Firms and Skills

The Evolution of Worker Sorting

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ABSTRACT

We document a significant increase in the sorting of workers by cognitive and noncognitive skills across Swedish firms during 1986–2008. During this period, worker skill differences between firms increased, while within-firm skill differences fell. A significant fraction of the increase in the between-firm differences in cognitive skill is due to high-skilled workers moving into the information and communications technology (ICT) sector. Within-firm skill differences fell in all major industries, but particularly in the manufacturing sector. Combined with steeper firm-level skill gradients, the increase in sorting can account for 45 percent of the increase in between-firm wage dispersion during our period of study.

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I. Introduction

In this work, we use Swedish data to investigate how the sorting of workers to firms has changed over time. Our key result is that sorting by skill has increased, implying larger skill differences between firms and smaller skill differences within firms.

Our study is motivated on three different grounds. First, a theoretical literature has argued that technological change (Kremer 1993; Acemoglu 1999; Caselli 1999) and globalization (Feenstra and Hanson 1996; Kremer and Maskin 2006; Grossman and Rossi-Hansberg 2008) might increase skill differences among firms. Changes in the sorting of workers is thus one stylized fact against which these models can be tested. Second, the extent to which workers are sorted by skill could affect both economic and social outcomes. Overall wage inequality is increasing in the degree of sorting if worker skills are complements (for example, Sattinger 1975) or if fair-wage considerations compress wage differences between low- and high-skilled workers in the same firm (Akerlof and Yellen 1990; Bewley 1999). More generally, the extent of social interaction between different strata in society is lower if workplaces are internally homogeneous. Third, the increase in wage inequality observed in many countries since around 1980 appears to be largely driven by increasing wage differentials between, rather than within, firms.[1] A basic step in understanding this change in the structure of wages is to test whether increasing firm wage differentials are explained by larger between-firm differences in worker skills.

Assessing changes in sorting requires access to measures of worker skills that are comparable over time. Previous research on the evolution of worker sorting has either focused on occupations (Kramarz, Lollivier, and Pele 1996; Kremer and Maskin 1996; Dunne, Haltiwanger, and Troske 1997; Dunne et al. 2004, Card, Heining, and Kline 2013), education (Card, Heining, and Kline 2013), or, following Abowd, Kramarz, and Margolis (1999, henceforth AKM), used worker fixed effects from wage regressions that control for firm fixed effects (Iranzo, Schivardi, and Tosetti 2008; Card, Heining, and Kline 2013; Song et al. 2019).[2] With the exception of Iranzo, Schivardi, and Tosetti (2008), who study Italy, this literature finds increasing segregation of workers across firms. Yet each of these approaches faces potential problems. Changes in the occupational structure could reflect changes in technology rather than changes in the composition of workers' skills. Educational attainment may not be fully comparable over time; higher education has expanded in most countries, and students' choices between different fields of education change in response to the economic environment.

1. Evidence from Sweden (Nordström Skans, Edin, and Holmlund 2009), the United States (Dunne et al. 2004; Davis and Haltiwanger 1991; Barth et al. 2016; Song et al. 2019); the UK (Faggio, Salvanes, and Van Reenen 2010), West Germany (Card, Heining, and Kline 2013), and the Czeck Republic (Eriksson, Pytliková, and Warzynski 2013) point to an increasing importance of wage differentials between firms or plants. In contrast, Cardoso (1999) on Portugal 1983–1992 and Alvarez et al. (2018) on Brazil 1988–2012 find decreasing between-firm wage inequality.

2. Barth et al. (2016) consider worker segregation over time in the U.S. economy. Their measure of observable skill is the predicted value from a regression of log wages on education and experience. Since they allow the return to education and experience to vary by year, their skill measure is not time invariant at the level of the individual. In this sense, their concept of skill is different from ours. Hellerstein and Neumark (2008) consider sorting by educational attainment, but do not consider changes in sorting over time.

The worker effect in an AKM model is an imperfect measure of skill because it also reflects the return to skill and other worker characteristics.[3]

We study the evolution of sorting using data on workers' cognitive and noncognitive skills from the Swedish military enlistment. The enlistment skill measures are strong predictors of future labor markets outcomes (Lindqvist and Vestman 2011), comparable over time, and available for 28 cohorts of Swedish men. Because the enlistment evaluations were administered to Swedish men at the age of 18, the skill measures are not directly affected by the expansion of higher education or changes in labor market conditions. Matching the enlistment skill measures for each worker with information about their employer in a given year, we are able to quantify changes in sorting in the Swedish private sector between 1986 and 2008.

We document a substantial increase in sorting by cognitive and noncognitive skill, with workers becoming more similar within firms (falling within-firm variance of skills) and more dissimilar between firms (increasing between-firm variance). The size of the increase is nontrivial—for example, the between-firm share of the sample variance of cognitive skills increased from 17.1 percent to 24.1 percent, an increase of 41 percent. This increase in sorting is in particular due to an increase in the share of firms with highly skilled workforces. The trend towards increased sorting is robust to a wide range of tests regarding how we measure sorting, the sample used, adjustment for measurement error in skills, and using plants instead of firms as the unit of analysis. For comparison, we also investigate sorting by educational attainment and worker effects from an AKM model. We find increasing sorting for both measures, but the increase for worker effects takes place about a decade later than that for cognitive and noncognitive skills.

We next use information on firms' industry classification to get a sense of the broad patterns behind the increase in sorting. We show a flow of high-skilled workers into the information and communications technology (ICT) sector explains a large fraction of the increasing sorting by cognitive skill. The expansion of the ICT sector implied a more polarized distribution of cognitive skill across industries, with a few high-tech industries at the high end of the spectrum. We also show that the trend toward more internally homogeneous firms is a feature of all major industries, but particularly strong in the manufacturing sector.

In the last section of the paper, we investigate whether sorting can explain changes in the Swedish wage structure. As in many other countries, wage inequality rose in Sweden between 1986 and 2008 due in particular to larger between-firm wage differentials. We show about 45 percent of the increase in private sector between-firm wage inequality between 1986 and 2008 can be accounted for by the combination of increased sorting by skill and steeper between-firm skill gradients, with sorting being relatively more important.

We next present our approach for measuring sorting in Section II, the data in Section III, and the main results in Section IV. We discuss our further decompositions of the change in sorting in Section V and whether increasing sorting can account for changes in the wage structure in Section VI. Section VII concludes the paper. Online Appendixes A–F provide additional material.

3. A recent literature has pointed to identification problems in standard AKM models in the presence of search frictions and complementarities in the production function (for example, Gautier and Teulings 2006; Eeckhout and Kircher 2011; Lopes de Melo 2018; Hagedorn, Law, and Manovskii 2017; Bagger and Lentz 2018).

II. Data

In order to analyze ability sorting over time, we match information on cognitive and noncognitive skills from the Swedish military enlistment with employer–employee data. The first cohort for which we have enlistment data is men born in 1951, who were enlisted in 1969. Because it is possible to match individuals to firms in Sweden from 1986 and onwards, we can obtain a complete series of worker skill–firm matches at a given age for men at or below the age of 35. To obtain a sample of comparable individuals over time, we therefore restrict our main sample in each year to men between the ages of 30 and 35. We exclude men younger than 30 to avoid a sample selection effect due to the expansion of higher education over time. The total sample consists of essentially all male Swedish citizens born between 1951 and 1978.

We link employees to their employers using the RAMS database, which contains information on all workers employed in a firm at some point in time in each year. RAMS includes annual worker earnings by employer, the month employment started and ended, and firm-level information, such as type of ownership and industry.[4] For workers who had more than one employer during a given year, we retain only the employer where earnings were highest.

We make some further restrictions on the sample. First, we restrict our sample to firms where we observe at least two men with complete records from the military enlistment. The reason for excluding firms with only one observation is that we are interested in studying the variation in skills both within and between firms. Second, we restrict our sample to firms in the private sector with at least ten employees, thus excluding small private firms and firms controlled by the public sector or private nonprofit organizations. We include private firms registered in Sweden even if they are controlled from outside of Sweden, for example, subsidiaries of foreign firms. Finally, we exclude men with zero or missing earnings in a given year. These sample restrictions do not seem to have a major effect on how the representativeness of our sample changes over time (see Online Appendix Figure A2).

Information on basic demographics, including earnings, year of birth, and educational attainment, is taken from the LOUISE database, which covers the entire Swedish population. We lack information about educational attainment prior to 1989 for about 10 percent of the sample. For this group we impute educational attainment between 1986 and 1989 using educational attainment in 1990. We translate highest educational degree into years of schooling, which we use as our measure of educational attainment.

We obtain information on individual worker wages from the Structural Wage Statistics (SWS), which is based on annual surveys on a subsample of firms.[5] When a worker has no observable SWS wage in a given year, we first check if they have a reported SWS wage from an adjacent year (±2) with the same employer, and adjust this

4. The industry classifications in RAMS have changed somewhat over time. In particular, the industry classification used from 1990 onwards (SNI92) is not perfectly comparable with earlier industry classification (SNI69). We impute industry backwards for 1986–1989 for firms alive in 1990. For the subsample of firms not alive in 1990, we translate two-digit industry codes from SNI69 to SNI92 using the official concordance (Statistics Sweden 1992).

5. There is some variation across years in terms of the exact sampling procedure and in the number of sampled firms, but small firms are less likely to be sampled throughout our study period.

wage to the wage drift in the industry. In case no adjacent SWS wage is available, we set the wage equal to the predicted value from a regression of SWS wages (including those imputed in the first step) on a high-order polynomial of the worker's average monthly pay from RAMS. A detailed description of our imputation method is available in Online Appendix A3.

We obtain data on cognitive and noncognitive skills from Swedish military enlistment records. The enlistment usually takes place the year a Swedish man turns 18 or 19 and spans two days involving tests of health status, physical fitness, cognitive ability, and an interview with a certified psychologist.[6] For the cohorts we consider, the enlistment was mandatory for all Swedish men, and exemptions were only granted to men with severe physical or mental disabilities. About 90 percent of the men in our sample were eventually enlisted to the military service. Lindqvist and Vestman (2011) provide a detailed account of the enlistment procedure, the tests of cognitive skill, and the enlistment interview.

Between 1969 and 1994, the enlistment test of cognitive ability consisted of four parts, testing verbal, logical, spatial, and technical ability.[7] The results of these tests were then transformed by the enlistment agency to the "stanine" scale—a discrete variable ranging from one to nine that approximates a normal distribution. The basic structure of the test remained intact until 1994, although the actual test questions changed in 1980. There have also been slight changes in the mapping from the subtest scores to general cognitive ability over the years (see Grönqvist and Lindqvist 2016). A new version of the test based on the stanine scale was introduced in 1994. The youngest cohort in our main sample (men born in 1978) were enlisted in 1996 and 1997. We standardize the one to nine cognitive score for each enlistment cohort to mean zero and unit variance. A potential concern with this procedure is that standardization hides changes in the underlying distribution of abilities. As discussed in closer detail in Online Appendix A2, there is some evidence of a "Flynn effect"—a secular rise in cognitive test scores—but no trend in the dispersion of cognitive test scores over time.

At the enlistment, conscripts were also interviewed by a certified psychologist for about 25 minutes. The objective of the interview was to assess the conscript's ability to cope with the psychological requirements of the military service and, in the extreme case, war. Each conscript was assigned a score in this respect from the same stanine scale as for cognitive ability. The instructions for how to evaluate conscripts were unchanged until 1995, when they were subject to slight revisions. The character traits considered beneficial by the enlistment agency include social maturity, psychological energy (focus and perseverance), intensity (activation without external pressure), and emotional stability (Mood, Jonsson, and Bihagen 2012). Each subdomain was graded on a five-point scale, but these grades were only meant as a guide for the overall stanine score. Compared to other measures of personality, like the "Big Five" (for example, Goldberg

6. Because only nine years of primary school are mandatory in Sweden, the level of schooling among draftees may differ by up to a couple of years depending on whether they attend secondary school. Hence, we cannot rule out the possibility that variation in measured cognitive and noncognitive skill is partly due to differences in educational attainment.

7. Carlstedt (2000) argues that the enlistment test of cognitive skill is a good measure of general intelligence (Spearman 1904). In this regard, the measure of cognitive skills differs from the AFQT, which has a relatively stronger focus on "crystallized" intelligence, that is, skills that are teachable (personal interview with Berit Carlstedt, November 26, 2009).

1990), the psychologists' evaluation is set apart both by the method (semistructured interview instead of survey questions) and by the focus on identifying individuals capable of handling a specific real-life situation (the military service) rather than quantifying certain personality traits. We use the psychologists' overall evaluation as a measure of noncognitive skill and undertake the same standardization as for cognitive ability.

The measures of cognitive and noncognitive ability have a modest positive correlation (0.39), suggesting that they capture different types of ability. Lindqvist and Vestman (2011) show that while both skill measures predict labor market outcomes, cognitive ability is relatively more important in skilled nonmanagerial occupations, while managers and workers in unskilled occupations have a higher return to noncognitive ability.

Online Appendix Figure A2 shows how our sample restrictions affect the share of workers with observable skills from the enlistment and the mean and variance of cognitive and noncognitive skills. The restriction to private firms with at least ten employees implies that our main sample covers between 50 percent and 60 percent of all employed men between 30 and 35.[8] While the population mean and variance are standardized to zero and one in all years, average cognitive and noncognitive skills in our sample increased by about 0.06 standard deviations during the first part of the 1990s. There is also a secular decrease in the sample variance over the entire study period, from slightly above one to about 0.95 in case of cognitive skill. A likely explanation for this development is that the economic crisis of the early 1990s (discussed further in Section IV.B) implied a shift toward a permanently higher level of unemployment, thereby making it harder for men from the low end of the skill distribution to become employed.

III. Measuring Sorting

We quantify sorting by decomposing the variance of cognitive and noncognitive skills. We choose a simple variance decomposition over alternative methods because it has the advantage of being intuitive, widely understood, and easy to relate to the literature that decomposes wages into between- and within-firm components. Since our skill measures are continuous, indexes that measure the sorting of different types of workers (such as occupational categories) are not well suited to our data.

Let C_{ijt} denote the cognitive skill of worker i in firm j in year t. The sample variance of cognitive skill in year t, $\frac{1}{N_t}\sum_i(C_{ijt}-\bar{C}_t)^2$, can be expressed as the sum of the variance within and between firms:

$$(1)\quad \underbrace{\frac{1}{N_t}\sum_j\sum_i(C_{ijt}-C_{jt})^2}_{\text{within firms}} + \underbrace{\frac{1}{N_t}\sum_j N_{jt}(C_{jt}-\bar{C}_t)^2}_{\text{between firms}},$$

where C_{jt} is the average level of cognitive skill in firm j, N_{jt} is the number of workers in firm j, and N_t is the total number of workers in the economy in year t. In an economy where firms either hire low-skilled workers (for example, McDonald's) or high-skilled

8. Online Appendix Figure A2 shows a dip in the total number of employed workers between 1990 and 1995. This is due to missing draft data for about two-thirds of men born in 1960 (most of whom were enlisted in 1978). Since these men turned 30 in 1990 and 35 in 1995, they enter the sample in 1990 and leave it in 1996.

workers (for example, Google), the within-firm component is small, while the between-firm component is large. The other extreme is an economy where all firms have the same average level of skill. By studying the evolution of the within- and between-firm variances, we can quantify the degree to which sorting by skill has increased or decreased. The population variances of cognitive and noncognitive skills are set to one by construction, but the sample variance may be either higher or lower than one depending on selection into the sample. Consequently, the within-firm variance may change even though the between-firm variance remains fixed, and vice versa. The between-firm variance can be decomposed further into the variance in skill between industries, and between firms within the same industry.

There are a number of issues to consider regarding variance decompositions as a way to measure sorting. First, an implicit assumption in Equation 1 is that we observe all workers in all firms. In fact, since we restrict attention to men ages 30–35, we observe n_{jt} out of N_{jt} workers in a given firm, where $n_{jt} \leq N_{jt}$. When $n_{jt} < N_{jt}$ we get a measurement error in the firm-level mean of skills, which inflates the between-firm variance and deflates the within-firm variance in Equation 1. All decompositions shown in the paper have been adjusted to correct this problem, but to save space we show the adjusted decompositions in Online Appendix B1. Relatedly, we have chosen to weigh each firm by the number of observed workers (n_{jt}) rather than the actual number of employees (N_{jt}).

Second, since the number of workers at each firm is finite, the between-firm variance would be larger than zero also under random matching of workers to firms. To get a benchmark value of sorting, we randomly draw workers to firms without replacement from the set of workers in the sample and conduct the variance decomposition in Equation 1. Repeating this process 1,000 times provides a bootstrap-type test of sorting by comparing the true between-firm variance with the percentiles in the distribution of simulated variances.

Third, the enlistment skill measures are affected by measurement error (Lindqvist and Vestman 2011). Measurement error inflates the within-firm variance relative to the between-firm variance. The importance of this effect in turn depends on the size distribution of firms, which may change over time and thus give rise to spurious changes in the measured level of sorting. In Online Appendix B2, we outline a procedure, based on the estimated reliability ratios from Lindqvist and Vestman (2011), that allows us to gauge the share of the within- and between-firm variance that can be attributed to measurement error. We report these results as a robustness check rather than as our main case.

Fourth, our baseline results are based on the presumption that skills are approximately normally distributed. We test the importance of this assumption by transforming the skill measures to uniform distributions. Following Ahlin (2020), we also estimate sorting nonparametrically by Kendall's tau rank correlation.

Fifth, our sample is restricted to men between the ages of 30 and 35. To investigate the robustness of our results, we shorten the time period (1997–2008), which allows us to study sorting for men between 30 and 45. We also follow Grönqvist, Öckert, and Vlachos (2017) and impute cognitive and noncognitive skills for women using the enlistment records of close male relatives (see Online Appendix A1). As this imputation method implies significant measurement error in skills, the estimated level of sorting for women is spuriously low.

IV. Sorting by Skill 1986–2008

In this section, we document the evolution of skill sorting in the Swedish economy.

A. Main Results

Figure 1 shows the between- and within-firm variances for cognitive and noncognitive skill from 1986 to 2008. The exact numbers for 1986, 1997, and 2008 are shown in Column 1 of Table 1.

Panel A of Figure 1 shows the between-firm variance of cognitive and noncognitive skill increased over time, in particular from 1986 to 1995. Conversely, Panel B shows the within-firm variance fell for both skill measures. Both the increase in the between-firm variance and the decrease in the within-firm variance are bigger and continue for a longer period of time for cognitive skill. We can thus conclude that sorting has increased: people working in the same firm have become more similar, while workers in different firms have grown more different in terms of their noncognitive and cognitive skills. The reason the lower within-firm variances are not fully reflected in larger between-firm variances is the decrease in the sample variances of cognitive and noncognitive skill (see Online Appendix Figure A2).

The increase in sorting is largely driven by an increase in the share of high-skilled firms (see Online Appendix Figure C1 and Table C2). For example, the share of workers employed by firms where the average cognitive skill is one standard deviation or more above the population average increased from 2.3 percent to 4.8 percent between 1986 and 2008 (see Table C2). As another way of illustrating the increase in sorting, we calculate the probability that the cognitive skill levels of two randomly selected workers in the same firm differ by more than three standard deviations. For a firm with the average within-firm variance, this probability fell from 2.1 percent in 1986 to 1.2 percent in 2008.

Could the sorting pattern in Figure 1 arise by chance? Online Appendix Table C1 shows that the answer to this question is a clear "no." For example, the 99th percentile of our simulated between-firm variances in cognitive skill was 0.018 in 1986 and 0.019 in 2008, an order of magnitude smaller than the between-firm variances we observe in the data.

Table 1 shows the increase in sorting documented in Figure 1 is robust to the tests discussed in Section III—that is, assuming skills are uniformly distributed; expanding the population to also include older men (for the years 1997–2008), women, or workers in public-sector firms; restricting the sample to medium-sized and large firms; or measuring sorting at the plant level.[9] Figure C2 shows sorting as measured by Kendall's rank correlation also increases over time. Table 1 further shows adjusting the sorting pattern for measurement error in skills increases the level of the between-firm variance by about 15 percent for cognitive skills and by about 40 percent for noncognitive skills, but does not affect the trend toward increased sorting.

9. We exclude public entities within public administration, defense, education, health services, and extraterritorial bodies.

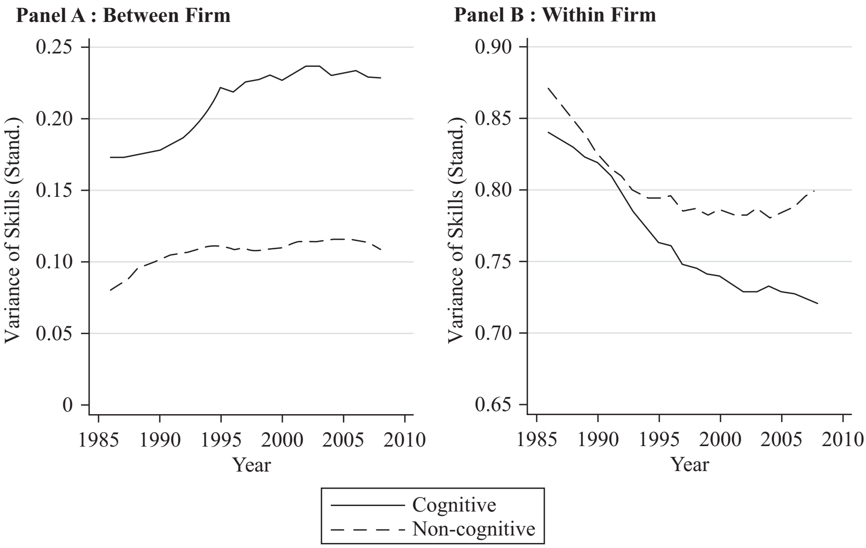

Figure 1

Sorting by Cognitive and Noncognitive Skill

Notes: The sample includes men 30–35 years old employed at private firms with at least ten employees. Variance components are corrected for sample size according to the procedure in Online Appendix B1.

Online Appendix Figures C3 and C4 show sorting also increases according to all submeasures of cognitive and noncognitive skill discussed in Section II.[10] For the cognitive submeasures, the level of sorting is highest for logic and verbal ability, though the increase is most dramatic for spatial ability. For the noncognitive submeasures, we see both a higher level and more positive trend for sorting by social skills, consistent with an increasing importance of social skills in the labor market (Deming 2017).

The fact that we see similar patterns for all skill measures raises the question whether workers are just sorted according to one underlying type of skill, which loads positively on both cognitive and noncognitive skills, as well as their submeasures. As a rough test of this hypothesis, we regress our measures of cognitive and noncognitive skills on each other and save the residuals. Online Appendix Figure C5 shows sorting increases for both of these residualized skill measures, indicating sorting increases by multiple dimensions of skill.

B. An Artifact of the 1990s Crisis?

The main increase in sorting by cognitive skill coincides with the Swedish economic crisis of the early 1990s. The crisis had several causes (Englund 1999). Deregulation of

10. Because the coverage of submeasures falls dramatically after 2005, Online Appendix Figures C3 and C4 only show the evolution of sorting up to 2005.

Table 1
Robustness of Basic Sorting Patterns

				Sample				Firm Size		
	Baseline (1)	ME Corrected (2)	Uniformly Distributed Skills (3)	Men 30–45 (4)	+ Women 30–35 (5)	+ Public-Sector Firms (6)	– Low-Skilled Men[a] (7)	≥50 Employees (8)	≥100 Employees (9)	Plants (10)
Panel A: Cognitive Skill										
Between-firm variance										
1986	0.173	0.197	0.173		0.141	0.166	0.143	0.151	0.139	0.209
1997	0.225	0.258	0.226	0.198	0.173	0.230	0.203	0.200	0.186	0.265
2008	0.229	0.264	0.232	0.228	0.178	0.233	0.206	0.191	0.172	0.264
Within-firm variance										
1986	0.840	0.817	0.836		0.863	0.848	0.747	0.875	0.890	0.811
1997	0.747	0.714	0.758	0.781	0.799	0.751	0.697	0.787	0.803	0.722
2008	0.721	0.686	0.734	0.734	0.773	0.722	0.690	0.755	0.768	0.693
Panel B: Noncognitive Skill										
Between-firm variance										
1986	0.081	0.111	0.079		0.072	0.076	0.070	0.061	0.055	0.099
1997	0.109	0.156	0.114	0.097	0.094	0.111	0.096	0.088	0.080	0.135
2008	0.110	0.156	0.113	0.108	0.092	0.112	0.091	0.088	0.081	0.130
Within-firm variance										
1986	0.872	0.841	0.887		0.894	0.879	0.829	0.889	0.895	0.849
1997	0.786	0.739	0.822	0.806	0.828	0.790	0.744	0.803	0.805	0.763
2008	0.801	0.755	0.825	0.794	0.842	0.801	0.762	0.814	0.816	0.782

Notes: The table shows the variance decompositions outlined in Section III of the paper. See Online Appendix Table C1 for the results from simulated variance components under random allocation of workers to firms (for the baseline case).

a. The share of the sample with low education falls dramatically over time. The cutoff, ten years or fewer of education, implies that 35 percent are dropped in 1986, compared to 14 percent in 1997 and 8 percent in 2008. This is due to the rapid expansion of upper-secondary education.

financial markets in the mid 1980s, combined with expansive macroeconomic policies, caused a boom in asset prices and a financial sector with high leverage. In the early 1990s, a tax reform and a shift in monetary policy caused a sharp increase in after-tax interest rates. This, together 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 strong negative impact on the real economy. The number of bankruptcies almost tripled between 1989 and 1992 (Online Appendix Figure E1), GDP per capita fell three years in a row (1991–1993), and the unemployment rate quadrupled between 1990 and 1993 (Online Appendix Figure E2). While unemployment fell during the latter part of the 1990s, it settled on a level more than twice as high as the precrisis level, implying a structural shift in the Swedish labor market. As shown in Online Appendix Figure A2, the increase in unemployment coincides with an increase in the average skills of employed workers, suggesting low-skilled workers were more likely to lose their jobs during the crisis.

So could the increase in sorting just be an artifact of the crisis? While it is an open question whether the crisis affected the timing of the increase in sorting, we argue the higher level of sorting at the end of our sample period is unlikely to be a direct effect of the crisis. First, while the main increase in sorting by cognitive skill coincides with the economic crisis of 1991–1993, sorting started increasing *before* the crisis, and most of the increase in sorting by noncognitive skill took place before 1991. Second, the improvement in macroeconomic conditions from 1994 onwards did not lead to a reversal in sorting, and neither of the endpoints of our study period (1986 and 2008) are characterized by extraordinary macroeconomic conditions. Third, the men in our 2008 sample were between 13 and 18 years old in 1991, and thus too young to be directly affected by the crisis.[11] Fourth, while the crisis of the 1990s did lead to a permanently higher level of unemployment, the sorting pattern is robust to excluding men with the lowest educational attainment (who face the highest unemployment risk) from the sample (see Table 1, Column 7). Finally, as we show in Section V, a large fraction of the increase in sorting according to cognitive skill is due to the secular expansion of the ICT sector. Rather than being the main cause of the increase in sorting, it appears more likely that the economic crisis sped up a restructuring of the economy that would have taken place anyway.

C. Sorting by Other Worker Characteristics

We next turn to the question of how sorting by cognitive and noncognitive skill compares to sorting by worker characteristics used in the previous literature. We begin with educational attainment, for which Card, Heining, and Kline (2013) document increasing sorting in West Germany, 1985–2009. We consider educational attainment measured

11. Since we focus on men 30–35, a relevant question is whether this group was affected by the crisis in a different way compared to the population at large. Online Appendix Figure E3 shows the evolution of employment for men 30–34 years old and the whole working-age population. The employment pattern for men 30–34 years old 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 precrisis years. The working-age population had the same drop in employment levels during the crisis, but employment did not increase as much postcrisis as for men 30–34 years old. An important explanation for this discrepancy is the expansion of higher education in the postcrisis period (in our sample, the average years of education increase by two years in between 1986 and 2008).

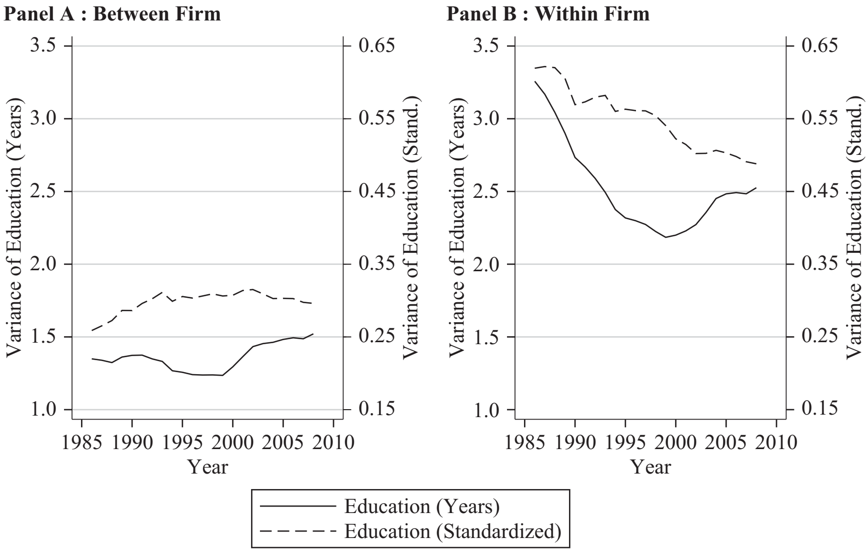

Figure 2

Sorting by Education

Notes: Educational attainment is measured in years of schooling (A) and years of schooling standardized by cohort (B). The sample includes men 30–35 years old with observable cognitive and noncognitive skills employed at private firms with at least ten employees. Variance components are corrected for sample size according to the procedure in Online Appendix B1.

both in years of schooling and—to account for changes educational attainment over time—years of schooling standardized to unit variance by cohort. Figure 2 shows sorting increases for both measures, though the time pattern for the standardized measure is more similar to that of the enlistment skill measures.[12]

Several studies instead analyze sorting based on worker and firm fixed effects from AKM models (Iranzo, Schivardi, and Tosetti 2008; Card, Heining, and Kline 2013; Song et al. 2019). We estimate AKM models annually using a rolling nine-year window for all men in the private sector between age 24 and 60, thereby limiting the study period to 1989–2005 (see Online Appendix D for further details regarding the estimation). To facilitate comparison with the enlistment skill measures, we standardize the worker effects to unit variance for each cohort in each year. We then follow Iranzo, Schivardi, and Tosetti (2008) and Song et al. (2019) in decomposing the variance of worker effects into between- and within-firm components, thus asking if high-wage workers to an increasing extent work in the same firms. Figure 3 shows this variance decomposition both for our main sample of men 30–35 years old and for the full estimation sample.

12. Online Appendix Figure C6 shows the trend toward increased sorting by educational attainment is present, though somewhat attenuated, when we increase the sample to men in the private sector between 24 and 60, or private-sector workers of both genders (age 20–64).

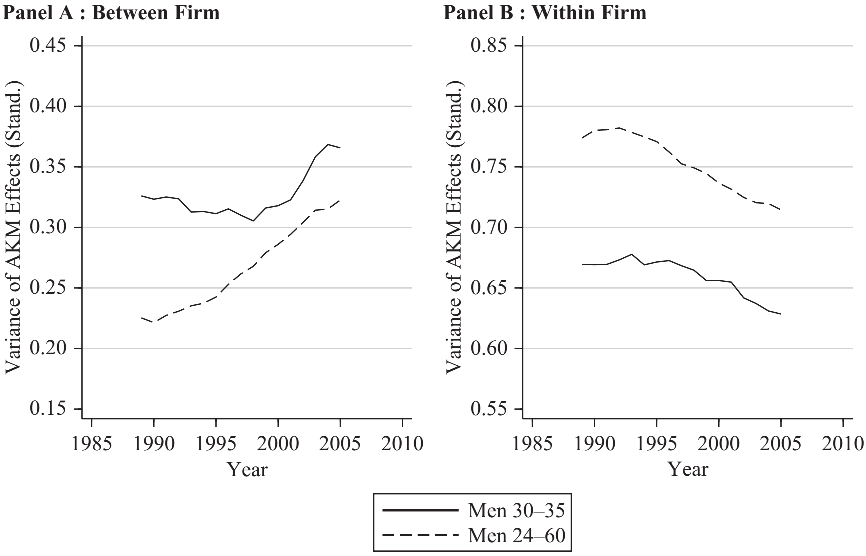

Figure 3

Sorting by Worker Effects from the Abowd, Kramarz, and Margolis Model

Notes: The figure shows the variance components of worker effects standardized by cohort from the AKM model described in Online Appendix D. The sample includes male workers between age 24 and 60 in private-sector firms with at least ten employees (A) and men 30–35 years old with observable cognitive and non-cognitive skills employed by private-sector firms with at least ten employees (B). Variance components are corrected for sample size according to the procedure in Online Appendix B1.

Consistent with Song et al. (2019), we see increasing sorting by worker effects for both samples, but the increase in sorting occurs about a decade later compared to the enlistment skill measures.

A potential explanation for the discrepancy in timing is that AKM worker effects and the enlistment skill measures reflect different worker characteristics.[13] To gauge the plausibility of this explanation, we regress the worker effects on cognitive and noncognitive skills for each year between 1989 and 2005. Online Appendix Figure D1 shows the R^2 from these regressions is at most 0.24, implying worker effects indeed reflect much beyond cognitive and noncognitive skills.[14] The characteristics reflected in worker effects may further change over time, for example, due to shifts in the demand for different types of skills. A recent literature has also pointed to identification problems in standard AKM models in the presence of search frictions and complementarities in the production function (Gautier and Teulings 2006; Eeckhout and Kircher 2011; Lopes de Melo 2018; Hagedorn, Law, and Manovskii 2017; Bagger and Lentz 2018). If the extent of these problems changes over time, so could the mapping between

13. Examples of worker characteristics that might be included in AKM worker effects but are unrelated to skills are union membership, willingness to negotiate wages, and personal connections with employers.
14. Butschek and Sauermann (2019) also regress AKM worker effects on cognitive and noncognitive skills from the Swedish military draft with broadly similar results.

worker effects and skills. Notably, Online Appendix Figure D1 shows the R^2 fell during the crisis years (1990–1994)—the same period during which we see increasing sorting by cognitive skills but not for worker effects—and increased from the mid 1990s onwards—the period that saw increasing sorting by worker effects.

Online Appendix D includes additional material from the AKM model. Figure D2 shows the standard deviation of the unstandardized worker and firm effects increases over time, reflecting the increase in wage inequality we discuss further in Section VII. Figure D3 shows the evolution of the correlation between worker and firm effects for both men 30–35 years old and the full sample. In line with previous literature on the United States (Song et al. 2019) and Germany (Card, Heining, and Kline 2013), the correlation increases over time, implying high-wage workers to an increasing extent work in high-wage firms.[15] This type of assortative matching between workers and firms could, but need not, be related to increasing sorting by skills and worker effects. High-wage workers could work in the same firms (implying a high between-firm variance of worker effects) without there being assortative matching between workers and firms. Conversely, while assortative matching implies between-firm differences in average worker effects cannot be zero, an increase in assortative matching could in principle coincide with a decrease in sorting by worker effects.

V. Decomposing the Change in Sorting

To get a sense of the broad patterns behind the increase in sorting, in this section we use information on firms' industry classifications to further decompose the change in the between- and within-firm variances of cognitive and noncognitive skill.

A. Decomposing the between-Firm Variance

To set the scene, Figure 4 shows the between-firm variance decomposed into the variance between two-digit industries and the variance between firms within the same industry. For cognitive skill, the bulk of the increase in the between-firm variance is due to larger skill differences between industries. As we show below, the main factor behind this development is the inflow of skilled workers into the ICT sector. In comparison, between-industry skill differences are less important for the evolution of sorting by noncognitive skills.

We now turn to a more detailed look at the between-industry variance. Table 2 lists the mean skill level and employment share of all major industries in 1986 and their changes between 1986 and 2008. The key result in Table 2 is the big increase—from 1.4 percent to 8.4 percent—in the share of the sample employed by the IT industry (NACE 72).[16]

15. Two previous papers use the framework by Abowd, Kramarz, and Margolis (1999) to gauge the extent of assortative matching between workers and firms in Sweden. Davidson et al. (2014) find greater openness to trade improves the matching between workers and firms in industries with greater comparative advantage. Bahar Baziki, Ginja, and Borota Milicevic (2016) find stronger worker–firm assortative matching in ICT-intensive industries.

16. The growth in the ICT sector is not an artifact of our focus on a sample of relatively young men. Online Appendix Figure C8 shows that the ICT sector increased by a factor of two or three also for the entire male

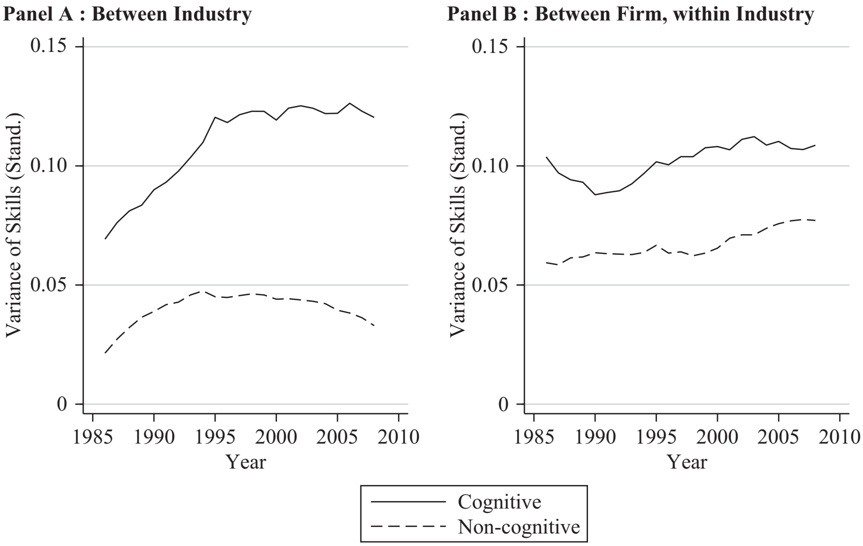

Figure 4

Decomposing the between-Firm Variance: Industries

Notes: The sample includes men 30–35 years old with observable cognitive and noncognitive skills employed at private firms with at least ten employees. Variance components are corrected for sample size according to the procedure in Online Appendix B1.

Despite the dramatic increase in the employment share, the average cognitive skill of workers in the IT industry remained constant, at 0.75 standard deviations above average, the highest among the large industries in our data. At the same time, manufacturing of telecom products (32) increased the average level of cognitive skill from 0.45 to 0.61. Table 2 also shows that the average level of cognitive skills declined in a number of low-skilled service industries, including retail (52), construction (45), transportation (60), and sales and repair of motor vehicles (50). We also see decreasing employment shares for manufacturing industries other than telecom, where the initial skill level was typically low. As shown in Figure C7, the net result of these reallocations of workers across industries is a much more polarized distribution of industry-average cognitive skills, with the ICT industries (IT and telecom) at the high end of the spectrum.[17]

The (modest) increase in the between-industry variance of noncognitive skill is not explained by any particular industry. Yet a notable change is the significant upgrading of

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workforce (age 21–64), the entire female workforce (age 21–64), and for relatively young female workers (age 30–35).

17. We show in Online Appendix F that the key developments we see in Sweden—increasing employment shares for IT-related services and decreasing employment shares for manufacturing—are present also in other industrialized countries. More broadly, the correlation in changes in employment shares for ten broad sectors in Sweden and 15 other countries is 0.94.

Table 2
Average Skills by Industry

		Cognitive Skill		Noncognitive Skill		Share Workers (Percent)	
NACE	Industry	1986	Change 1986–2008	1986	Change 1986–2008	1986	Change 1986–2008
72	Computer and related activities	0.75	0.00	0.27	0.00	1.40	7.04
32	Manufacture of radio, television, and communication equipment	0.45	0.16	0.09	0.15	1.92	0.10
65	Financial intermediation, except insurance and pension funding	0.32	0.10	0.23	0.25	2.70	–0.48
74	Other business activities	0.25	0.05	0.12	0.05	7.83	4.99
51	Wholesale trade and commission trade, except of motor vehicles	0.13	–0.16	0.12	–0.01	9.96	–1.51
22	Publishing, printing, and reproduction of recorded media	0.10	0.05	–0.09	0.03	2.59	–1.22
55	Hotels and restaurants	0.08	–0.29	–0.04	–0.03	1.33	0.35
63	Supporting and auxiliary transport activities	0.07	–0.24	0.04	–0.12	1.53	0.44
24	Manufacture of chemicals and chemical products	0.05	0.11	–0.03	0.14	1.72	–0.17
52	Retail trade, repair of personal and household goods	–0.07	–0.07	–0.04	–0.02	2.37	1.80
64	Post and telecommunications	–0.08	0.33	0.29	–0.18	0.03	1.68

(*continued*)

Table 2 (*continued*)

		Cognitive Skill		Noncognitive Skill		Share Workers (Percent)	
NACE	Industry	1986	Change 1986–2008	1986	Change 1986–2008	1986	Change 1986–2008
34	Manufacture of motor vehicles, trailers, and semitrailers	–0.09	0.01	–0.10	0.02	5.34	–0.48
29	Manufacture of machinery and equipment n.e.c.	–0.11	0.10	–0.09	0.09	7.04	–1.33
50	Sale, maintenance, and repair of motor vehicles and motorcycles	–0.17	–0.14	–0.05	–0.11	2.96	0.02
70	Real estate activities	–0.22	0.18	–0.07	0.17	1.84	–0.89
45	Construction	–0.23	–0.06	–0.03	0.00	10.30	0.85
21	Manufacture of paper and paper products	–0.25	0.09	–0.11	0.09	4.20	–2.84
28	Manufacture of fabricated metal products	–0.28	–0.05	–0.21	–0.04	4.24	–0.96
15	Manufacture of food products and beverages	–0.28	–0.09	–0.19	0.01	3.39	–1.18
27	Manufacture of basic metals	–0.36	0.10	–0.22	0.08	1.96	–0.30
60	Land transport, transport via pipelines	–0.36	–0.09	–0.29	–0.04	2.78	0.04
20	Manufacture of wood and of products of wood	–0.44	0.03	–0.21	0.05	2.56	–0.99

Notes: Mean of skills and relative sizes of industries in 1986, and the changes between 1986 and 2008. Only industries with at least 1.5 percent of the workforce in 1986 or 2008 are included. The sample is restricted to men 30–35 years old employed at firms with at least ten employees. The description of some industries has been abbreviated.

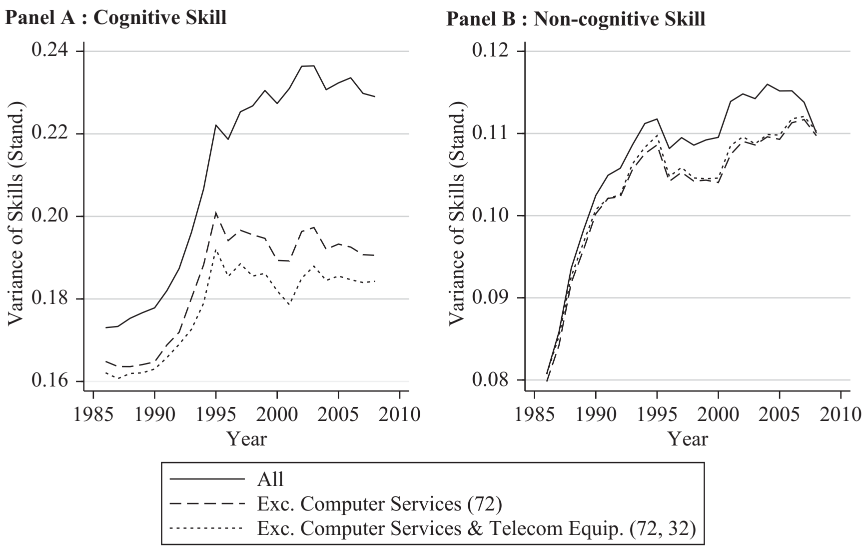

Figure 5

Counterfactual between-Firm Variance: Excluding the ICT Sector

Notes: The sample includes men 30–35 years old with observable cognitive and noncognitive skills employed at private firms with at least ten employees. Variance components are corrected for sample size according to the procedure in Online Appendix B1.

noncognitive skills in financial intermediation (+0.25 standard deviations).[18] This may reflect changes in the types of activities performed by the financial sector, such as the growth of investment activities, following financial liberalization in the mid 1980s.

As an illustration of the importance of the ICT sector, Figure 5 shows removing the IT and telecom industries from the sample takes out more than one-half of the increase in the between-firm variance of cognitive skill. In comparison, the ICT sector is much less important for the increase in the between-firm variance for noncognitive skill. The connection between sorting by cognitive skill and ICT sector growth is suggestive of technological change in line with the models of Caselli (1999) and Acemoglu (1999). In these models, the introduction of a new technology (for example, ICT), may induce a switch from a pooling equilibrium to a separating equilibrium where only firms that invest in the new technology hire skilled workers. However, as our data do not allow us to study how ICT is used in other industries, we cannot directly test this prediction.

18. Böhm, Metzger, and Strömberg (2015) report a slight decline in the average noncognitive skill in the Swedish financial sector between 1991 and 2010. The reason we obtain a different result is that our data also include 1986–1990, when the average noncognitive skill in the financial sector increased substantially.

Table 3
Average within-Firm Variance by Industry

		Cognitive Skill		Noncognitive Skill		Share Workers (%)	
NACE	Industry	1986	Change 1986–2008	1986	Change 1986–2008	1986	Change 1986–2008
34	Manufacture of motor vehicles, trailers, and semitrailers	1.06	–0.13	0.92	–0.09	5.34	–0.48
24	Manufacture of chemicals and chemical products	1.04	–0.18	0.94	–0.14	1.72	–0.17
32	Manufacture of radio, television, and communication equipment	0.97	–0.26	0.89	–0.16	1.92	0.10
15	Manufacture of food products and beverages	0.95	–0.11	0.90	–0.07	3.39	–1.18
21	Manufacture of paper and paper products	0.95	–0.18	0.89	–0.05	4.20	–2.84
29	Manufacture of machinery and equipment n.e.c.	0.93	–0.08	0.83	–0.01	7.04	–1.33
20	Manufacture of wood and of products of wood and cork	0.93	–0.16	0.80	–0.04	2.56	–0.99
27	Manufacture of basic metals	0.91	–0.07	0.82	0.09	1.96	–0.30
55	Hotels and restaurants	0.87	–0.16	1.02	–0.13	1.33	0.35
28	Manufacture of fabricated metal products, except machinery	0.87	–0.07	0.85	–0.05	4.24	–0.96
22	Publishing, printing, and reproduction of recorded media	0.83	–0.09	1.01	–0.10	2.59	–1.22
63	Supporting and auxiliary transport activities	0.80	–0.03	1.00	–0.19	1.53	0.44

(*continued*)

Table 3 (*continued*)

NACE	Industry	Cognitive Skill 1986	Cognitive Skill Change 1986–2008	Noncognitive Skill 1986	Noncognitive Skill Change 1986–2008	Share Workers (%) 1986	Share Workers (%) Change 1986–2008
51	Wholesale trade and commission trade, except of motor vehicles	0.79	–0.13	0.88	–0.09	9.96	–1.51
74	Other business activities	0.78	–0.11	0.86	–0.06	7.83	4.99
52	Retail trade, repair of personal and household goods	0.78	–0.03	0.89	–0.02	2.37	1.80
60	Land transport, transport via pipelines	0.78	–0.02	0.83	–0.08	2.78	0.04
70	Real estate activities	0.77	–0.09	0.85	–0.01	1.84	–0.89
45	Construction	0.75	–0.13	0.80	–0.05	10.30	0.85
50	Sale, maintenance, and repair of motor vehicles and motorcycles	0.74	–0.07	0.79	–0.02	2.96	0.02
65	Financial intermediation, except insurance and pension funding	0.63	–0.02	0.86	–0.13	2.70	–0.48
72	Computer and related activities	0.54	0.05	0.81	–0.03	1.40	7.04
64	Post and telecommunications	0.45	0.32	0.96	–0.13	0.03	1.68

Notes: Average within-firm variance of skills and relative sizes of industries in 1986, and their changes between 1986 and 2008. Only industries with at least 1.5 percent of the workforce in 1986 or 2008 are included. The sample is restricted to men 30–35 years old employed at firms with at least ten employees. The description of some industries has been abbreviated.

B. Decomposing the within-Firm Variance

The fall in the within-firm variance documented above could either reflect a general trend toward more internally homogeneous firms or increasing employment shares for industries in which firms were internally homogeneous to begin with. Online Appendix Table C3 shows the former explanation—a general trend across industries—is most important; changes in industry structure play a minor role for the decline in the within-firm variance. To provide a more detailed picture, Table 3 shows the average within-firm variance for each major industry in 1986 and how the variances changed between 1986 and 2008. In 1986, firms in manufacturing industries were much more internally heterogeneous than firms in service industries. For example, the average variance of cognitive skill was above the population variance (that is, one) in manufacturing of motor vehicles (NACE 34) and chemical products (24), compared to 0.63 for financial intermediation (65) and 0.54 for the IT industry (72). However, while the within-firm variance of cognitive skill fell in almost all industries, the fall was particularly big in manufacturing industries, implying much smaller differences across industries in 2008.

VI. Sorting and Firm Wage Differentials

In this section, we ask whether the increase in sorting is relevant for understanding the evolution of the wage structure. A large literature documents increasing wage inequality in developed countries in recent decades. In many western countries, this increase is in large part due to larger between-firm wage differentials (recall Footnote 1). In line with previous research on Sweden by Nordström Skans, Edin, and Holmlund (2009), Figure 6 and Table 4 show a similar pattern for our sample of 30- to 35-year-old men. The variance of log wages increased by 46 percent between 1986 and 2008, the bulk of which (61 percent) could be attributed to an increase in the between-firm wage variance. Online Appendix Figure C9 shows expanding the sample to all private-sector workers between 24 and 60 gives a similar increase in between-firm wage inequality, but a larger increase in within-firm wage inequality.[19]

Increased sorting by skill is a potential explanation for the increase in firm wage differentials. Alternatively, the gradient between skills and wages may have become steeper, for example, due to increasing complementarities between worker skills. In this section, we undertake a simple descriptive exercise to see to what extent within- and between-firm skill differentials can account for changes in the wage structure. Our analysis offers a complementary view to papers using the AKM model for similar purposes (Card, Heining, and Kline 2013; Song et al. 2019) in that we disentangle the effect of sorting from the effect of changes in skill gradients. This is not possible in an AKM framework without assuming worker effects only reflect the return to worker skills.

To simplify the exposition, we combine the measures of cognitive and noncognitive skill into a unidimensional skill measure, s_{ijt}, for worker i in firm j at time t, where

19. We impute wages for the extended samples using the same procedure as for the main sample (see Section II). Yet because women and young and old men are less likely to work full-time compared to prime-age males, the imputation based on monthly earnings may be less accurate. This is a caveat to bear in mind when looking at Online Appendix Figure C9.

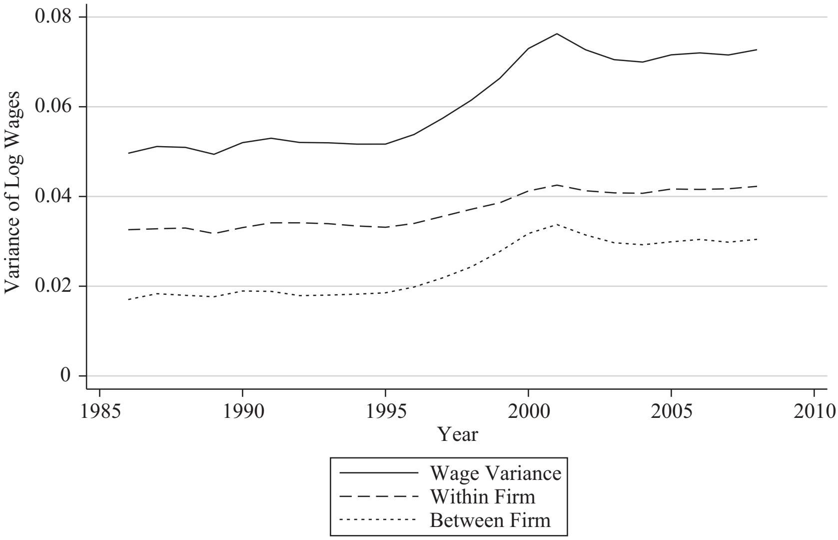

Figure 6

Decomposing the Variance of Wages

Notes: The sample includes men 30–35 years old with observable cognitive and noncognitive skills employed at private firms with at least ten employees. Variance components are corrected for sample size according to the procedure in Online Appendix B1.

Table 4

Decomposing the Variance of Wages

	Actual Variance		Predicted Variance		Residual Variance		Counterfactual Predicted Wage Variance	
	1986 (1)	2008 (2)	1986 (3)	2008 (4)	1986 (5)	2008 (6)	(7)	(8)
Total	0.0496	0.0727						
Between firms	0.0170	0.0305	0.0096	0.0156	0.0074	0.0149	0.0127	0.0119
Within firms	0.0326	0.0423	0.0039	0.0032	0.0287	0.0391	0.0035	0.0036
Gradients			1986	2008			1986	2008
Sorting			1986	2008			2008	1986

Notes: Wage variance decompositions as described in Section VI of the paper. The variance components in Columns 3–4 and 7–8 are constructed using the 1986 or 2008 skill gradients or sorting patterns as indicated.

the relative weights are determined by a standard wage regression.[20] Using this measure, we decompose the between- and within-firm variance of wages into components explained and unexplained by worker skills. Beginning with the between-firm variance, we estimate regressions of the form

$$(2) \quad w_{jt} = \alpha_{bt} + \beta_{bt} s_{jt} + u_{jt},$$

where w_{jt} is the mean (log) wage at firm j at time t and s_{jt} is the firm-level mean of s_{ijt}. We weigh each firm in these regressions by the number of workers. Consequently, β_{bt} is defined as the change in firm-average log wages from a one standard deviation increase in average worker skills. We define β_{bt} at the firm level to capture possible complementarities between workers, and between skills and technology.[21] Based on Regression 2, we then decompose the between-firm variance of wages as

$$(3) \quad \underbrace{Var(w_{jt})}_{\text{Total BF variance}} = \underbrace{Var(\hat{w}_{jt})}_{\text{Predicted variance}} + \underbrace{Var(\hat{u}_{jt})}_{\text{Unexplained variance}} .$$

Since $\hat{w}_{jt} = \hat{\beta}_{bt} s_j$, we have that

$$(4) \quad Var(\hat{w}_{jt}) = \hat{\beta}^2_{bt} Var(s_{jt}),$$

implying the predicted between-firm wage variance can increase because of steeper firm-level skill gradients ($\hat{\beta}_{bt}$), larger between-firm skill differences ($Var(s_{jt})$), or a combination of the two.[22] We use Equation 4 for counterfactual analyses where we either allow sorting or gradients to change over time (while keeping the other fixed at its 1986 level).

Figure 7 shows the evolution of the total and predicted between-firm wage variances from Equation 3 and the counterfactual analyses based on Equation 4. Table 4 provides the corresponding numbers for 1986 and 2008. Like the total variance, the predicted wage variance increased up until year 2000 and then fell slightly. The predicted variance accounts for more than 50 percent of the total between-firm wage variance in 1986 and 2008, and 45 percent of the increase in the total variance between 1986 and 2008.

20. To determine the relative weights given to cognitive and noncognitive skill, we pool all years 1986–2008 and regress wages in each year on second-order polynomials in cognitive and noncognitive skill, their interaction effect, and age and year fixed effects. We then define s_{ijt} as each worker's predicted value based on the coefficients for cognitive and noncognitive skill, and normalize s_{ijt} to mean zero and unit variance.

21. An alternative approach for investigating the role of skills for firm wage differentials is to regress individual wages on skills and then study the between-firm variance of the residuals. However, if there are complementarities between workers, or between worker skills and technology, this approach is likely to underestimate the importance of skills as a determinant of between-firm wage differentials. Given that complementarities in production are a key factor behind sorting, this is a serious limitation even for a purely descriptive exercise.

22. As discussed in Section III, the fact that we only observe a subset of workers at each firm implies we get a measurement error in s_{jt} that inflates $Var(s_{jt})$ and biases $\hat{\beta}_{bt}$. Because the measurement error in s_{jt} reflects actual within-firm skill differences between workers (with a gradient of β_{wt}), the bias in $\hat{\beta}_{bt}$ is positive if and only if $\beta_{bt} > \beta_{wt}$, which our estimates strongly indicate is the case. As described in more detail in Online Appendix B1, all predicted between- and within-firm variances presented in this section are based on variances adjusted for measurement error in s_{jt} and a bias-corrected version of $\hat{\beta}_{bt}$.

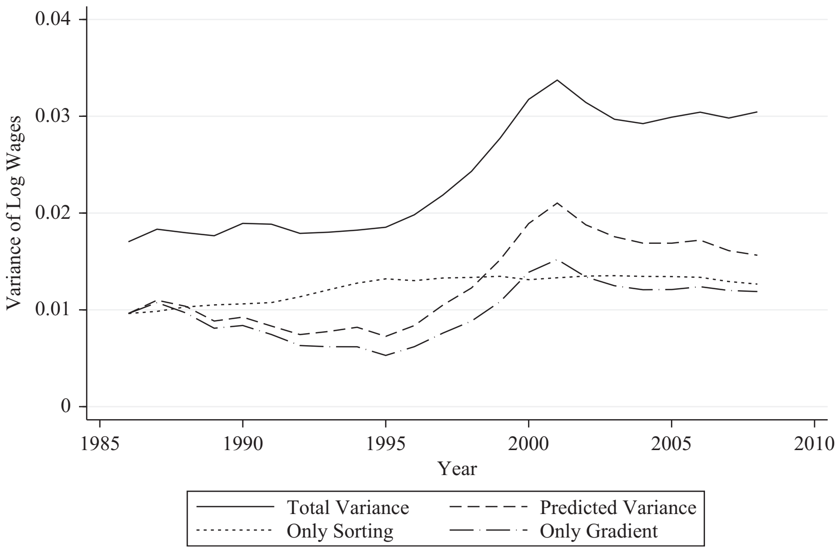

Figure 7

Decomposing the between-Firm Variance of Wages

Notes: The sample includes men 30–35 years old with observable cognitive and noncognitive skills employed at private firms with at least ten employees. The predicted and counterfactual variances are based on Equation 3 and corrected for sample size according to the procedure in Online Appendix B1.

The counterfactual analyses show both increased sorting and steeper gradients explain the increase in the predicted variance, but the effect of increased sorting is bigger.[23]

VII. Conclusions

Using direct and time-consistent measures of cognitive and noncognitive skills, we document a substantial increase in the sorting of workers to Swedish firms between 1986 and 2008. We also find increasing sorting by educational attainment and AKM worker effects, though the increase in sorting by worker effects takes place about a decade later. A conceivable explanation for the discrepancy in timing is that the type of worker characteristics captured by worker effects changes with shifts in labor demand and changes in labor market institutions.

Having established that sorting has increased, we show the growth of the ICT sector can account for about one-half of the increase sorting by cognitive skill. We also show

23. Table 4 shows the predicted between-firm variance was 0.0096 in 1986 and 0.0156 in 2008, implying an increase of 0.0060. Comparing the counterfactual variances in Column 7 and 8 with the predicted variance in 1986 indicates 0.0031 (0.0127 – 0.0096) of the increase is due to increased sorting and 0.0023 (0.0119 – 0.0096) due to steeper gradients.

the trend toward internally more homogeneous firms is present across all major industries, though most pronounced in manufacturing.

Finally, we investigate whether sorting can account for changes in the structure of wages in Sweden. We show about 45 percent of the increase in between-firm wage inequality between 1986 and 2008 can be accounted for by the combination of increased sorting by skill and steeper between-firm skill gradient.

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