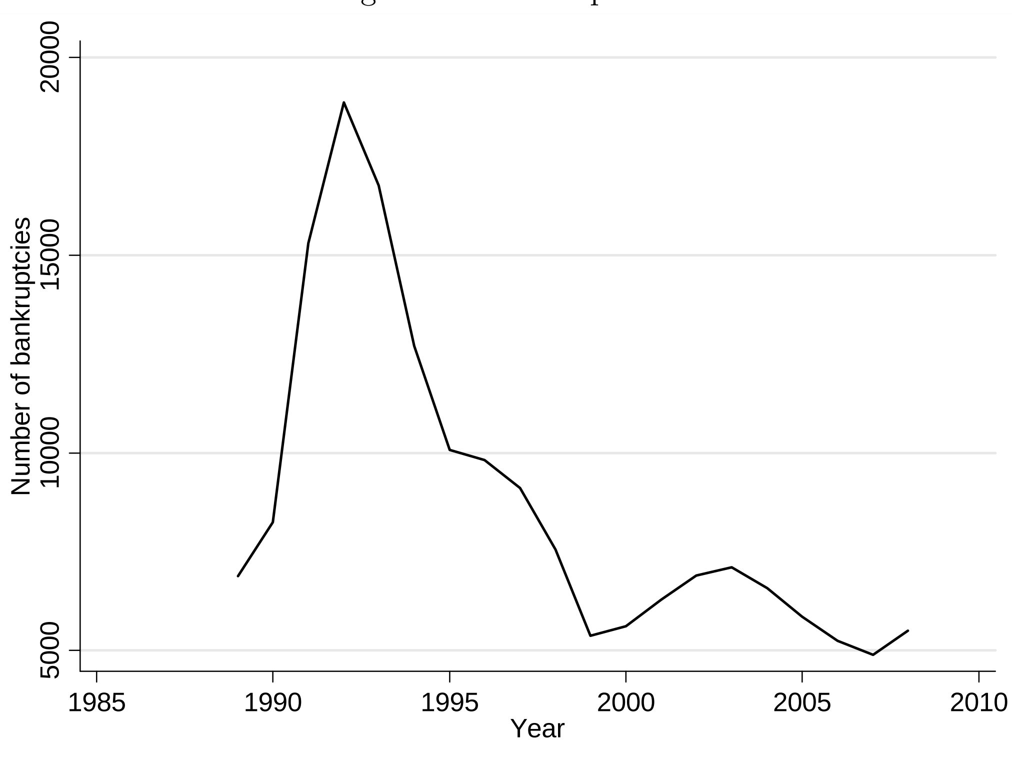
Figure D3. Correlation btw. worker and firm effects



Appendix E: The Swedish economy 1986-2008

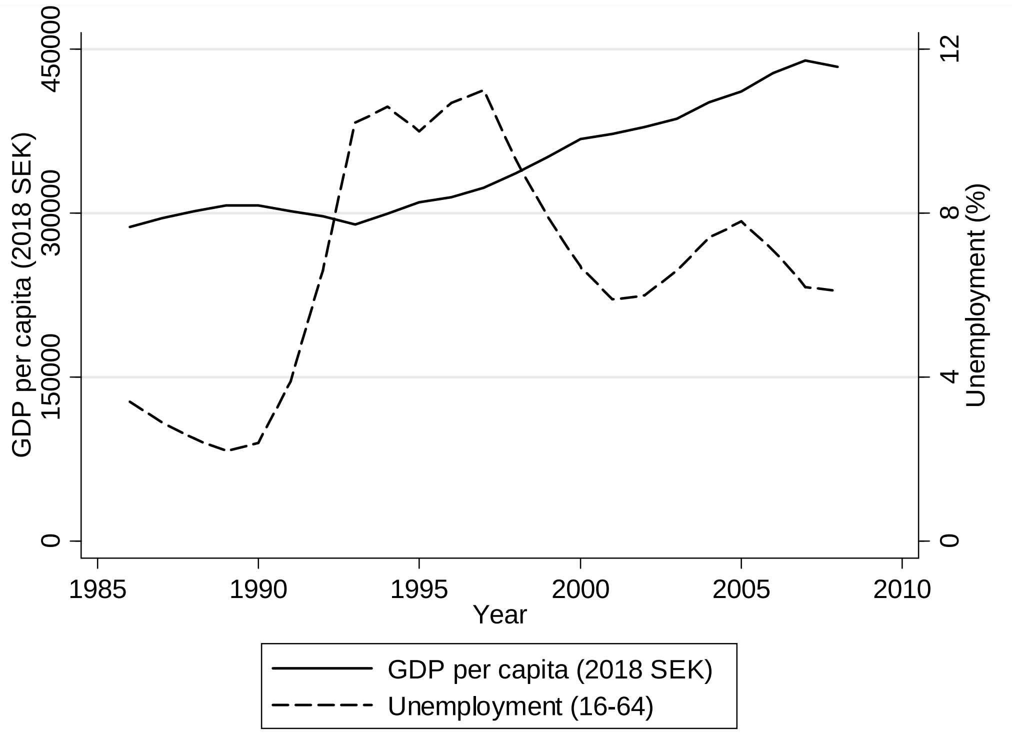
This section provides a short summary of the macroeconomic development in Sweden over the course of our study period (1986-2008). The main macroeconomic event during this period was the Swedish banking crisis of the early 1990's. The crisis had several causes (Englund 1999): deregulation of financial markets in the mid 1980's combined with expansive macroeconomic policies caused a boom in asset prices and a financial sector with high leverage. In the early 1990's, a tax reform combined with a shift in monetary policy caused a sharp increase in after-tax interest rates. This, combined with unrest on European currency markets, lead to a fall in real estate prices which in turn caused credit losses among financial institutions in Sweden. The crisis in the financial system had a strongly negative impact on the real economy. The number of bakruptcies almost tripled between 1989 and 1992 (Figure E1). GDP per capita fell three years in a row (1991-1993) while the unemployment rate quadrupled between 1990 and 1993 (Figure E2). While unemployment fell during the latter part of the 1990's, it settled on a level more than twice as high as the pre-crisis level, implying a structural shift in the Swedish labor market. As we show in Figure A2, the increase in unemployment coincides with an increase in the average skills of employed workers, suggesting that low-skilled workers lost their jobs during the crisis.

Figure E1. Bankruptcies



Note: The figure shows the number of firms that filed for bankraptcy in Sweden in a given year. Source: UC via Ekonomifakta.

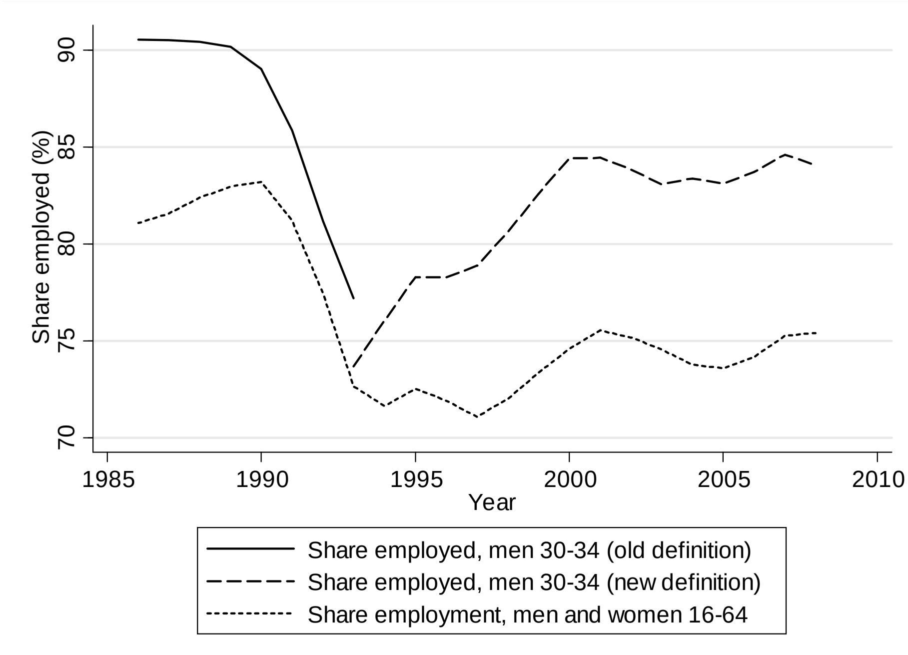
Figure E2. GDP per capita and unemployment



Sources: Statistics Sweden (GDP per capita) and AKU via Ekonomifakta (unemployment). AKU is a survey-based measurement of the Swedish labor market.

Since we focus on men between 30 and 35, a relevant question is whether this group was affected by the crisis in a different way compared to the population at large. Figure E3 shows the evolution of employment for 30-34 year-old men and the whole working-age population. The employment pattern for 30-34 year-old men is the mirror image of the evolution of unemployment: employment fell sharply in the years of the crisis, bounced back, but eventually settled on a lower level than the pre-crisis years. The working age population had the same drop in emplyment levels during the crisis, but employment did not increase as much post-crisis as for men between 30 and 34. An important explanation for this discrepancy is the expansion of higher education in the post-crisis period (in our sample, the average years of education increase by two years in between 1986 and 2008).

Figure E3. Share employed

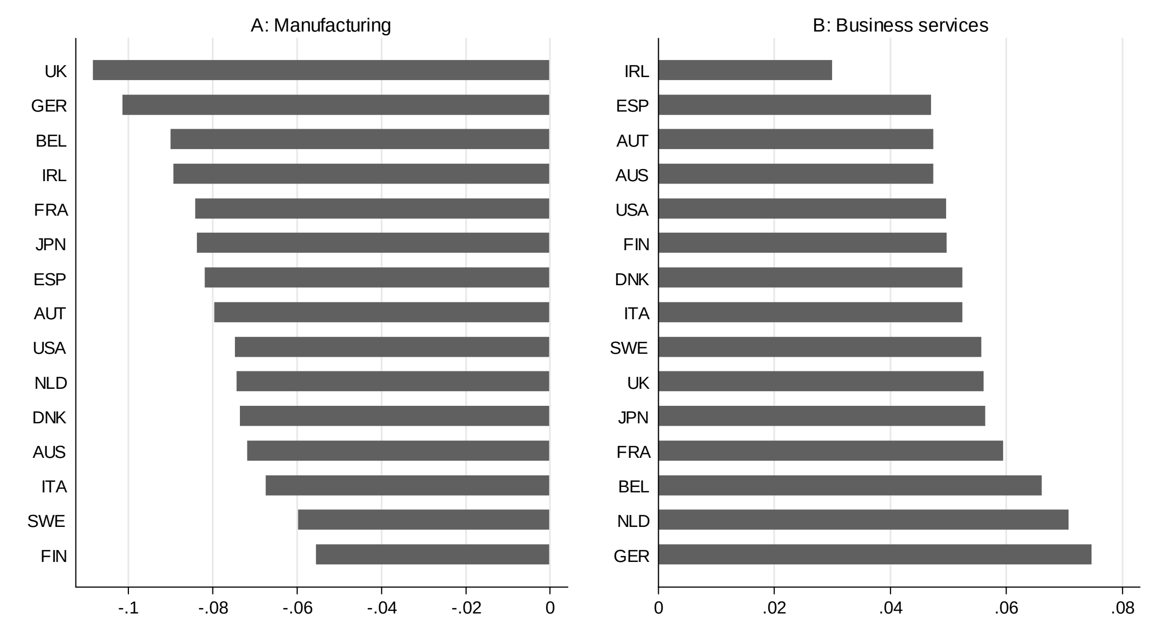


Sources: Statistics Sweden's RAMS data base and population registers (share employed among men 30-34). AKU via Ekonomifakta and population registers from Statistics Sweden (share employed men among men and women 16-64). RAMS is a register based on administrative data while AKU is a survey-based measurement of the Swedish labor market. The definition of "employment" changed in RAMS in 1993 and we therefore show the value for both the old and new definitions for 1993.

Appendix F

In this appendix, we compare the development of employment patterns in Sweden and other industrialized countries. Using the 2009 release of the EU KLEMS database, we derive employment shares for major industrial sectors by dividing each sector's employment by the total number of employees.[3] Changes in employment shares between 1986 and 2006 are shown in Figure F1 for manufacturing and business services. For these two sectors, the development in Sweden is in line with the development in other economies. We also correlate changes in employment shares for 10 broad sectors (AB-K) between Sweden and the other 14 countries. The correlation coefficient is 0.94, again suggesting that changes in employment patterns are similar in Sweden and other advanced economies.

Figure F1. Changes in employment shares across sectors

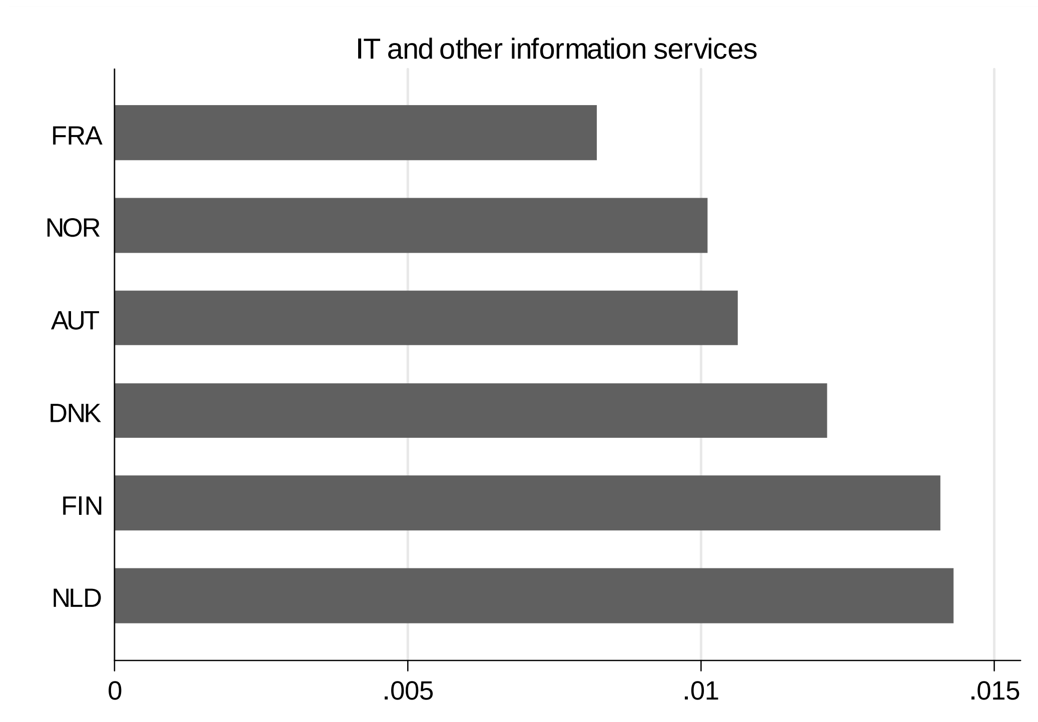


Note: Changes in employment shares between 1986 and 2006 for manufacturing (industry D) and business services (industries 71 to 74). Countries included are Austria, Australia, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Japan, the Netherlands, Spain, Sweden, the UK, and the US. Source: EU-KLEMS, release 2009.

[3] The 2009 release is the version of EU KLEMS with the largest overlap with our main period of analysis. This version of EU KLEMS contains information on employment by major industrial sector up until 2007 but coverage is limited for the last year. Countries included in the analysis are Austria, Australia, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Japan, the Netherlands, Spain, Sweden, the UK, and the US. EU KLEMS is accessed at http://www.euklems.net/.

Unfortunately, EU-KLEMS does not contain specific information on IT-related services and we instead turn to the 2012 release of OECDs STAN database.[4] Over the relevant time-period, information on IT-related services are available only for six countries and Sweden is not included. Moreover, the industry classification does not map perfectly with the NACE codes we have in our Swedish data. Still, the fact that Figure F2 show increasing the employment shares for IT-related services in all observed countries does suggest that employment patterns in Sweden are at least qualitatively similar to comparable countries.

Figure F2. Changes in the employment share of IT



Note: Changes in employment shares between 1986 and 2008 for IT and other information services manufacturing (industries 62 and 63). Countries included are Austria, Denmark, Finland, France, the Netherlands, and Norway. Source: OECD STAN, release 2012.

[4] We use the 2012 release of STAN indicators (ISIC rev. 4, SNA93) which is accessed at https://stats.oecd.org/.

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