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 non-cognitive skills across Swedish firms between 1986 and 2008. The weight of the evidence suggests that the increase in sorting is due to stronger complementarities between worker skills and technology. In particular, a large fraction of the increase can be explained by the expansion of the ICT sector and a reallocation of engineers across firms. We also find evidence of increasing assortative matching, in the sense that workers who are particularly skilled in their respective educational groups are more likely to work in the same firms. Changes in sorting pattens and skill gradients can account for a about half of the increase in between-firm wage dispersion.

Keywords: Skill sorting; skilled-biased technological change; outsourcing; globalization; cognitive skills; non-cognitive skills; personality; employer-employee matched data.

JEL codes: J24, J62, L21, O33

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1 Introduction

In this paper we study how the sorting of workers to firms has changed over time. We do so by using detailed and direct measures of workers' cognitive and non-cognitive skills linked to firm level data covering the entire Swedish private sector. Our main finding is that there has been a substantial increase in the sorting of workers by skill between 1986 and 2008, with larger skill differences between firms and smaller differences within firms. The main driving force behind the increase in sorting is the expansion of the ICT sector.

The extent to which workers are sorted by skill is likely to affect both economic and social outcomes. For example, wage inequality is increasing in the degree of sorting if worker skills are complements (e.g. 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). Relatedly, sorting of workers by skill is a potential explanation for firm and industry wage differentials.[1] More generally, the extent of social interaction between different strata in society is lower if workplaces are internally homogeneous. The degree of sorting therefore has potentially far-reaching consequences for the formation of social networks, the marriage market, segregation in the housing market, and for social cohesion in general.[2]

There are a number of reasons to believe that technological change and globalization increase sorting. For example, the theoretical literature has stressed that firms investing in new technology face a higher return to hiring skilled workers (Acemoglu, 1999; Caselli, 1999). Another possibility is that more complex production processes strengthen the complementarity between workers' skills, implying that unskilled workers constitute "weak links" in firms with skilled workers (Kremer, 1993). Globalization increases the scope for skill-sorting by narrowing the set of tasks that needs to be performed domestically (Feenstra and Hanson, 1996; Grossman and Rossi-Hansberg, 2008) and by allowing skilled workers in rich countries to match with workers in developing countries rather than unskilled workers in their own country (Kremer and Maskin, 2006). To the extent that these models capture recent changes in the world economy, firms should become more different in terms of the skill level of their workforces. In other words, the economy might to an increasing extent be divided into Google-type firms that employ the most highly skilled workers and firms like McDonald's that employ the least skilled.

Assessing changes in sorting over time has proven difficult, in particular due to a lack of skill measures that are comparable over time. Previous research on the evolution of worker

[1] There is a large literature on worker skills and productivity and wage differences across plants, firms and industries. See, for example, Blackburn and Neumark (1992) and Gibbons and Katz (1992) on industry wage differentials and Haltiwanger et al. (1999) and Haskel et al. (2005) on firms and plants.

[2] See Jackson (2010) for an overview of social networks and their impact on economic behavior.

sorting has either focused on occupations (Kramarz et al., 1996; Kremer and Maskin, 1996; Dunne et al., 1997, 2004; Card et al., 2013), education (Card et al., 2013) or skill measures derived from wage data (Iranzo et al., 2008; Card et al., 2013). This literature typically finds increasing segregation of workers across firms. Each approach faces potential problems, however. Changes in the occupational structure could reflect changes in technology rather than changes in the composition of workers' skills. Relatedly, skilled-biased technological change may increase the dispersion of wages, even though the underlying distribution of skills remains unchanged. Using educational attainment as a measure of skill may not solve the problems of comparability over time; higher education has expanded in most countries and students' choices between different fields of education change in response to the economic environment.[3] Further, educational attainment, by construction, does not capture heterogeneity in skill within educational groups.[4]

In this paper, we study the evolution of sorting using data on workers' cognitive and non-cognitive 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. Since 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 and 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. The richness of the data also allows us to study aspects of sorting not possible in previous studies; in particular whether sorting of educational groups or assortative matching drive changes in sorting by skill.

We document a substantial increase in sorting concentrated to the first half of the 1990s. During this period, workers became more similar within firms (falling within-firm variance of skills) and more dissimilar between firms (increasing between-firm variance) with respect to both cognitive and non-cognitive skills. The increase in sorting is non-trivial: For example, the share of the sample variance of cognitive skills explained by sorting to firms increased from 17.1 % to 24.1 %, an increase by 41 %. Relatedly, the share of workers employed by firms with average cognitive skills one standard deviation above the population average has more than doubled. The trend towards increased sorting is robust to a wide range of tests

[3] Skill levels can change quite rapidly within fields of education: Grönqvist and Vlachos (2008) document that the average cognitive ability among entering teachers declined by more than half a standard deviation between 1992 and 2007.

[4] That income inequality within educational groups has increased suggests that within-group skill heterogeneities are becoming increasingly important (Machin, 1996; Katz et al., 1999). Altonji et al. (2012) provide an overview of the returns to secondary and post-secondary education across different majors.

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.

Why did sorting increase? We divide our attempt to address this question into two parts. First, we take a broad perspective and study changes in the distribution of skill across industries. This analysis shows that a flow of high-skilled workers into IT and telecom (ICT) explains a large fraction of the increasing differences in cognitive skill across firms. There is also evidence of skill-downgrading in low-tech service industries such as retail, construction, and transportation. As a result, the distribution of cognitive skill across industries has become polarized with a few high-tech industries at the high end of the spectrum. The trend toward smaller skill differences within firms is strongest in industries where the within-firm variance was initially large. For example, in 1986 a number of manufacturing industries had an average within-firm variance of cognitive skill above the population variance (which we normalize to 1). In 2008, only three of the major industries had an average within-firm variance of cognitive skill above 0.85. Yet the shift toward smaller skill differences within firms is present in all major industries.

In the second part of our analysis, we ask whether the increase in sorting is due to stronger assortative matching between workers or a reallocation of educational groups (defined by duration and field of study) with different average skills across firms. Sorting by educational groups is prevalent if, for example, engineers (high-skilled on average) and mechanics (low-skilled on average) work in different firms. Assortative matching between workers is strong if the highest skilled workers in each educational group work in the same firms, e.g. if particularly clever engineers work with particularly clever mechanics. We find evidence of both stronger assortative matching and increased sorting by educational groups. However, changes in the structure of educational groups across firms explains a much larger share of the overall increase in sorting. So why did sorting of educational groups increase? Two competing explanations are skill-biased technological change (Acemoglu, 1999; Caselli, 1999) and outsourcing. We show that the growth of the ICT sector and sorting patterns of engineers can account for a substantial share of the increase in sorting by educational groups, suggesting that technological change is at least part of the story. In a similar vein, we use variation within firms over time to analyze what factors correlate with a changes in assortative matching between workers. We find tentative evidence that assortative matching is positively correlated with skill up-grading, suggesting that technological change may be a driving force also in this case.

In sum, the evidence in both types of analyses is consistent with the growth of the ICT leading to a stronger complementarity between worker skills and technology as in standard models of technological change (Acemoglu, 1999; Caselli, 1999): Following the introduction of a new technology, the economy may switch from a pooling equilibrium to a separating equilibrium where only skilled workers work with the new technology. The trend toward increasing sorting is also consistent with the increasing polarization in the labor market of advanced economies, with routine jobs disappearing while both high- and low-skilled non-routine jobs become more prevalent (Acemoglu and Autor, 2011; Adermon and Gustavsson, 2011).

We conclude the paper with a simple accounting exercise regarding the relationship between sorting and wages. Between 1986 and 2008, the variance of wages among the workers in our sample increased by 47 percent, mainly due to a 70-percent increase in the between-firm wage variance.[5] We show that sorting by skill – together with steeper firm-level gradient between wages and skills – can account for close to 50 percent of the increase in between-firm wage inequality. While we make no claims as to the underlying causal mechanisms, this analysis suggests that the sorting of workers by skill is relevant for understanding the evolution wage inequality in Sweden over recent decades.

We discuss the previous literature on skill sorting in the next section and the construction of the data set in Section 3. Our approach for measuring sorting is discussed in Section 4 and the main results in Section 5. The mechanisms behind the observed changes in sorting are discussed in Section 6 and 7. We discuss sorting of skills and the evolution of wage inequality in Section 8. Section 9 concludes the paper. We present additional material in five appendices denoted A (data description), B (additional results), C (results for plants), D (details regarding how we quantify sorting), and E (short background to changes in the Swedish economy 1986-2008).

2 Literature

The optimal allocation of skill across firms depends on the nature of the production function. Changes in sorting by skill is therefore either due to changes in the production function itself, or to changes in the constraints in the matching of workers to firms.[6] With respect to the production function, economic theory emphasizes the interaction between workers with different levels of skill, and between skills and technology. In the former case, the sorting pattern depends on whether worker skills are substitutes or complements.

If skills are complements, the marginal value of increasing the skill level of one worker is

[5] Prior to our study, Nordström-Skans et al. (2009) have documented that wage differentials between plants increased between 1985 and 2000.

[6] Sorting of workers could potentially arise also in the absence of any complementarities between skills, or between skills and technology, if firms use referrals to hire workers (Montgomery, 1991). Hensvik and Nordström Skans (2013) provide an empirical test of the Montgomery model using Swedish data.

increasing in the skill level of her co-workers.[7] For example, in Kremer (1993), one weak link – in the sense of a low-skilled worker – reduces the value of the production by an otherwise highly skilled chain of workers. In such a setting, a competitive labor market without search frictions ensures that workers are perfectly sorted by skill, implying that high- and low-skilled workers work in different firms.

If skills are substitutes, the marginal value of a worker's skill is lower the more skilled are the other workers in the firm. That is, productivity hinges on the skills of a few "superstars" (Rosen, 1981) rather than a high general level of skill. In order not to waste talent, optimal sorting then implies that the most skilled workers work in different firms. Consequently, skill differences will be large within firms and small between firms if skills are substitutes, while the converse is true if skills are complements. If skills are neither substitutes nor complements the allocation of skill across firms does not affect output, implying that sorting of workers to firms is random.[8]

The extent to which worker skills are complements or substitutes is likely to change when technology develops, although the direction of the change is not obvious a priori. For example, it could become more important to avoid "weak links" as production processes become more complex, suggesting that technological change increases skill complementarities. Alternatively, improvement in information technology may imply that skilled workers can leverage their skills over a wider set of problems, thereby increasing the extent to which high-skilled workers substitute for low-skilled workers (Garicano and Rossi-Hansberg, 2006).

If skills interact with technology, workers will be sorted across firms by skill to the extent that technology differs across firms. Acemoglu (1999) and Caselli (1999) develop models where skilled-biased technological change (SBTC) may shift the economy from a pooling equilibrium where firms hire both skilled and unskilled workers to a separating equilibrium where unskilled and skilled workers are sorted into different firms.[9] In these models, SBTC thus has the same effect on sorting as an increase in the complementarity between worker skills.

Apart from changes to the production function, sorting may be affected by changes in the scope for matching workers induced by globalization. Trade in tasks, or offshoring, allows for

[7] That skill complementarities can lead to positive assortative matching between workers with heterogenous skills and firms with heterogeneous skill demands goes back at least to Becker (1973) model of the marriage market. See also the literature on matching in labor markets with two-sided heterogeneity (Shimer and Smith, 2000; Legros and Newman, 2002, 2007).

[8] A more formalized argument of "weak links" and "superstars" in the production function is provided in Milgrom and Roberts (1990) with the concepts of "supermodularity" and "submodularity".

[9] There is a large literature on SBTC and its implications for the relationship between technology and skills. This literature does not, however, directly analyze worker sorting. See Acemoglu (2002), Hornstein et al. (2005), and Acemoglu and Autor (2011) for surveys. Goldin and Katz (2008) provide a thorough analysis of the relation between technological change and worker skills.

skill-sorting by narrowing the set of tasks that needs to be performed domestically (Feenstra and Hanson, 1996; Grossman and Rossi-Hansberg, 2008). Globalization also opens up for the formation of international teams, allowing skilled workers in rich countries to match with workers in developing countries rather than unskilled workers in their own country (Kremer and Maskin, 2006). Grossman and Maggi (2000) link standard trade theory with the organization of production by letting the distribution of skills differ between countries. These differences give rise to comparative advantages in sectors where skills are either complements (supermodular) or substitutes (submodular).[10] For a country such as Sweden, where the dispersion of skill among the workforce is relatively low in an international comparison (Blau and Kahn, 2005), the theory predicts that production of services where worker skills are complements will increase with trade, thereby increasing the optimal segregation by skill.

A small empirical literature has sought to estimate whether sorting has increased over time.[11] Kremer and Maskin (1996) find evidence of increased workplace segregation in the UK (1984-1990), and the US (1976-1987), using data on occupations. Kramarz et al. (1996) also document increasing sorting in France between 1986 and 1992 using occupational data. Dividing employees into production and non-production workers, Dunne et al. (1997, 2004) document increases in workplace segregation in US manufacturing between 1975 and 1992. Following Abowd et al. (1999) in using worker fixed effects from a wage regression that controls for firm fixed effects as a measure of skill, Iranzo et al. (2008) find no indication of an increase in skill sorting using data on Italian manufacturing firms between 1981 and 1997. However, as argued by Eeckhout and Kircher (2011) and de Melo (2013) the relation between worker and firm fixed effects can exhibit important non-linearities and may therefore be difficult to interpret. Finally, Card et al. (2013) document increased sorting across plants with respect to both occupational mix, education, and worker fixed effects from wage regressions in West Germany between 1985 and 2009.[12] Card et al. (2013) also find evidence of stronger assortative matching as measured by the correlation between firm and worker fixed effects.

[10] There is a growing theoretical literature on international trade with heterogeneous workers (e.g. Ohnsorge and Trefler, 2007; Costinot, 2009; Costinot and Vogel, 2010). These models focus on allocation between industries and not how workers with different skill levels are matched to each other.

[11] There are also a small set of papers that study sorting in the cross-section, e.g., Hellerstein and Neumark (2008).

[12] Barth et al. (2011) consider worker segregation over time in the US 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.

3 Data

In order to analyze ability sorting over time, we match information on cognitive and non-cognitive skills from the Swedish military enlistment with employer-employee data. The first cohort for which we have enlistment data are men born in 1951, who were enlisted in 1969. Since 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 sample in each year to men between the age of 30 and 35. We exclude men below the age of 30 from the sample to avoid a sample selection effect due to the expansion of higher education. The total sample consists of essentially all male Swedish citizens born between 1951 and 1978.

We link employees to their employers using the RAMS data base which contains information on all workers employed in a firm at some point in time each year. RAMS includes worker annual earnings by employer, the month employment started and ended, and firm level information such as ownership and industry.[13] For workers who are recorded as having more than one employer during a given year, we retain only the employer from which a worker reported the highest earnings.

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 10 employees, excluding firms controlled by the public sector and private non-profit organizations.[14] We include private firms registered in Sweden even if they are controlled from outside of Sweden, for example subsidiaries to 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 Figure A5.1).

Information on basic demographics, including earnings, year of birth and educational

[13] 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 1986-1989 for firms alive in 1990. For the subsample of firms not alive in 1990, we translate 2-digit industry codes from SNI69 to SNI92 using the official concordance (SCB, 1992).

[14] There are two reasons for restricting the sample to private firms. First, the factors which the theoretical literature has pointed out as drivers of sorting (primarily skilled-biased technological change and globalization) are likely to have a stronger impact in the private sector. Second, "firms" and "plants" are not well-defined in the public sector. For example, all workers who are employed by the same municipality could belong to the same "plant".

attainment, is taken from the data base LOUISE 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 wages from the Structural Wage Statistics (SWS) which is based on annual surveys on a subsample of firms.[15] When wages are missing from the SWS, we impute wages using the SWS from other years within the same employer-employee match and adjust the wage according to the wage drift in the industry. For employer-employee matches where no wage is available from the SWS, we set the wage equal to the predicted value from a regression of (observed and imputed) wages from the SWS on a high-order polynomial in the average monthly pay from RAMS.[16]

For a subset of industries (mainly in manufacturing), we have rough data on trade from which we construct two variables. $Trade_{kt}$ equals the total value of exports and imports in industry k divided by total turnover while $China\_import_{kt}$ equals imports from China divided by turnover. We think of $China\_import_{kt}$ as a proxy for competition from and outsourcing to low-wage countries. Since not all goods and services are traded, trade data are missing for several industries. Rather than dropping these industries from the analysis, we set trade to zero in such cases and check if the results are sensitive to this imputation (see Appendix A).

3.1 Skill measures

We obtain data on cognitive and non-cognitive skills from Swedish 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. For the cohorts we consider, the military enlistment was mandatory for all Swedish men and exemptions were only granted to men with severe physical or mental handicaps. 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. The results of these tests were then

[15] 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. In a given year, wages from the SWS is available for about 50 percent of the workers in our sample.

[16] We restrict the sample to workers for which the employer-employee match lasted for at least 3 months.

transformed by the enlistment agency to the "stanine" scale – a discrete variable ranging from 1 to 9 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, 2013). 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) did the enlistment in 1996 and 1997. We standardize the 1-9 cognitive score for each draft 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 Appendix A3, 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 to the psychologists for how to evaluate conscripts was unchanged until 1995 when it was subject to slight revisions. The character traits considered beneficial by the enlistment agency include willingness to assume responsibility; independence; outgoing character; persistence; emotional stability, and power of initiative. Motivation for doing the military service was not considered beneficial for functioning in the military. We use the psychologists' evaluation as a measure of non-cognitive skill and undertake the same normalization to zero mean and unit variance as for cognitive ability. The measures of cognitive and non-cognitive 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 occupations while workers in unskilled occupations have a higher return to non-cognitive ability.

Figure A5.1 shows how our sample restrictions affect the share observed workers and the mean and variance of cognitive and non-cognitive skills. The restriction to private firms with at least 10 employees implies that our main sample covers between 50 and 60 percent of all employed men between 30 and 35.[17] While the population mean and variance are normalized to 0 and 1 in all years, average cognitive and non-cognitive skills in our sample increased by about 0.06 standard deviations during the first part of the 1990's. There is also a secular

[17] The dip in the total number of employed workers between 1990 and 1995 is due to missing draft data for about 2/3 of men born in 1960 (most of whom did the military draft in 1978). Since these men turn 30 in 1990 and 35 in 1995, they enter the sample in 1990 and leave it in 1996. The Swedish Enlistment Agency do not have an explanation as to why data from the 1978 draft is missing.

decrease in the sample variance over the entire study period, from slightly above 1 to about 0.95. As Figure A5.1 makes clear, the reason for these changes in the sample distribution of skill over time is not the exclusion of the public sector or small private firms, but changes in the selection of workers into the labor market. A contributing factor to this development is that economic crisis of 1991-1993 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 (see Appendix E).

4 Measuring sorting

We quantify sorting by decomposing the variance of cognitive and non-cognitive skills. We choose a simple variance decomposition over alternative methods since it has the advantage of being intuitive, widely understood and easy to relate to the literature that decompose 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_{ij} denote the cognitive skill of worker i in firm j. The sample variance of cognitive skill, $\sum_i \sum_j \left(C_{ij} - \overline{C}\right)^2$, can be expressed as the sum of the variance within and between firms:

$$\underbrace{\frac{1}{N} \sum_j \sum_i \left(C_{ij} - C_j\right)^2}_{\text{within-firm variance}} + \underbrace{\frac{1}{N} \sum_j N_j \left(C_j - \overline{C}\right)^2}_{\text{between-firm variance}}, \tag{1}$$

where C_j is the average level of cognitive skill in firm j, N_j is the number of workers in firm j and N is the total number of workers in the economy. In an economy where firms either hire low-skilled ("McDonald's") or high-skilled workers ("Google"), the within-firm component is low while the between-firm component is high. 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 over time. The population variances of cognitive and non-cognitive skills are set to 1 by construction, but the sample variance may be either higher or lower than 1 depending on selection into the sample. Consequently, the within-firm variance may change even though the between-firm variance remains fixed, and vice versa, if the sample variance changes.

The between-firm variance can be decomposed further into variance in skill between industries, and between firms within the same industry. We can also decompose the covariance between cognitive and non-cognitive skill into between- and within-firm components. The between-firm covariance tells us whether firms that employ workers with high cognitive skill also employ workers with high non-cognitive skills.[18] The expressions for these two decompositions are shown in Appendix D1.

There are a number of issues to consider regarding the use of variance decompositions as a way to measure sorting of workers to firms. First, an implicit assumption in our variance decompositions is that we observe all workers in all firms. In fact, since we restrict attention to men between the age of 30 to 35, we observe n_j out of N_j workers in a given firm, where $n_j \leq N_j$. When $n_j < N_j$ we get a measurement error in the firm-level mean of skills, C_j, which inflates the between-firm variance and deflates the within-firm variance in (1). All decompositions shown in the paper are adjusted for sample size, but, to save on space, we show the adjusted decompositions in Appendix D2. Relatedly, we have chosen to weigh each firm by the number of observed workers (n_j) rather than the actual number of employees (N_j) in (1).[19]

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 (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.[20] Comparing the actual and simulated between-firm variances is a first simple test of what forces drive sorting in the aggregate. If worker skills are complements, or if there is a complementarity between worker skills and technology (and technology differs across firms), then the actual between-firm variance should exceed the simulated variances. If, in contrast, there are no or weak complementarities between worker skills and technology and worker skills are substitutes, the observed level of sorting should be below the simulated level.

Third, the enlistment skill measures are likely affected by measurement error. Using data

[18] Since cognitive and non-cognitive skills are positively correlated at the level of the individual, the sum of the within- and between-firm components is positive. However, depending on how skills are valued across firms, the between-firm covariance could in principle be negative. For example, if cognitive and non-cognitive skills are substitutes in the firm-level production function, we expect firms to focus on hiring workers with either high cognitive or high non-cognitive skill.

[19] There are two reasons for this choice. First, weighting firms by the number of observed workers is more efficient. Weighting firms by the actual number of workers would imply that a number of firms with few observed workers would get a large weight, thus increasing random noise. Second, since our sample is restricted to men in the age of 30-35 in the first place, weighting firms by the actual number of workers would not be representative of the entire population of workers unless one is willing to assume that sorting patterns are exactly identical for 30-35 year old men compared to the population as a whole.

[20] A similar approach is used by Ahlin (2010).

on monozygotic and dizygotic twins, Lindqvist and Vestman (2011) estimate a reliability ratio of 0.868 for cognitive and 0.703 for non-cognitive skills.[21] As shown in Appendix D, measurement error inflates the within-firm variance relative to the between-firm variance. Since the effect of measurement error on the estimated firm mean of skills is smaller the larger are firms, a change in the size distribution of firms over time could affect the share of the measurement error variance that is attributed to within- and between-firm components. We derive a correction for measurement error based upon the assumption that measurement error is classical. In essence, we use the estimated reliability ratios from Lindqvist and Vestman (2011) to simulate measurement errors for each worker in our data. We then use the simulated errors to estimate the share of the within- and between-firm variance which can be attributed to measurement error. We report these results as a robustness check rather than as our main case.

Fourth, we assume that the enlistment skill measures follow a normal distribution. Although a reasonable benchmark case, it is fair to ask how robust our results are to monotone transformations of skills or non-parametric ways of quantifying sorting. To test the sensitivity to distributional assumptions, we transform the enlistment skill measures to alternative distributions (uniform and Beta distributions with different skewness) which we then decompose into between- and within firm components. To estimate sorting non-parametrically, we first rank all firms in each year according to the average level of skills. We then calculate the Kendall's tau rank correlation between the rank of each firm and the skill level of each individual.[22]

Fifth, our sample is restricted to men between the age of 30 and 35. An advantage of this restriction is that the high mobility of young male workers implies that we are likely to detect changes in sorting patterns quickly. Still, the external validity would be stronger if the same sorting patterns are present for female workers and older male workers. Following Grönqvist et al. (2012), we impute cognitive and non-cognitive skills for women using the draft records of close male relatives (see Appendix A2). We then decompose the variance in skills for both women and men following the same procedure as for men. Because we have to impute cognitive and non-cognitive skills of females, measurement error in skill is much larger for this group, leading to a spuriously low level of sorting across firms. To test the robustness of our results with respect to age, we study the sorting patterns from 1996 to 2008 for male workers between the age of 30 and 45.[23]

[21] The lower reliability ratio of non-cognitive skills arguably reflects the additional error introduced by the fact that different psychologists evaluate different conscripts (Lindqvist and Vestman, 2011).

[22] Our approach for quantifying sorting using Kendall's tau is similar to Ahlin (2010).

[23] As a further way of assessing whether our results are sensitive to the specific sample used, we compute the yearly correlations between the firm-level average skill for 30-35 year-old men and, respectively, women

Finally, while we focus on firms in the decomposition above, the corresponding analysis for plants is presented in Appendix C1.[24] As it turns out, the main results for plants and firms are very similar, and therefore we focus on firms in the paper in the interest of brevity.

5 Sorting by skill 1986-2008

In this section, we document the evolution of skill sorting in the Swedish economy over the last 25 years. We begin with the most basic question: Has skill sorting increased or decreased?

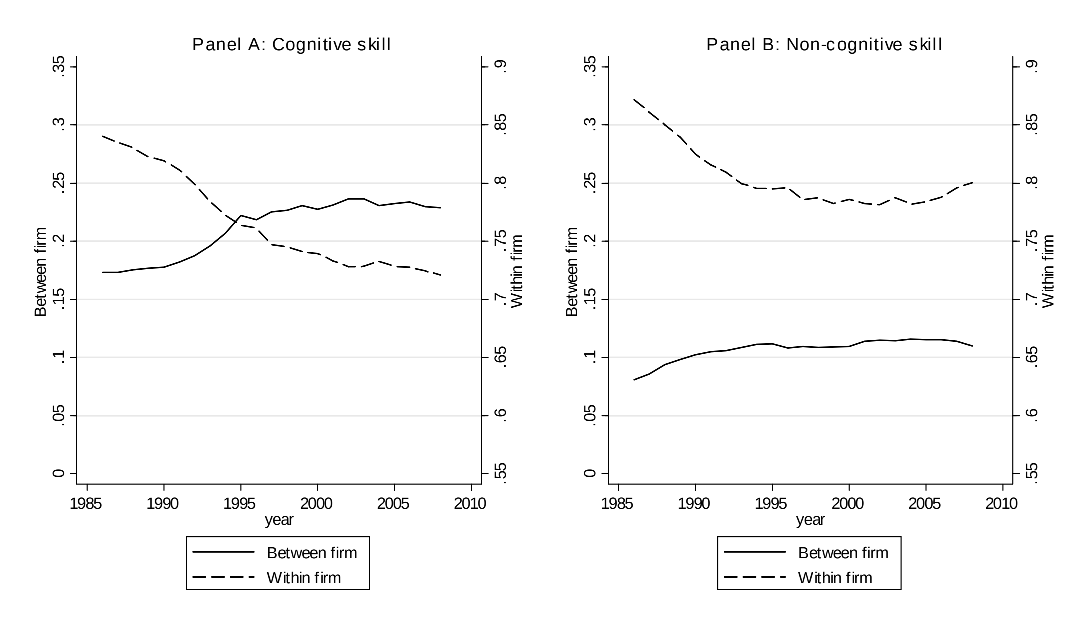
Figure 1 shows the evolution of the within- and between-firm variance for the enlistment skill measures between 1986 and 2008. Panel A shows that the within-firm variance in cognitive skill fell from 0.840 in 1986 to 0.721 in 2008. At the same time, the between-firm variance increased from 0.173 to 0.229. 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 cognitive skills. The reason the fall in the within-firm variance is not fully reflected in a corresponding increase in the between-firm variance is the decrease in the sample variance of cognitive skill documented in Figure A5.1. As shown in Panel B, the trend for non-cognitive skills is similar to that of cognitive skills, even though the between-firm variance is substantially lower. Could the sorting pattern in Figure 1 arise by chance? Table B1.1 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 is 0.018 in 1986 and 0.019 in 2008, an order of magnitude smaller than the between-firm variances we measure in the data. Consequently, there is substantially more sorting in the data than would be expected if workers were randomly allocated to firms.

Notably, most of the increase in the between-firm variance coincides with the Swedish economic crisis of 1991-1993 (see Appendix E). However, the increase in sorting is evident already in the late 1980's (falling within-firm variance and slightly increasing between-firm variance) and continues throughout the study period for cognitive skills. Moreover, as we show in Section 6 and 7, the main factor behind the increase in sorting is the rise of the IT and telecom industries, which have little to do with the economic crisis.

between 30 and 35 as well as men between 30 and 45. If the sorting pattern of 30-35 year-old men changes relative to women of the same age or older men, we expect these correlations to increase or decrease over time. However, as shown in Figure A5.2, the correlations are quite stable with a slight increase for women and a slight decrease for older men.

[24] A drawback with using plants as the unit of analysis in our context is that, since plants are smaller, the restriction to plants with at least two observations implies that we lose some observations from the data.

Figure 1. Sorting over time

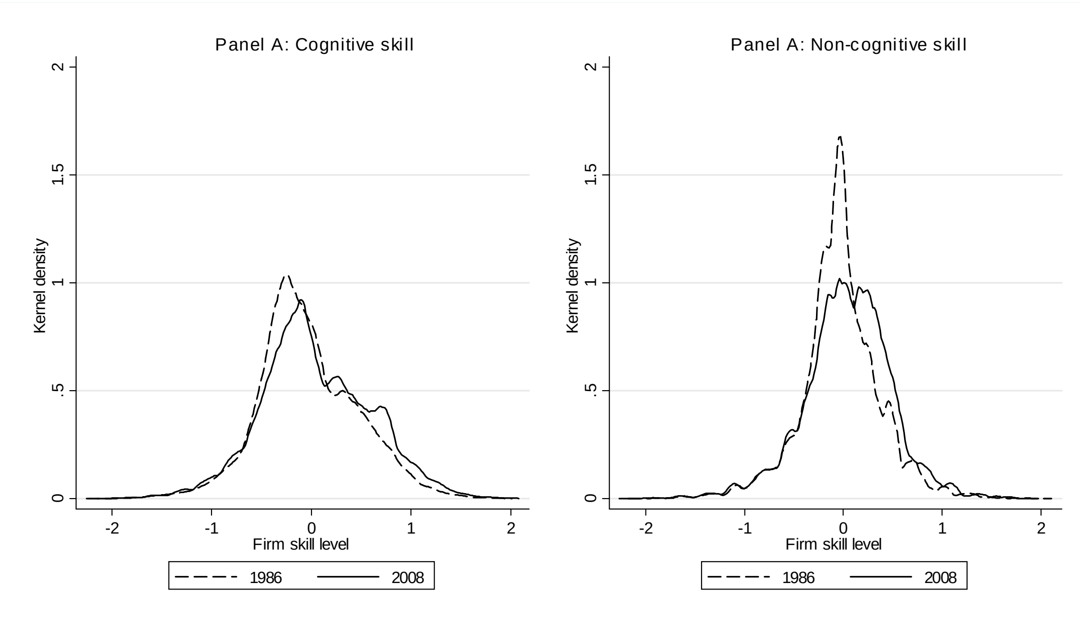


Note: The sample includes 30-35 year-old men employed at firms with at least 10 employees. Variances are corrected for firm-level sample size.

Figure 2 shows kernel density plots for the firm-level distribution of skills. This figure makes clear that in particular the share of workers in high-skilled firms have increased. For example, the share of workers employed by firms with average cognitive skill 1.00 standard deviations above the population average increased from 2.3 % to 4.8 % (Table B1.2). Also visible in the figure is the slight increase in average skills in our sample of 0.07-0.08 standard deviations (see Figure A5.1). Yet despite the increase in sample average skill, the share workers in low-skilled firms also increased.[25]

[25] Figure 2 and Table B1.1 are not adjusted for the measurement error in average skills due to us observing skills only for a subset of workers (see the discussion in Section 3). This implies that skill variances in Figure 2 are not directly comparable to the between-firm components in Figure 1 (which are adjusted for sample size). However, Figure A5.3 shows that changes in the size distribution of firms between 1986 and 2008 are small. Similarly, re-estimating the variance decompositions without adjustment for the number of observed and employed workers at each firms give a similar pattern of increasing sorting, implying that Figure 2 gives a reasonably (though not exactly) correct correct picture of changes over time.

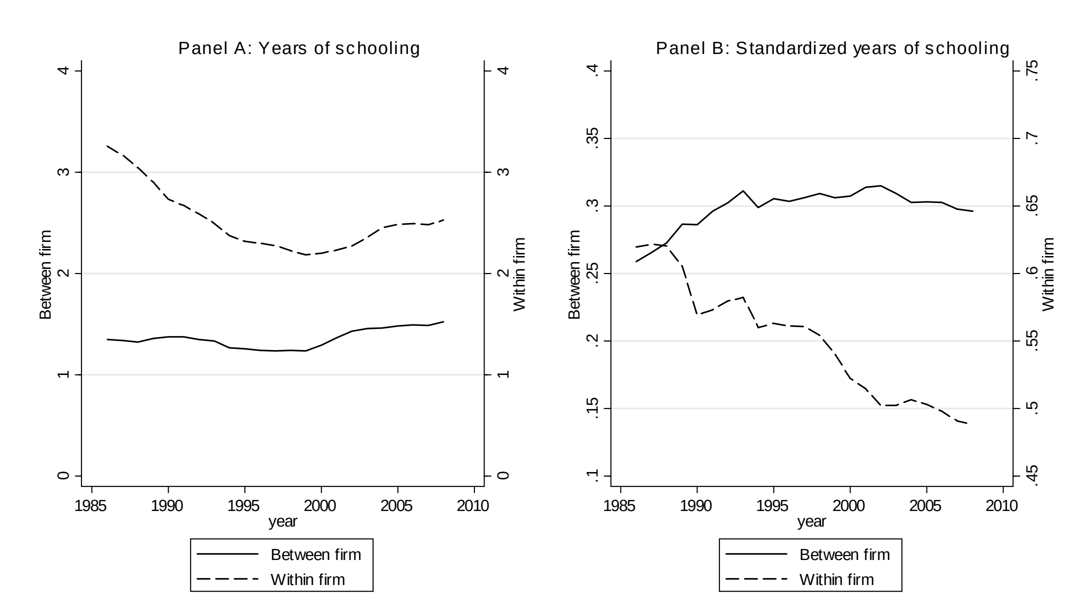
Figure 2. Distribution of firm average skill



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.

The increase in sorting documented in Figure 1 is robust to a number of different specification tests, reported in Appendix B1. First, the trend toward an increase in sorting remains the same when we adjust for measurement error in skills (Figure B1.1). However, measurement error increases the level of the between-firm variance by about 15 % for cognitive skill and by about 40 % for non-cognitive skill, depending on which year we consider. The within-firm variance falls by the same absolute amount as the between-firm variance increases. However, while measurement error thus leads us to understate the extent to which workers are sorted according to non-cognitive skill in a given year, the increase in sorting over time is very similar regardless of whether we adjust for measurement error. Second, we find increasing sorting also when assuming that skills follow alternative distributions (Figure B1.2-B1.4) or when we use Kendall's rank correlation to measure sorting (Figure B1.5). Third, the sorting pattern for 1996-2008 is similar regardless whether we consider men between age 30 and 45 instead of men between 30 and 35 (Figure B1.6). Similarly, adding females to the male sample does not change the trend toward an increase in sorting (Figure B1.7). Fourth, including public entities (Figure B1.8) or restricting the sample to medium-sized and large firms (Figure B1.9A-B) changes the level of skill sorting, but not the general trend.[26] Finally, Figure B1.10 shows that the between-firm component of the covariance between cognitive and non-cognitive skill is positive and increasing throughout our study period while the within-firm component falls over time. Firms that hire workers with above-average cognitive skill thus to an increasing extent also hire workers who are above average in terms of their non-cognitive skills. This in turn implies that the increase in sorting by cognitive and non-cognitive skill documented above is not a result of firms specializing on hiring workers of a particular type of skill.

Figure 3. Sorting by education



Note: Between and within-firm variances in educational attainment expressed in years of schooling (Panel A) and years of schooling standardized by cohort (Panel B). The sample includes 30-35 year-old men employed at firms with at least 10 employees. Variances corrected for firm-level sample size.

In Figure 3, we present the main sorting patterns when we replace cognitive and non-cognitive skills with educational attainment. Panel A shows the results when educational attainment is expressed in terms of year of schooling. Panel B shows the results when we standardize educational attainment by cohort and then convert this measure to a normal distribution. In both cases do we find an increase in sorting, with a higher fraction of the total variance explained by differences in average educational attainment between firms.

[26] We exclude public entities within public administration, defence, education, health services and extraterritorial bodies.

6 Which industries drive changes in sorting?

Having documented that sorting has increased, we now turn to the question *why* this has happened. We do so in two sections that represent complementary ways of looking at the data. In this section, we undertake a detailed analysis of which industries drive the increase in sorting. We begin with a closer look at the between-firm variance, and then turn to the within-firm variance. Even though the increase in the between-firm variance is directly related to the fall in the within-firm variance (and vice versa), it is useful to analyze them separately in order to gain insight into the kind of mechanisms at play.

6.1 Decomposing the between firm variance

Figure 4 shows the results when the between-firm variance of skills is decomposed into skill differences between industries, and differences in skill between firms within the same industry. We document a substantial increase, from 0.069 to 0.120, in the between-industry variance of cognitive skill from 1986 to 1995. The pattern is similar for non-cognitive skills up until the mid 1990's when the between-industry variance fell somewhat. In general, sorting at the industry level appears to be more important for cognitive than for non-cognitive skills. Figure 4 also shows that the variance in skill between firms within the same industry increases from 1990 to 2003.

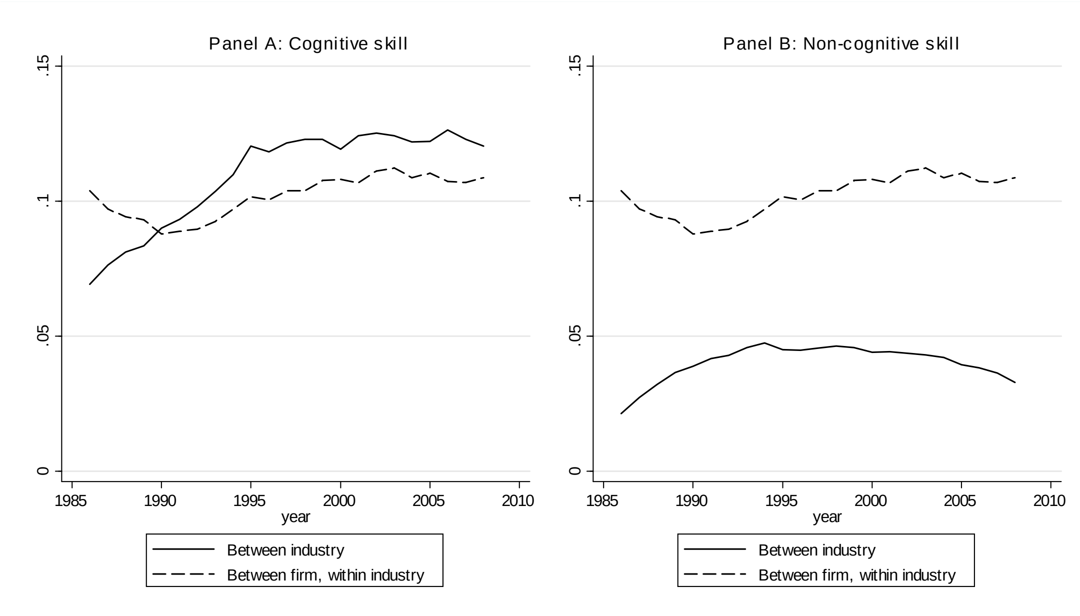
The main reason for the increase in the between-industry variance of cognitive skill is the inflow of skilled workers to IT and telecom. Table 1 lists the mean skill level for all major industry in our data, the change in means between 1986 and 2008 and employment shares.[27] In 2008, 8.4 % of 30-35 year old men worked in the IT industry, up from 1.4 % in 1986.[28] Despite the increase in size, the average cognitive skill of workers in the IT-sector 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 standard deviations above average. Table 1 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). The pattern in the data is thus broadly consistent with the predictions from the models by Caselli (1999) and Acemoglu (1999): after the introduction of a new technology (in our case ICT), workers with high and low cognitive skills select into different

[27] The industry with the highest average level of cognitive skills – research and development – is not included in the Table 1 as it employes less than 2 percent of the workforce.

[28] The growth in the ICT sector is not an artefact of our focus on a sample of relatively young men. Figure B2.1 shows that the ICT sector increased by a factor of two or three also for the entire male workforce (age 21-64), the entire female workforce (age 21-64) and for relatively young female workers (age 30-35).

sectors.

Figure 4. Decomposing the between-firm variance



Note: Between industry and between-firm within-industry skill variances. The sample includes 30-35 year-old men employed at firms with at least 10 employees. Variances corrected for firm-level sample size.

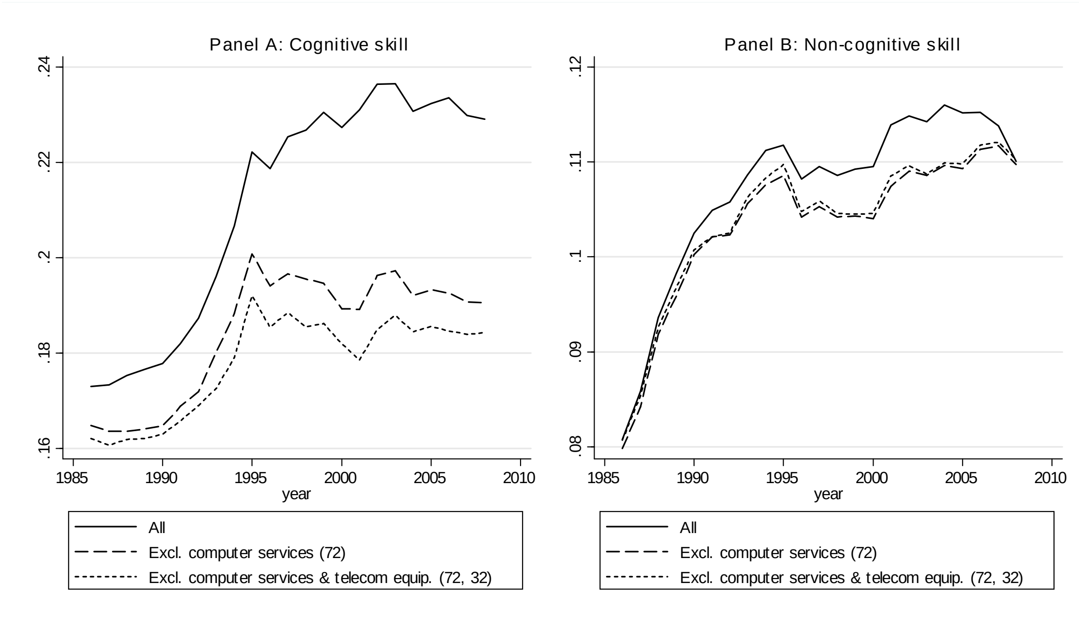
The (smaller) increase in the between-industry variance of non-cognitive skill is not due to changes in the relative size or skill level of any particular industry. However, a notable change in the distribution of non-cognitive skill across industries is instead the significant upgrading of non-cognitive skills in financial intermediation (+0.25 standard deviations). This is may reflect changes in the types of activities performed by the financial sector, such as the move towards internet banking and the growth of investment activities following financial liberalization.

[TABLE 1 HERE]

As an illustration of the importance of the ICT sector for the increase in sorting by cognitive skill, Figure 5 shows the "counterfactual" evolution of the between-firm variance of skill when IT and telecom are removed from the sample.[29] In comparison, the ICT sector is much less important for the increase in the between-firm variance for non-cognitive skill.

[29] Figure 5 is only meant as an illustration of the importance of the ICT sector. Since sorting into different industries is clearly not independent, Figure 5 should be interpreted as showing the counterfactual sorting pattern in a literal sense, i.e., what would have happended had there been no expansion of ICT.

Figure 5. Counterfactual between-firm variance



Note: Between-firm skill variances including and excluding Computer services and Telecom equipment. The sample consists of 30-35 year-old men employed at firms with at least 10 employees. Variances are corrected for firm-level sample size.

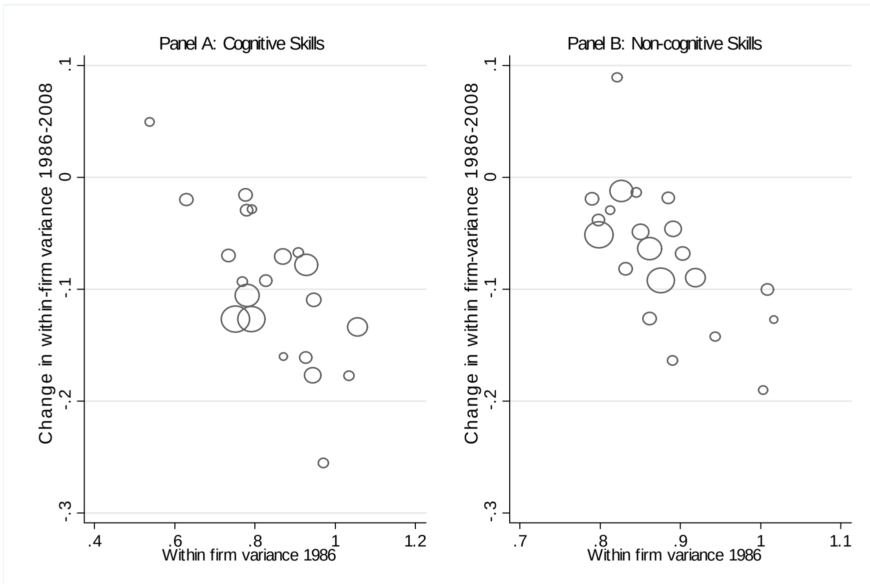
6.2 Decomposing the within-firm variance

A fall in the within-firm variance can come about because industries in which the average within-firm variance is initially small increase in relative size, because the average within-variance falls across all industries, or due to the interaction between these two factors. As shown in Table B3.1, the fall in the within-firm variance is mostly due to a fall in the within-firm variance for fixed industry shares. While industries with a low initial within-firm variance of cognitive skill did increase in size relative to other industries, this effect can only explain a small share of the overall trend.

[TABLE 2 HERE]

Table 2 shows the average within-firm variance in 1986 by industry, as well as the change between 1986 and 2008. The average within-firm variance in 1986 was significantly higher in manufacturing than in service industries. For example, the average variance of cognitive skill was above population variance (normalized to 1) in manufacturing of motor vehicles (NACE 34) and chemical products (24). In comparison, the average within-firm variance of cognitive skill was 0.63 in financial intermediation (65) and 0.54 in computer services (72). Table 2 also shows that the within-firm variance in cognitive skill fell in almost all industries, reflecting a move toward internally more homogeneous firms. As illustrated by Figure 6, the average within-firm variance fell much more in industries with internally heterogeneous firms in 1986 (high average within-firm variance), implying convergence across industries.[30]

Figure 6. Convergence in within-firm variance across industries



Note: Panel A shows the average within-firm variance of cognitive skills at the 2-digit industry level in 1986 plotted against the change in the same variance between 1986 and 2008. Panel B shows the same plot for non-cognitive skills. The sample consists of 30-35 year-old men employed at firms with at least 10 employees. Post- and telecommunications (NACE 64) has been excluded from the sample. Variances are corrected for firm-level sample size.

Table 3 provides additional evidence regarding what factors at the industry level correlate with a shift toward lower within-firm variance. More precisely, columns (1)-(8) report the results from regressions with (i) the change in the industry-average within-firm variance between 1986 and 2008 ("the long difference") or (ii) the level of the industry-average within-firm variance in a given year, as dependent variables. The level-regressions include industry fixed effects. Columns (9) and (10) instead show regressions with the industry-average cognitive or non-cognitive skills as dependent variables. The main result in Table 3 is that the convergence across industries shown in Figure 6 is robust to controlling for factors related to trade or (average) skills. As shown in columns (1)-(2) and (5)-(6), an increase in the average

[30] Post- and telecommunications (NACE 64) has been excluded from Figure 6 in order to increase visibility. In 1986 only 0.03 % of the workforce worked in this industry which is an extreme outlier in Panel A of Figure 6 (see Table 2).

within-firm variance in 1986 by 0.1 standard deviations is associated with an approximately 0.05 standard deviations larger reduction in the average within-firm variance between 1986 and 2008. Notably, firms in the manufacturing sector did not experience a sharper fall in the within firm variance when we control for the initial within-firm variance. There is no indication in the data that expanding world trade in general explain the shift toward firms with more homogeneous labor forces. However, the fixed-effects regressions in columns (3) and (4) show that skill upgrading (in particular non-cognitive skill) is associated with more homogeneous workforces in terms of cognitive skill. Moreover, Columns (9) and (10) show that skill upgrading is in turn associated with imports from China. These results are consistent with low-wage competition (from China and similar countries) leading to a restructuring of Swedish firms toward more high-skilled intensive production and more homogeneous workforces.

[TABLE 3 HERE]

7 Sorting of educational groups or assortative matching?

The previous section documented two basic facts about the change in sorting in the Swedish labor market. First, differences in cognitive skill between firms increased mainly due to the expansion and skill upgrading of the ICT sector. Second, differences in skill among workers in the same firm fell in all major industries, but the fall was larger for industries where the average within-firm variance was high to begin with. In this section, we look at the change in sorting from a different perspective. Specifically, we ask whether the increase in sorting was due to sorting of narrowly defined educational groups across firms, or stronger assortative matching of workers for a given allocation of educational groups.

7.1 Framework

Our analysis proceeds in two steps. In the first step, we decompose the total variance in skill into components between and within educational groups. Let $\widehat{C}_{ij}$ denote the average cognitive skill in the educational group individual i belongs to while C_{ij} denotes worker i's actual skill level. Consequently, $C_{ij} - \widehat{C}_{ij}$ equals worker i's residual from a regression of actual skills (C_{ij}) on educational groups fixed effects. The sample variance in cognitive skill can be decomposed as

$$\frac{1}{n}\sum_j\sum_i\left(\underbrace{\left(\widehat{C}_{ij}-\overline{C}\right)^2}_{\text{between-educational groups variance}}+\underbrace{\left(C_{ij}-\widehat{C}_{ij}\right)^2}_{\text{within-educational groups variance}}\right) \tag{2}$$

Our educational groups are defined by the interaction between field of study and years of schooling. For example, workers with a five-year tertiary degree in engineering belong to the same group. We use educational groups rather than occupation since good data on occupation is not available during the first part of our study period (1986-1995).[31] In total there are about 90 different educational groups in our data. Since educational attainment is set already at the time when the men in our sample enter the labor market changes in sorting between groups is *not* explained by sorting of workers to firms.

In the second step, we decompose the between- and within-group variances into between- and within-firm components. Let $\widehat{C}_j = \frac{1}{n_j}\sum_i \widehat{C}_{ij}$ denote the expected firm-level mean of cognitive skills in firm j conditional on the composition of educational groups in the firm. One way to think about $\widehat{C}_j$ is as a proxy for the skill-intensity of technology in a firm. For example, a firm that hires many engineers will have a high value of $\widehat{C}_j$. The between-group variance in cognitive skill can then be decomposed as

$$\underbrace{\frac{1}{n}\sum_j n_j\left(\widehat{C}_j-\overline{C}\right)^2}_{\text{between-firm between-educational groups}}+\underbrace{\frac{1}{n}\sum_j\sum_i\left(\widehat{C}_{ij}-\widehat{C}_j\right)^2}_{\text{within-firm between-educational groups}} \tag{3}$$

The between-firm between-group variance is the variance in cognitive skill explained by differences in the composition of educational groups across firms. For example, this component is large if some firms hire a high fraction of engineers (high-skilled on average) while other firms mostly hire mechanics (low-skilled on average). One way to think about the between-firm component is therefore as a measure of the differences in the skill-intensity of technology across firms. The within-firm between-group variance reflects the variance explained by the fact that each firm may encompass workers from many different educational groups, with different levels of skill. For example, the within-firm component is large if most firms employ both engineers and mechanics and low if most firms either only hire engineers or only hire mechanics.

We now turn to the variance within educational groups. Keeping with the same terminol-

[31] The difference between using educational or occupational groups in this context are quite small, however. The correlation between $\widehat{C}_j$ defined by education and $\widehat{C}_j$ defined by occupation was 0.91 in 1996 (the first year for which we have data on occupation) and 0.88 in 2008. The corresponding figures for $\widehat{N}_j$ are 0.85 and 0.81.

ogy as above, the within-group variance can be decomposed into between- and within-firm components:

$$\underbrace{\frac{1}{n}\sum_j n_j\left(C_j-\widehat{C}_j\right)^2}_{\text{between-firm within-educational groups}}+\underbrace{\frac{1}{n}\sum_j\sum_i\left(\left(C_{ij}-\widehat{C}_{ij}\right)-\left(C_j-\widehat{C}_j\right)\right)^2}_{\text{within-firm within-educational groups}}. \tag{4}$$

The between-firm within-group variance is the variance in the difference between firms' actual level of cognitive skills and the predicted level based on their composition of educational groups. This variance is large if the best workers in a given educational group work in the same firms, i.e., the more positive is worker-to-worker assortative matching. For example, assortative matching is positive if the most clever engineers tend to work in the same firms, and if the most clever engineers work with the most clever mechanics. The within-firm within-group variance is large if there is a high variance of skill within firms given the general skill level. For example, this component is large for a firm that employs both relatively skilled and relatively unskilled engineers. Stronger (positive) assortative matching of workers for a given technology is associated with an increase in the ratio of the first (between-firm within-group) component in (4) relative to the second (within-firm within-group) component.[32]

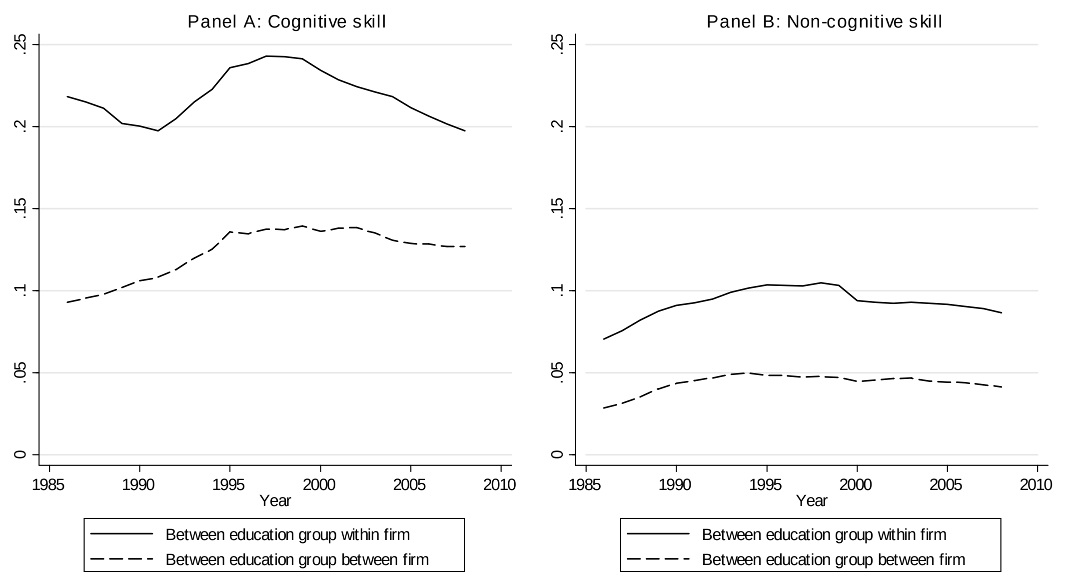
7.2 Results

Figure 7 shows the decomposition of the between-educational group variance in (3) between 1986 and 2008. The figure shows the absolute level of each component. There are three facts worth noting from this figure. First, the between-group variance (i.e., the sum of the between- and within-firm components) is much larger for cognitive and than for non-cognitive skill, reflecting the stronger relationship between cognitive skill and educational attainment (Lindqvist and Vestman, 2011). Second, most of the variance in skill between educational groups is within firms. This implies that many firms employ workers from educational groups with very different average skills. Third, the share of the between-group variance explained by the between-firm component is increasing over time. For cognitive skill, the between-firm share of the between-group variance increases from 29.9 % to 39.1 %, while the increase is from 28.8 % to 32.4 % for non-cognitive skill. These results suggest that differences between

[32] This footnote comments on the relationship between (3) and (4), and the between- and within-firm variances in decomposition (1). The total between-firm variance in cognitive skill is given by the sum of the between-firm components in (3) and (4) and a third component, $2\left(C_j-\widehat{C}_j\right)\left(\widehat{C}_j-\overline{C}\right)$, i.e., the covariance between $C_j-\widehat{C}_j$ and $\widehat{C}_j-\overline{C}$. A positive covariance means that firms that hire workers in high-skilled educational groups also hire workers who are more skilled than the average in their respective educational group. The total within-firm variance is given by the sum of the within-firm components in (3) and (4) plus the covariance multiplied by -1. The covariance thus cancels out when we sum up the total sample variance.

firms in terms of the skill-intensity of technology are increasing over time. In other words, firms have become more specialized in terms of the type of workers (as defined by education) they employ.

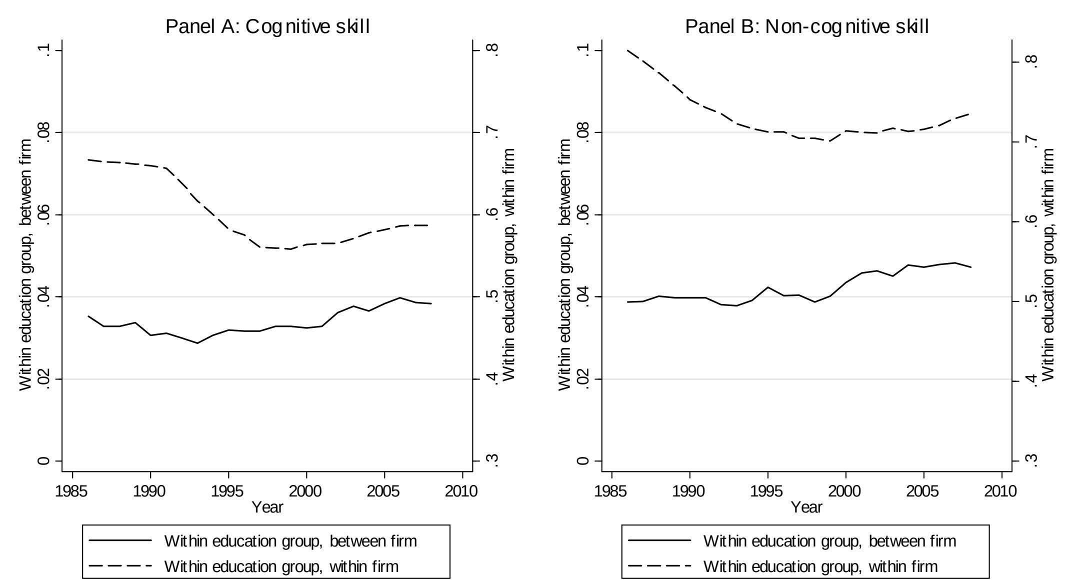
Figure 7. Decomposing the variance between educational groups



Note: The figure shows the within- and between-firm components of the variance in skills between educational groups. The sample consists of 30-35 year-old men employed at firms with at least 10 employees. Variances corrected for firm-level sample size.

Figure 8 shows the decomposition of the within-occupation variance in (4) between 1986 and 2008. As shown by the figure, sorting of workers between firms only accounts for a small share of the total variance in skill within educational groups. However, the between-firm share is significantly larger than predicted by random sorting at all points in time, suggesting that worker skills are complements (see Table B1.1). Moreover, the between-firm share of the within-group variance is increasing over time, from 5.0 % to 6.2 % for cognitive skill and from 4.5 % to 6.0 % for non-cognitive skill. Figure 8 thus suggests that assortative matching of workers has become more positive over time.

Figure 8. Decomposing the variance within educational groups



Note: The figure shows the within- and between-firm components of the variance in skills within educational groups. Skill variances within educational groups in their within- and between-firm components. The sample consists of 30-35 year-old men employed at firms with at least 10 employees. Variances corrected for firm-level sample size.

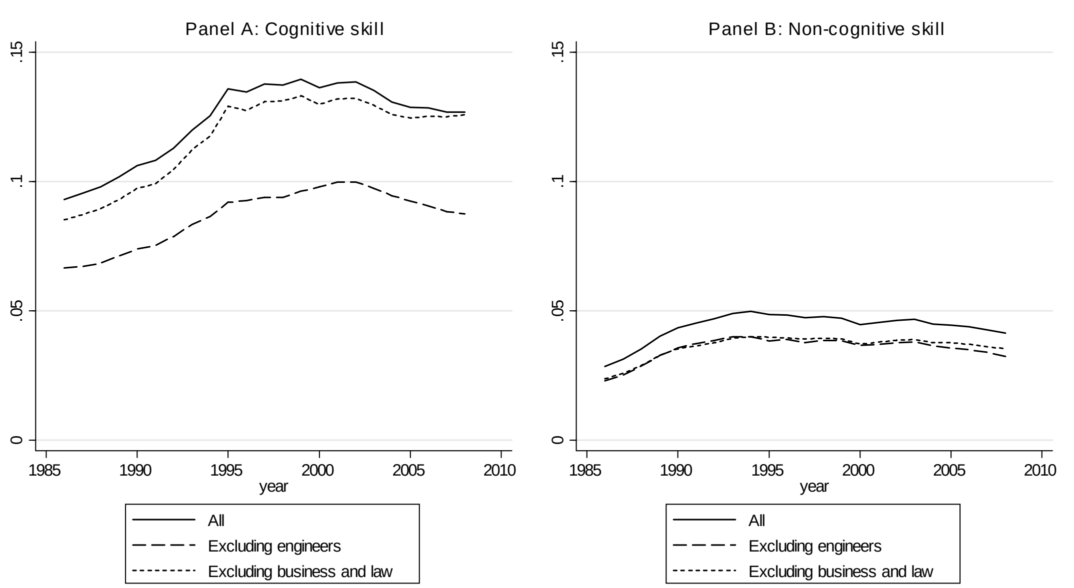
7.3 Mechanisms

We have shown that both increasing sorting of educational groups across firms and more positive assortative matching explain the increase in sorting. Before we conclude, we provide suggestive evidence regarding the mechanisms at play, beginning with the increase in the sorting of educational groups.

An increase in the sorting of educational groups between firms could come about for at least two different reasons. First, technological change may imply that skilled workers select into firms specializing in the new technology (Acemoglu, 1999; Caselli, 1999). Second, sorting of education groups could increase due to outsourcing. For example, consider a firm which both develops new products (skill-intensive) and manufactures them (not skill intensive). If product development and manufacturing is instead split into two different firms, differences in the skill-intensity of technology between firms would increase.

While we are unable to perfectly distinguish between these two mechanisms, a reallocation of educational groups across firms driven by sectors intensive in new technology (like ICT) or educational groups likely to work with new technology (such as engineers) is suggestive of technological change. In contrast, there is less reason to expect a general trend toward outsourcing to pertain specifically to sectors intensive in new technology. In Figure 5 we showed that the ICT sector could explain a large fraction of the overall increase in the between-firm variance with respect to cognitive skill. In Figure B4.1, we show that we obtain similar results if we conduct the same exercise for the between-group between-firm variance. In other words, the increase in the skill intensity of technology between firms is to a significant extent due to the growth of ICT. As an alternative exercise, we calculate "counterfactuals" for the between-firm between-group variance removing either "civil engineers" (defined as at least a four-year degree in engineering) or workers with at least a three-year degree in business administration or law. These two groups of workers are of roughly the same size and each constitute a small share of the overall sample.[33] Figure 9 shows that removing workers with a degree in business or law does not change the level or trend for the sorting of educational groups across firms. In contrast, removing civil engineers has a negative effect both on the level and the trend for cognitive skills.

Figure 9. Counterfactual between-group between-firm variance



Note: Between-occupation between-firm skill variances, including and excluding employees with Engineering, Business, and Law degrees. The sample consists of 30-35 year-old men employed at firms with at least 10 employees. Variances corrected for firm-level sample size.

[33]The share of the workforce with a higher degree in engineering increased from 4.7 % in 1986 to 7.5 % in 2008. Similarly, the share with a degree in business or law increased from 3.1 % to 5.6 %.

We now turn to the within-group variance. An increase in assortative matching could arise because complementarities between workers' skills become more positive (for example due to technological change), or because of lower costs from matching workers with similar levels of skill (for example due to liberalization of trade). In order to investigate which forces drive assortative matching, we estimate regressions of the following generic form

$$\begin{aligned}\sigma^2_{WGWF,jkt} &= \beta_0 + \beta_1 \log(Capital)_{jkt} + \beta_2 \log(Size)_{jkt} + \beta_3 \left(C_{jkt} - \widehat{C}_{jkt}\right) + \beta_4 \widehat{C}_{jkt} \\ &\quad + \beta_5 Trade_{kt} + \beta_6 China\_import_{kt} + \gamma_{jk} + \varepsilon_{jkt} \qquad (5)\end{aligned}$$

where $\sigma^2_{WGWF,jkt}$ is the the within-firm within-group variance for firm j in industry k at time t.[34] Low values of $\sigma^2_{WGWF,jkt}$ indicate strong (positive) assortative matching. $Capital_j$ is capital intensity, $Size_j$ is the number of employees, $\left(C_{jkt} - \widehat{C}_{jkt}\right)$ is the difference between the actual and predicted skill level of firm j and $\widehat{C}_{jkt}$ is the predicted skill level of firm j. $Trade_{kt}$ (total value of exports and imports in industry k divided by total turnover) and $China\_import_{kt}$ (total value of imports from China in industry k divided by total turnover) have the same definition as in the industry-level regressions in Table 3. We include a firm-level fixed effect, γ_{jk}, in all regressions. Each firm is weighted with the number of workers observed in our sample.

Our main interest in regression (5) are the variables related to technology and trade. If more complex production processes are associated with stronger complementarities, then we should observe a negative association between $\sigma^2_{WGWF,jkt}$ and the predicted skill level, $\widehat{C}_{jkt}$. Relatedly, we expect a negative sign of β_3 if "star" firms, with unexpectedly high skills given their technology, display stronger assortative matching. The sum of β_3 and β_4 gives the total relationship between the firm-level average of cognitive skill at time t (C_{jkt}) and $\sigma^2_{WGWF,jkt}$.[35]

The results from regression (5) are presented in Table 4. The main result is that an increase in skills is strongly associated with more positive assortative matching. This holds both for an increase in the predicted skill levels ($\widehat{C}_j$ and $\widehat{N}_j$) – what we may think of as the skill-intensity of a firm's technology – and for an increase in skill for given predicted skills ($C_j - \widehat{C}_j$ and $N_j - \widehat{N}_j$). Non-cognitive skill is the more robust predictor of assortative

[34] Since the between-firm component of the within-group variance does not vary at the firm level, we are not able to use the relative share of the within-firm component as the dependent variable.

[35] The regression analysis laid above does not allow us to obtain conclusive evidence behind the general strengthening of assortative matching. Apart from concerns regarding endogeneity and omitted variables, the fundamental problem is that, since we can only study variation within and between firms or industries, we cannot identify the effect of factors that affect the entire economy in the same fashion. It is an open question whether our findings can be extrapolated to the economy as a whole.

matching when both types of skill are entered as regressors in columns (4) and (8), but the high correlation between the firm-level average of cognitive and non-cognitive skill implies that these results are hard to interpret. We also find that firm size is positively correlated with $\sigma^2_{WGWF,jkt}$ (and thus negatively correlated with assortative matching). There is no statistically significant relation between the trade variables and our measure of assortative matching.

The results in Table 4 are consistent with an "O-ring"-type story of sorting (Kremer, 1993). That is, more complex production processes (which could in turn be due to technological change) increase complementarities between workers, inducing firms to match workers who are particularly good (or particularly bad) in the same firm.

[TABLE 4 HERE]

8 Sorting by skill and firm wage differentials

In this section, we relate the increase in sorting to changes in the structure of wages. As shown in Panel A of Figure 10, the total wage variance among the men in our sample increased by 42 percent between 1986 and 2008 (from 0.050 to 0.071), reflecting a sharp increase in wage inequality. In line with previous research, including a study on Swedish plants Nordström-Skans et al. (2009), Panel A of Figure 10 also shows that the increase wage inequality is disproportionately due to an increase in the between-firm wage variance (81 percent) than the within-firm variance (25 percent).[36] Interestingly, the main increase in the between-firm wage variance occurred after the increase in sorting during the first half of the 1990's.

We undertake a simple accounting exercise to see if the increase in between-firm wage inequality can be explained by the increase in sorting. To this end, we estimate regressions of the form

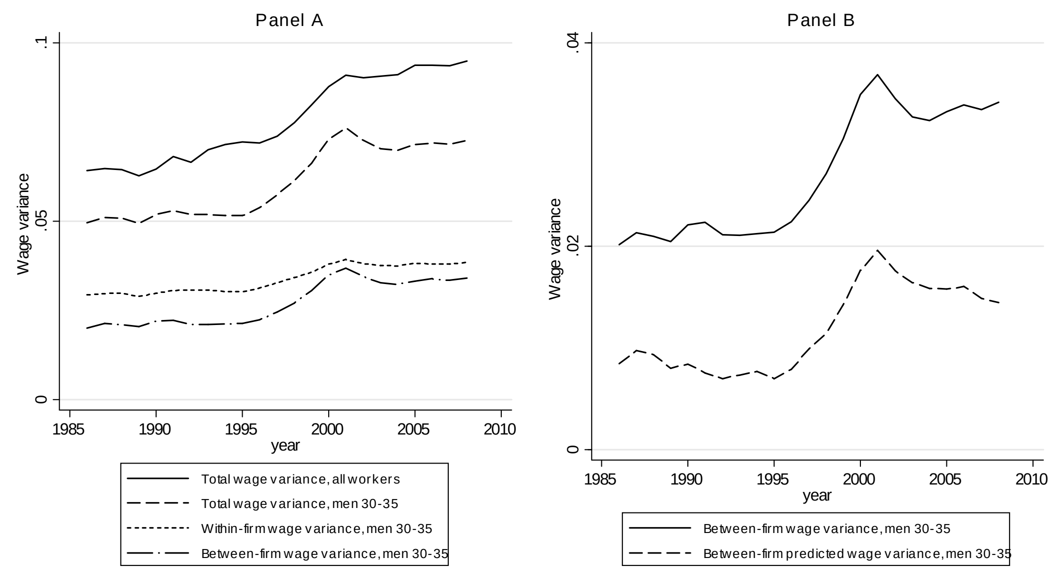
$$w_{jt} = \beta_{0,t} + \beta_{1,t} CS_{jt} + \beta_{2,t} NCS_{jt} + \beta_{3,t} \left(CS_{jt} * NCS_{jt} \right) + u_{jt}, \tag{6}$$

where w_{jt} is the mean (log) wage at firm j at time t, CS_{jt} is the average of cognitive skill in firm j at time t and NCS_{jt} the corresponding value for non-cognitive skill. Regressions are weighted by the number of observed workers per firm. Using the predicted wages from

[36]This literature includes studies of Czech firms 1998-2006 (Eriksson et al., 2009); the US manufacturing sector 1975-1992 (Dunne et al., 2004) and 1975-1986 (Davis and Haltiwanger, 1991); US plants (Barth et al., 2011); UK firms 1984-2001 (Faggio et al., 2010) and Portugese firms 1983-1992 (Cardoso, 1999). With the exception of Cardoso (1999), these papers find increasing wage differences between firms or plants.

these regressions ($\widehat{w}_{jt}$), we then decompose the between-firm wage variance into a component explained by firm skill differences and an unexplained component. An increase in the explained component could be due to an increase in the estimated firm-level skill gradients, an increase in between-firm skill differences, or a combination of both.

Figure 10. Decomposing the variance of wages



Note: Panel A shows the variance of log wages for all workers age 20-64 and 30-35 year-old men. Both samples restricted to firms with at least 10 employees. Panel B shows the between-firm variance in (log) wages and predicted (log) wages from regression (6).

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 worker skills, or between 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 is a key factor behind sorting, this is a serious limitation also for a purely descriptive exercise.[37]

We plot the evolution of the explained and total between-firm wage variance in Panel B of Figure 10. The explained variance increased from 0.0085 to 0.0144 between 1986 and 2008,

[37] A second, more ambitious, approach would be to estimate spillovers between workers by regressing individual wages on own and co-worker skill. Yet a recent theoretical literature suggest that the relationship between co-worker skills and wages may be very different from the relationship between co-worker skills and productivity due to "mismatch" (Eeckhout and Kircher, 2011; de Melo, 2013). Fredriksson et al. (2015) provides empirical evidence that worker skill-mismatch is relevant also in the Swedish labor market.

thereby explaining 47 percent of the increase in the overall between-wage variance. Notably, the increase in the explained between-firm variance occurs *after* the increase in sorting during the first half of the 1990's. The reason is that the increase in sorting is initially counteracted by falling skill gradients. From the mid 1990's the skill gradients start increasing, thereby also increasing the between-firm variance explained by sorting.

By fixing sorting or skill gradients at their 1986 levels, we derive counterfactual sorting patters that allow us to analyze the relative importance of changes in sorting and changes in the skill gradients over the course of the entire study period. The upper-right cell of Table 5 shows the counterfactual between-firm variance in predicted wages based on the sorting patterns in 1986 using the 2008 skill gradients. Comparing the upper and lower right cells reveals that 51 percent of the total increase is due to steeper skill gradients. The lower left cell displays the counterfactual variance using the 2008 sorting patterns and the 1986 skill gradients. Comparing this to the lower right cell shows that 36 percent of the total increase is due to sorting. The remaining 14 percent of the increase is attributed to the interaction between increased skill sorting and steeper skill gradients.

[TABLE 5 HERE]

The results in this section support three conclusions. First, our results suggest that sorting by skill is relevant for understanding the evolution of wage inequality. Second, inferring skill sorting from the wage distribution can lead to erroneous conclusions since sorting and skill gradients do not necessarily move together. Third, that both between-firm skill sorting and skill gradients have increased is consistent with stronger complementarities, either between worker skills or between skills and technology. However, the timing is puzzling. A standard model would predict that a strengthening of complementarities leads to a contemporaneous increase in sorting, skill gradients and firm wage differentials. In contrast, we find that the increase in sorting predates increases in both the total and explained predicted between-firm wage variance. The finding that sorting and skill gradients do not move together thus suggests that the adjustment process to stronger complementarities is not fully understood.

Although our approach is different, the results in this section are broadly in line with the recent findings in Card et al. (2013). Using wage regressions with additive worker and firm fixed effects, they find that increased worker heterogeneity, increased workplace-specific wage components, and increases in positive assortative matching between workers and firms can account for most of the increase in West German wage inequality. We, on the other hand, find that the combined impact of increased sorting and steeper skill gradients can account for a substantial share of the increase in between-firm wage variance. This increase can in turn account for a large component of the increase in the variance of wages.

9 Concluding remarks

Using direct and time consistent measures of cognitive and non-cognitive skills, we document a substantial increase in the sorting of workers to firms between 1986 and 2008. Over this period, the share of the sample variance of cognitive skills explained by between-firm skill differences increased by more than 40 %. While the bulk of the increase in sorting coincided with the Swedish economic crisis of 1991-1993, the trend toward increased sorting was present already in the late 1980's. The trend toward increased sorting is robust to a wide range of tests regarding the measurement of sorting, the sample used and adjusting for measurement error in skills. Combined with steeper firm-level skill gradients, the increase in sorting can account for about half of the increase in between-firm wage differentials between 1986 and 2008.

Why did sorting increase? Our results suggest that technological change is at heart of the story. The expansion of a small set of high-tech industries in the ICT sector led to increased sorting of workers across firms, in particular engineers. In this respect, our results bear out a central prediction in models of skilled-biased technical change (e.g. Acemoglu, 1999; Caselli, 1999); that new technology will increase skill sorting in the labor market. We have also showed that assortative matching between workers have become more positive over time, consistent with increasing complementarities between worker skills. The degree of assortative matching at the firm level is in turn associated with skill upgrading, suggesting that technological change may play a role also in this case. Overall, we do not find strong evidence that trade drives changes in sorting. However, caution is warranted in interpreting these results as our data on trade are admittedly crude. A priority for future research is to study the effect of trade on sorting using better data and a more credible identification strategy.

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Appendix A: Description of data

A.1 Educational groups

The educational groups used in Section 8 are based on the intersection between the duration and field of study. We generate five groups for duration: at most compulsory schooling; two years of secondary education; three years of secondary education; some post-secondary education; at least three years of post-secondary education. Field of study is based on the 26 detailed categories available in the Swedish SUN classification. In total, this procedure results in 90 educational groups.

A.2 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. (2012) 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; **?** 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.3 Trends in cognitive abilities

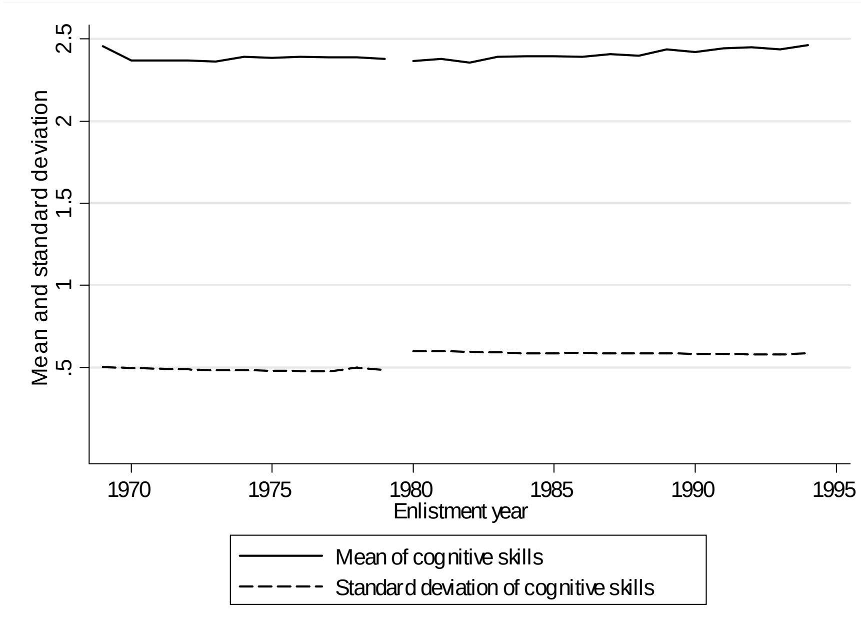
The analysis in this paper makes use of skill measures that are standardized by enlistment year. Standardization ensures that individuals at the same position in the overall skill distribution are compared over time, but may hide changes in the underlying distribution of skills. In this Appendix, we 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 A3.1 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.[38] We conclude from this exercise that standardization is unlikely to have any substantive impact on the analysis in this paper.

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

Figure A3.1 Trends in raw ability scores



Note: The figure shows the mean and standard deviation by draft 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.4 Trade data

In order to account for the relation between international trade and skill sorting, we use data on trade (scaled by total turnover) at the industry level. Two variables are created: total trade and imports from China. The first variable is intended to capture the general degree of internationalization of an industry and the second is a proxy for low-wage trade competition. The main limitation when constructing a consistent series is that industry trade data do not map well over time. The reason is that industry classification underwent a major change in 1995 when reporting moved from the SNI69 to the SNI92 system. SNI69 was based on ISIC Rev.2 while SNI92 is based on NACE Rev.1 and the differences are documented in Statistics Sweden (1992).

For these reasons we can only construct trade data for 30 industries (mainly in manufacturing) but in most of the remaining industries trade is likely to be limited. We therefore impute trade to be zero (0) in industries without trade data. As mentioned in the main text, the results are not sensitive to the inclusion or exclusion of these industries. Trade data are collected from Statistics Sweden's Statistical Database (Statistikdatabasen) and the series are "Varuimport och varuexport efter Varu-SNI69 och handelspartner" for the period

1986-94, "Varuimport och varuexport efter produktgrupp Prod-SNI97 och handelspartner" for the years 1995-97, and “Varuimport och varuexport efter produktgrupp SPIN 2002 och handelspartner” for years 1998-2008. Data on turnover is from the Firm Register (Företagsdatabasen), the same source as capital intensity and other firm level variables used in this paper.

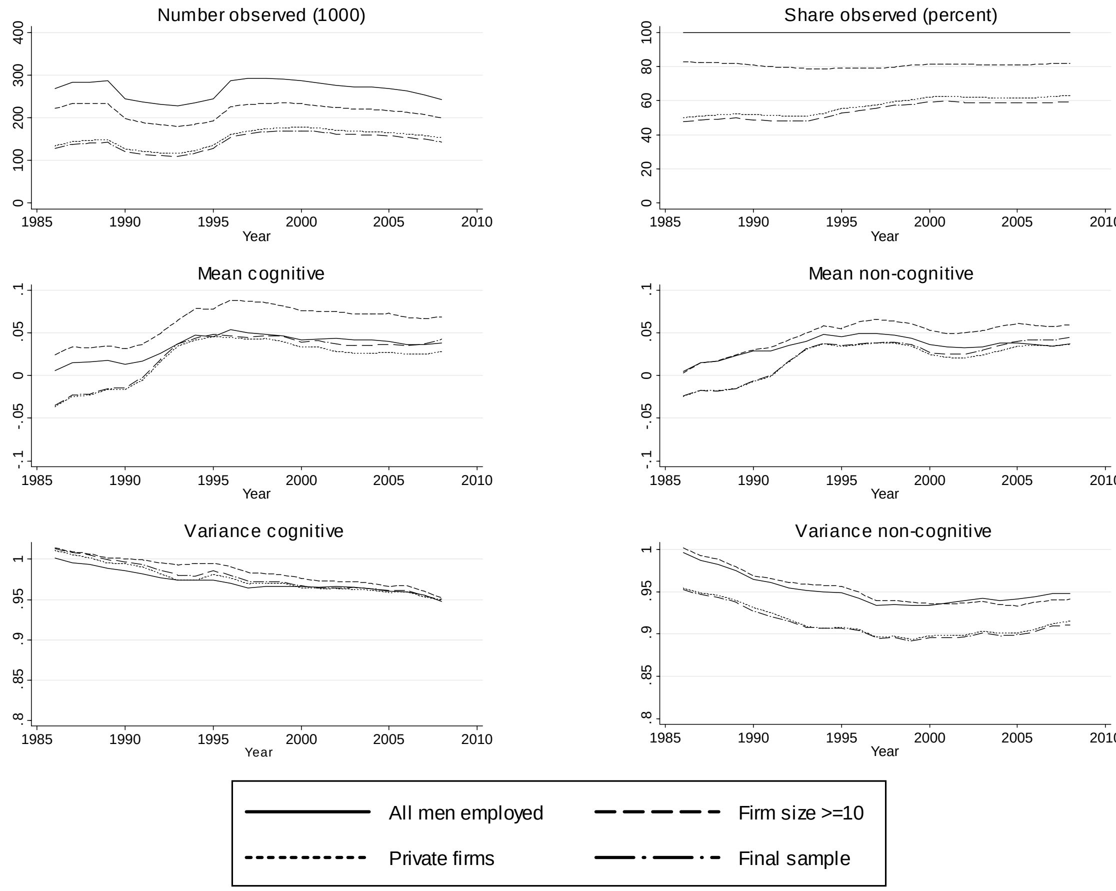
A.5 The final samples

The upper left panel of Figure A5.1 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 draft 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 draft record falls in 1990 and increases in 1996. The reason is that the draft 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 draft 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 draft 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 A5.1 shows the mean values and standard deviations 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 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. 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.

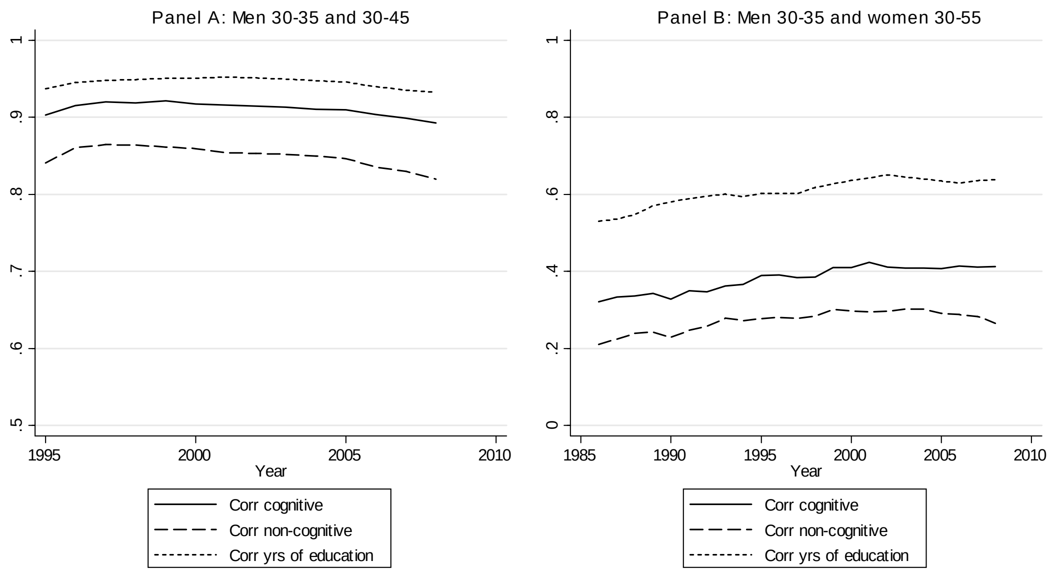
Figure A5.1 Sample descriptives and selection



Note: Sample size and skill moments from different sample restrictions. The sample draft include men in all with a complete draft record; the sample private include men in draft employed in a private firm and sample include men in private employed in a firm with at least 50 employees and more than one worker observed in the sample.

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 A5.2, 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.

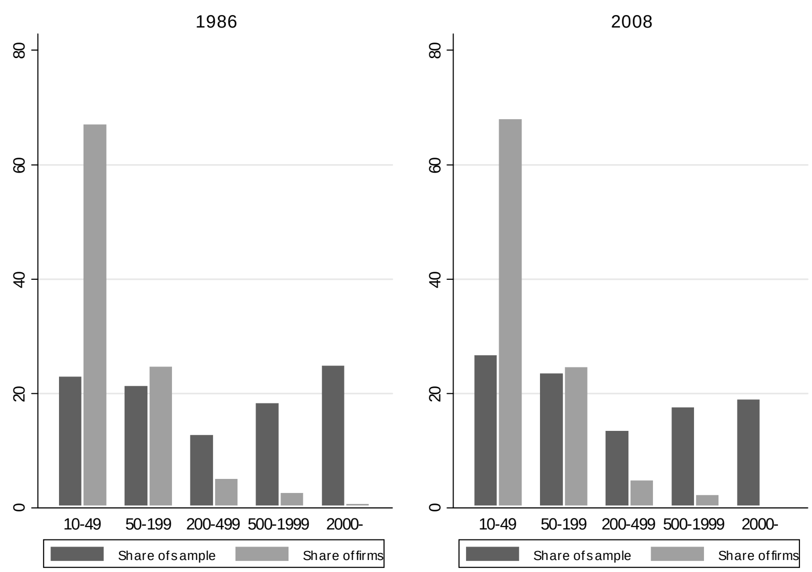
Figure A5.2 Correlations in firm-level average skills



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).

Finally, Figure A5.3 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 A5.3 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: Additional results

B.1 Simulations and additional results for section 5

Table B1.1 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 B1.1 shows the 1st, 50th and 99th percentile of the simulated variances from 1,000 draws. In addition to the between- and within-firm components of decomposition (1), Table B1.1 also shows the decomposition of the covariance (D2) described in Appendix D1 below and the decomposition of the variance between and within educational groups discussed in Section 7 of the paper.

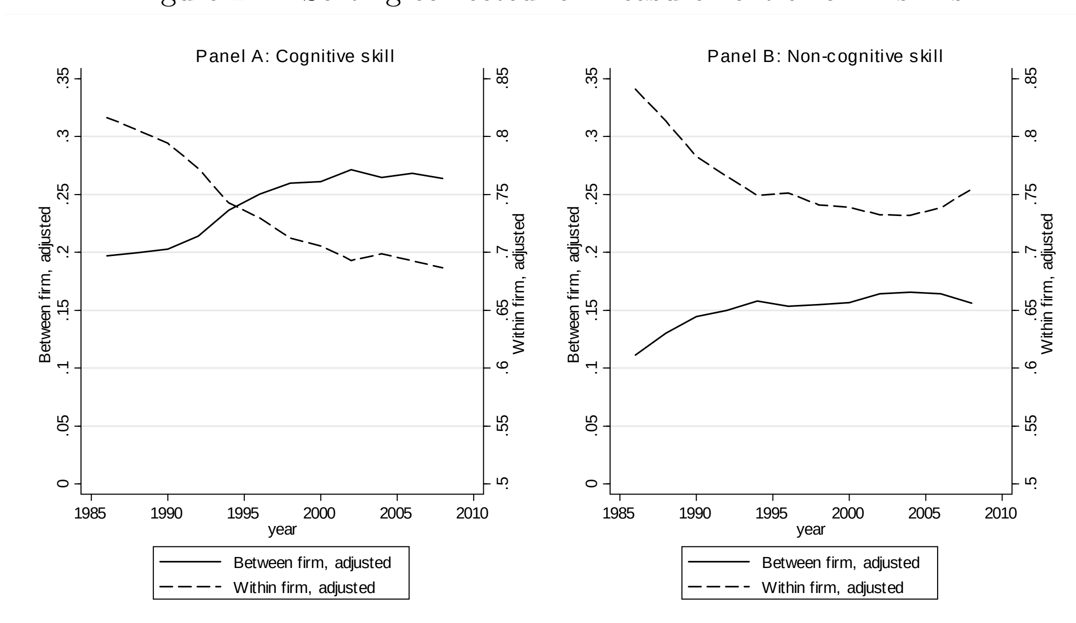
[TABLE B1.1 HERE]

Table B1.2 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 2.

[TABLE B1.2 HERE]

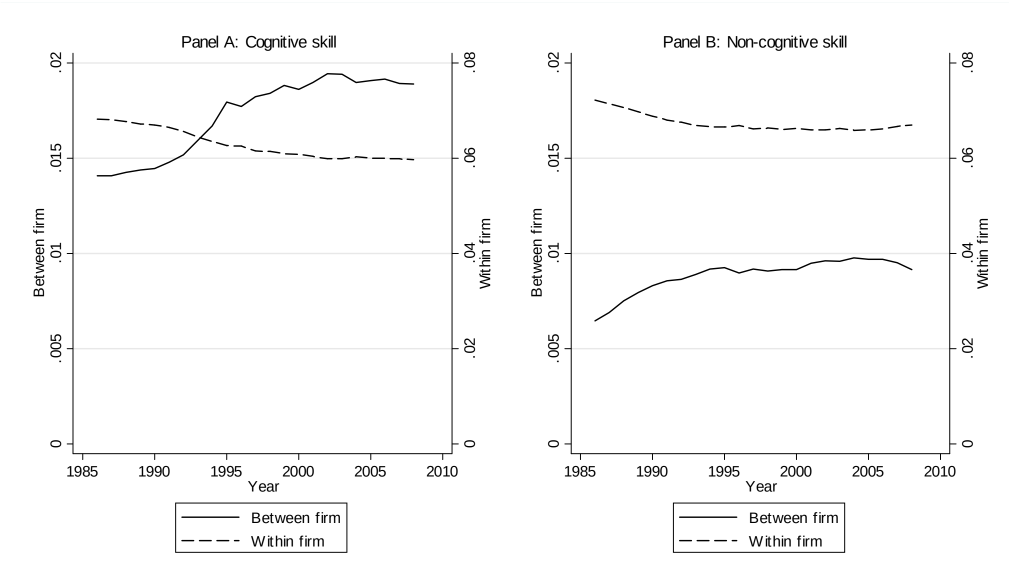
Below, we provide the additional graphical evidence for section 5.

Figure B1.1 Sorting corrected for measurement error in skills



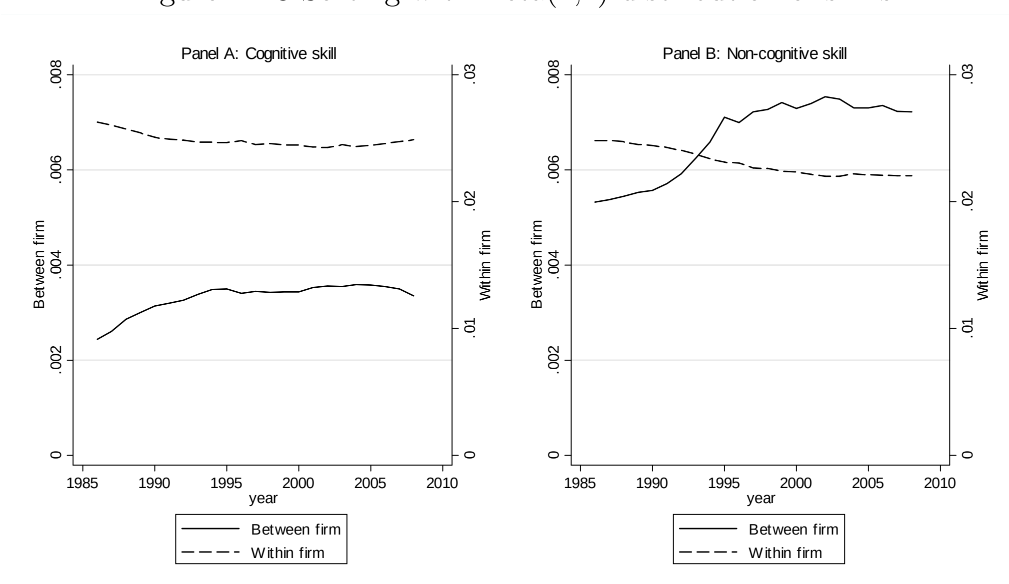
Note: Between- and within-firm variances adjusted for measurement error as outlined in Appendix D3 (medians based on 100 simulations). The sample includes 30-35 year-old men employed at firms with at least 10 employees. Variances corrected for firm-level sample size.

Figure B1.2 Sorting with uniform distribution of skills



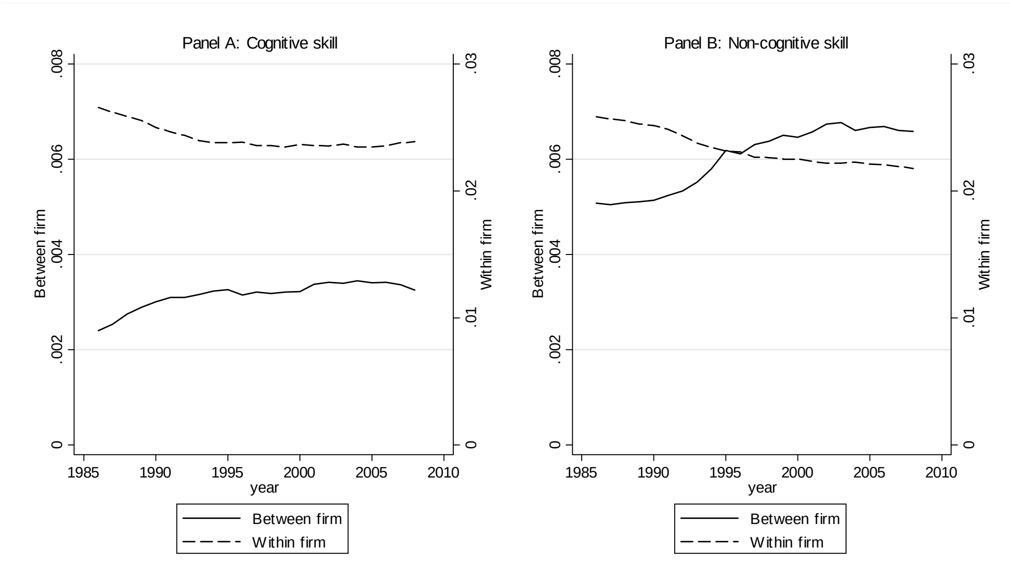
Note: Between- and within-firm variances, assuming uniformly distributed skills. The sample includes 30-35 year-old men employed at firms with at least 10 employees. Variances corrected for firm-level sample size.

Figure B1.3 Sorting with Beta(2,4) distribution of skills



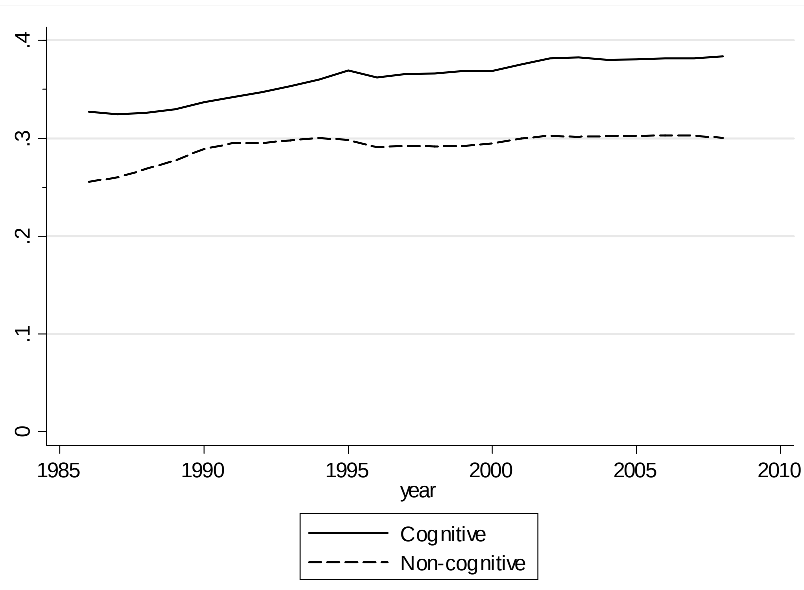
Note: Between- and within-firm variances, assuming skills follow a Beta(2,4)-distribution. The sample includes 30-35 year-old men employed at firms with at least 10 employees. Variances corrected for firm-level sample size.

Figure B1.4 Sorting with Beta(4,2) distribution of skills



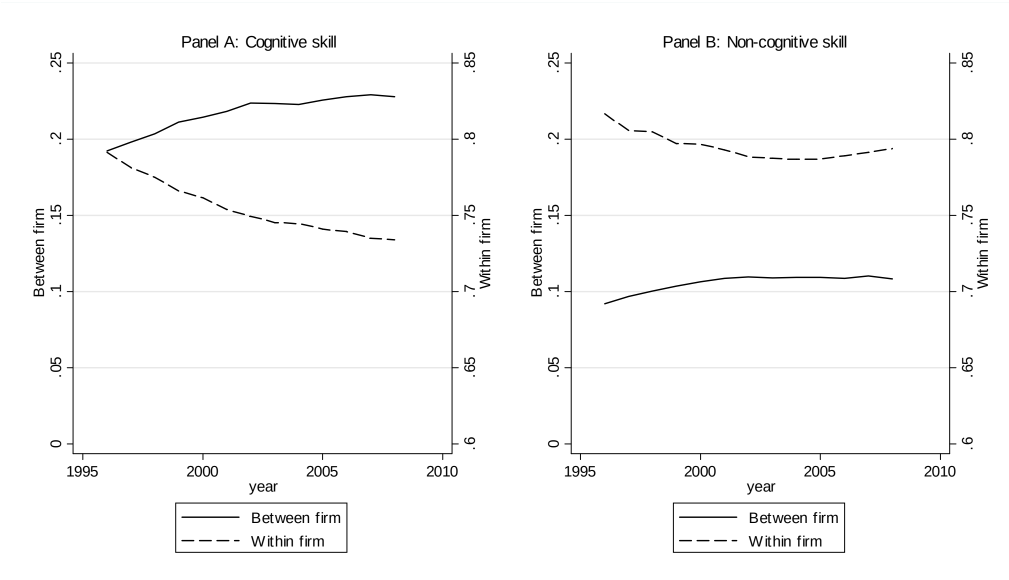
Note: Between- and within-firm variances, assuming skills follow a Beta(4,2)-distribution. The sample includes 30-35 year-old men employed at firms with at least 10 employees. Variances corrected for firm-level sample size.

Figure B1.5 Sorting measured with Kendall's rank correlation



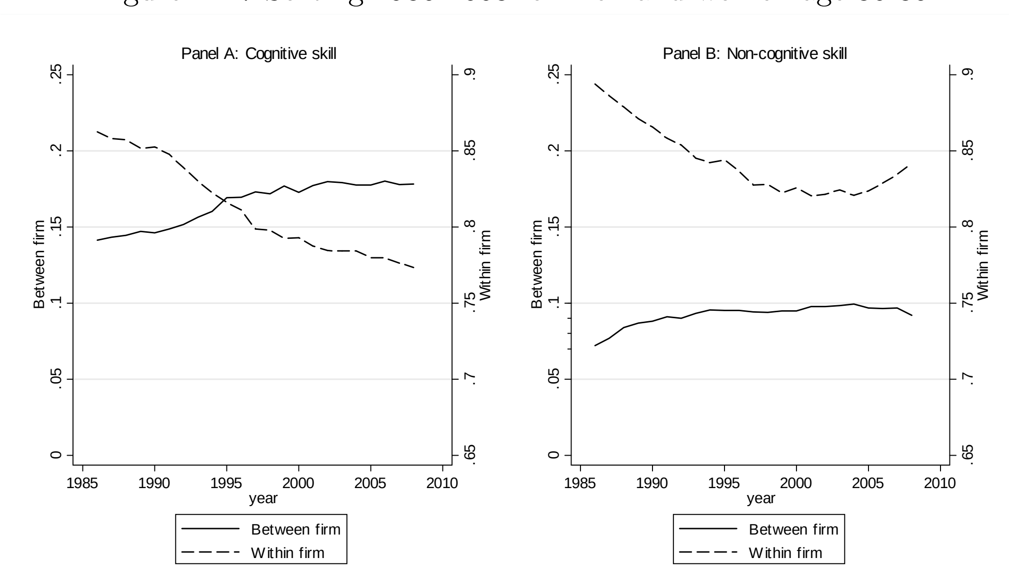
Note: The figure reports Kendall's rank correlation (tau-b) between each firm's rank in terms of average (cognitive or non-cognitive) skill, and the skill of each worker. The sample includes 30-35 year-old men employed at firms with at least 10 employees.

Figure B1.6 Sorting 1996-2008 for men age 30-45



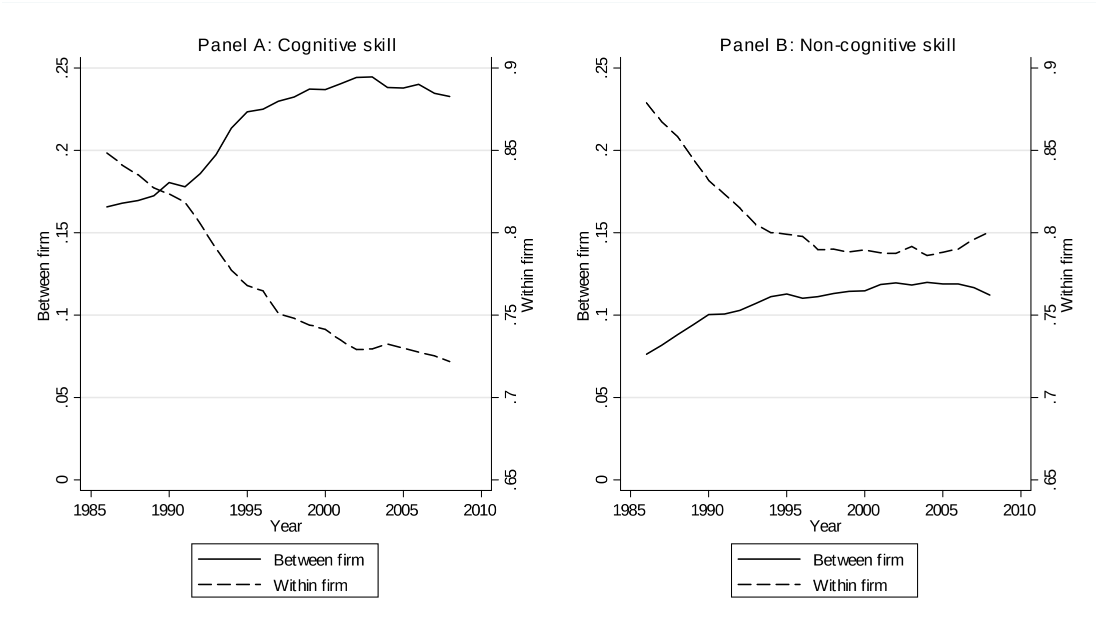
Note: Between- and within-firm variances. The sample includes 30-45 year-old men employed at firms with at least 10 employees. Variances corrected for firm-level sample size.

Figure B1.7 Sorting 1986-2008 for men and women age 30-35



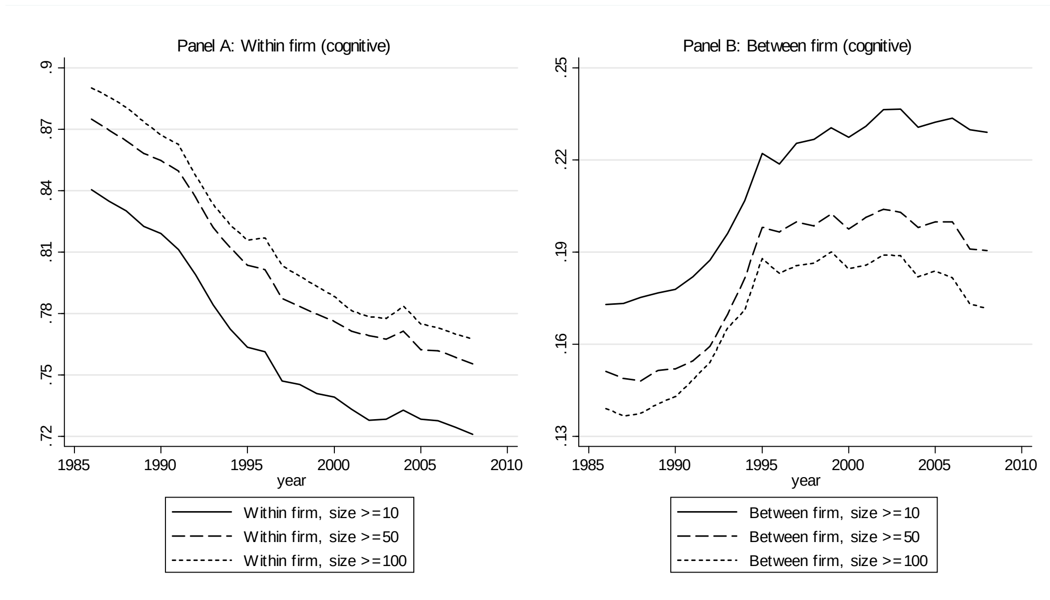
Note: Between- and within-firm variances. The sample includes 30-35 year-old men and women employed at firms with at least 10 employees. Variances corrected for firm-level sample size.

Figure B1.8 Sorting 1986-2008 including the public sector



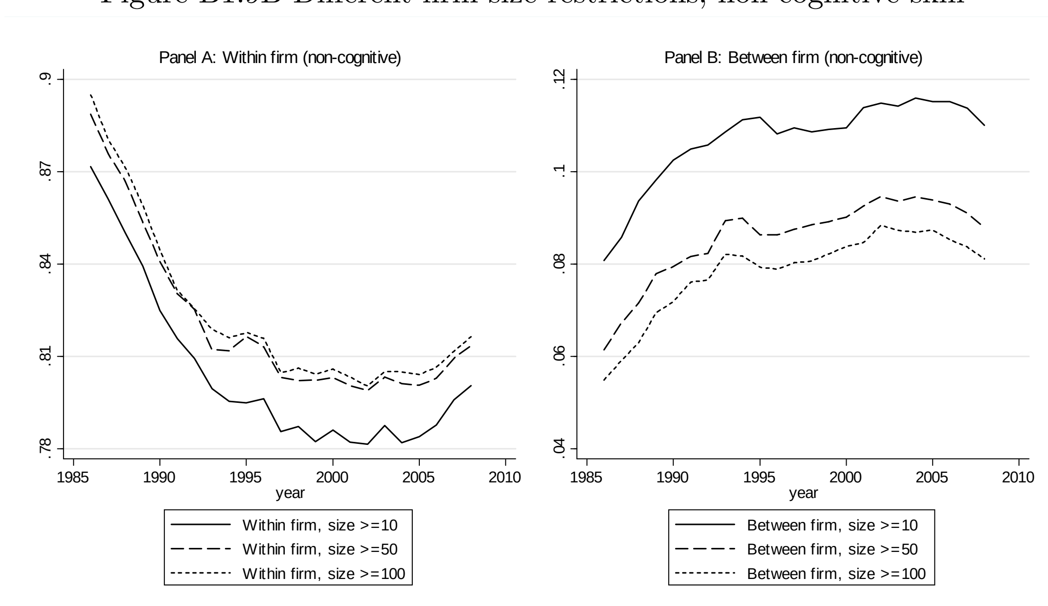
Note: Between- and within-firm variances. The sample includes 30-35 year-old men employed at private firms and public entities with at least 10 employees. Public entities within public administration, defence, education, health services and extraterritorial organizations are not included. Variances corrected for firm-level sample size.

Figure B1.9A Different firm size restrictions, cognitive skill



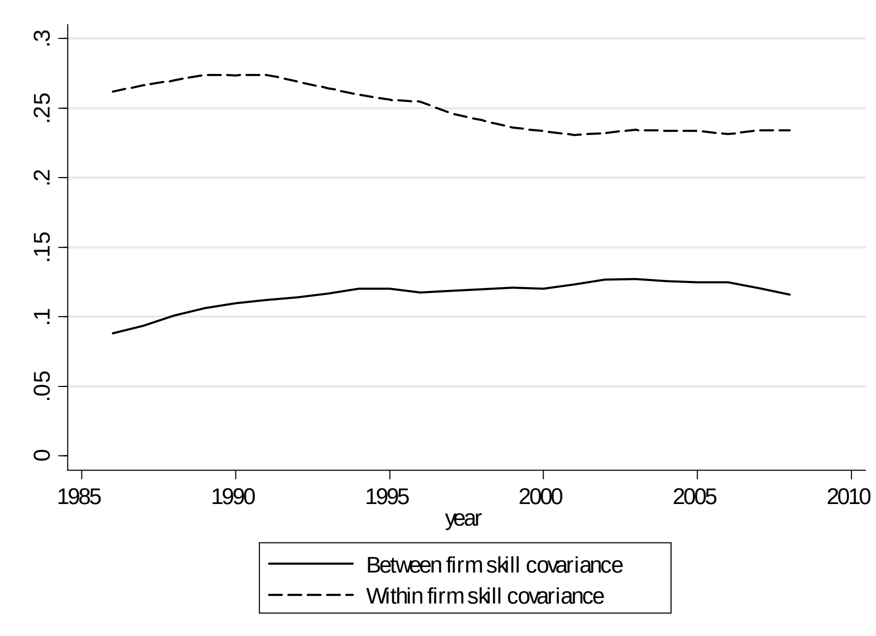
Note: Between- and within-firm variances of CS. The sample includes 30-35 year-old men employed at public or private firms with at least 10, 50 or 100 employees. Variances corrected for firm-level sample size.

Figure B1.9B Different firm size restrictions, non-cognitive skill



Note: Between- and within-firm variances of NCS. The sample includes 30-35 year-old men employed at public or private firms with at least 10, 50 or 100 employees. Variances corrected for firm-level sample size.

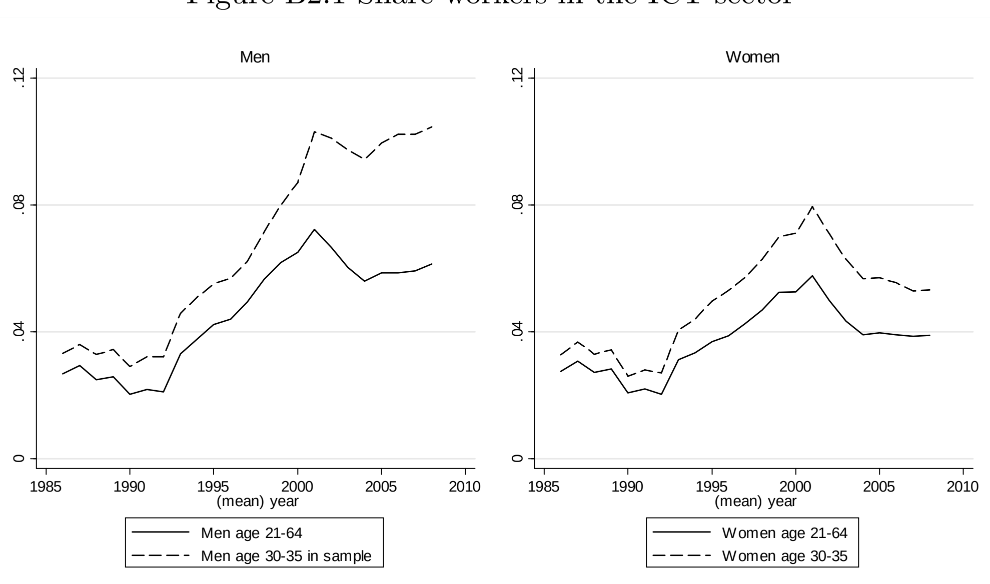
Figure B1.10 Decomposing the covariance



Note: Within and between-firm covariances between cognitive and non-cognitive skills. The sample includes 30-35 year-old men employed at firms with at least 10 employees. Covariances corrected for firm-level sample size.

B.2 Additional results for section 7.1

Figure B2.1 Share workers in the ICT sector



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

B.3 Additional results for section 7.2

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

$$\underbrace{\sum_k \alpha_{k,86}\Delta\sigma_k^2}_{\text{Change in WF variance}} + \underbrace{\sum_k \Delta\alpha_k\sigma_{k,86}^2}_{\text{Change in shares}} + \underbrace{\sum_k \Delta\alpha_k\Delta\sigma_k^2}_{\text{Interaction term}}, \tag{B1}$$

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 (B1) is the change in within-firm variance holding each industry's share of total employment fixed at its 1986 level. This term should be negative if increasing complementarities between skills in the production function or diffusion of new technology makes it more profitable to match workers of a given skill level in the same firm. The second term is the change in within-firm variance due to changes in the relative size of industries. If, as suggested by Grossman and Maggi (2000), Sweden has a comparative advantage in goods and services where worker skills are complements, falling trade costs should lead to an increase in the relative size of industries where the initial within-firm variance $\left(\sigma_{k,86}^2\right)$ is small and, consequently, a negative second term. The third term is the covariance between changes in the relative size of industries and changes in within-firm variance.

Table B3.1 shows decomposition (B1) 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.

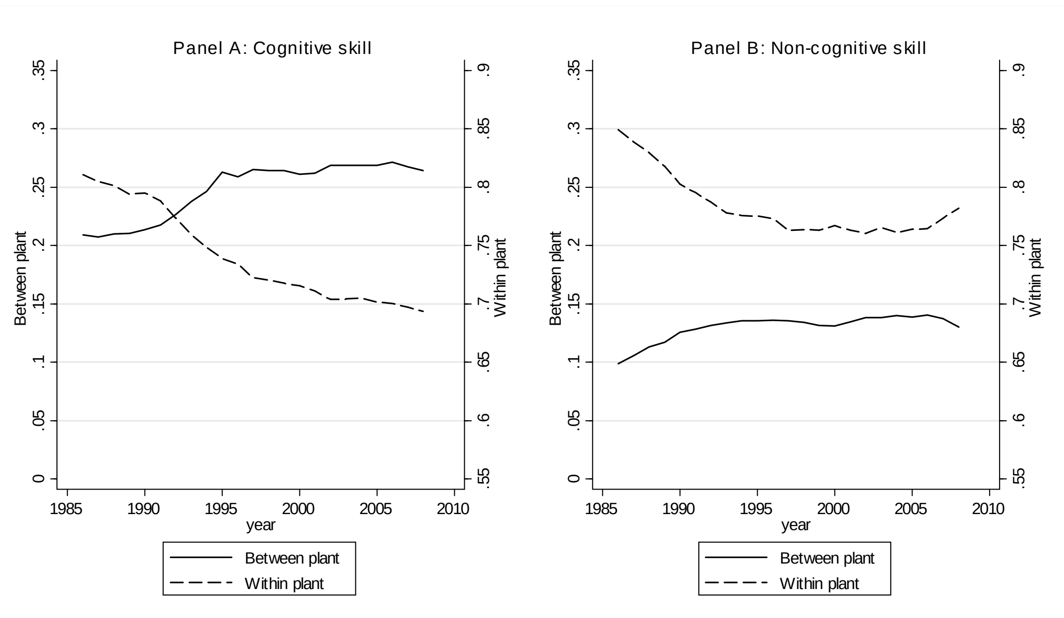
[TABLE B3.1 HERE]

Appendix C: Plant level analysis

In this section we present results using plant rather than firm level data. When doing this, the same sample restrictions are applied as in the analysis of firms. That is, we require that each plant employs at least two men with complete enlistment records and that the plant belongs to a firm with at has at least 10 employees. The general conclusion to be drawn from this appendix is that the patterns are similar when we analyze plants rather than firms.

Figure C1.1 plots the evolution of within- and between plant skill variance. The evolution of sorting is almost identical to the firm-level analysis, although the between-plant variance is somewhat higher than the between-firm variance at every point in time.

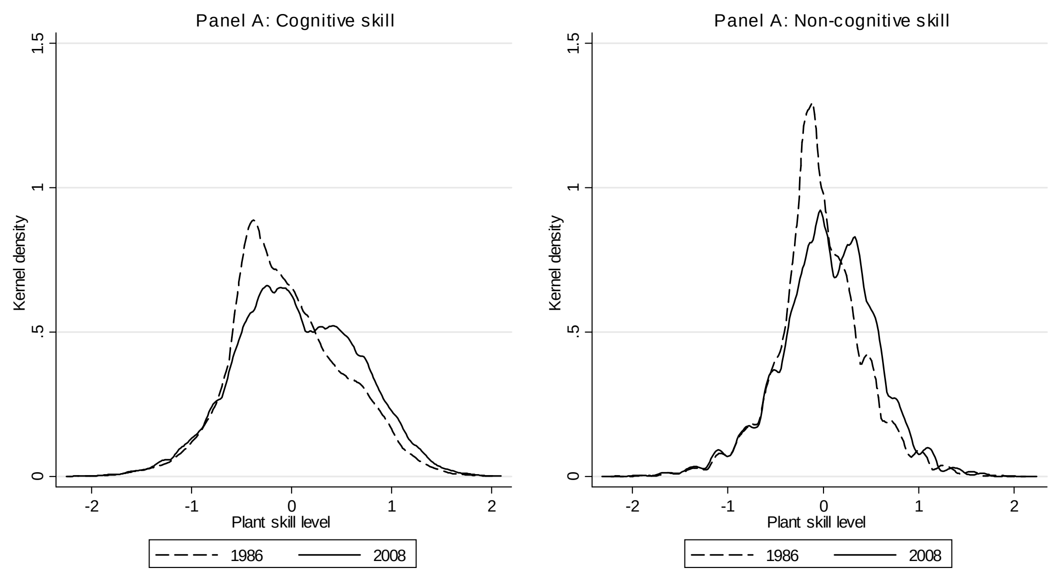
Figure C1.1 Sorting over time



Note: Between- and within-plant skill variances. The sample includes 30-35 year-old men employed at firms with at least 10 employees. Variances corrected for plant-level sample size.

Figure C1.2 shows the Kernel density plots of plant-average skills, similar to Figure 2 for firms. Again the results are similar, with a shift to the right (reflecting a higher mean of skills) and an increase in the variance.

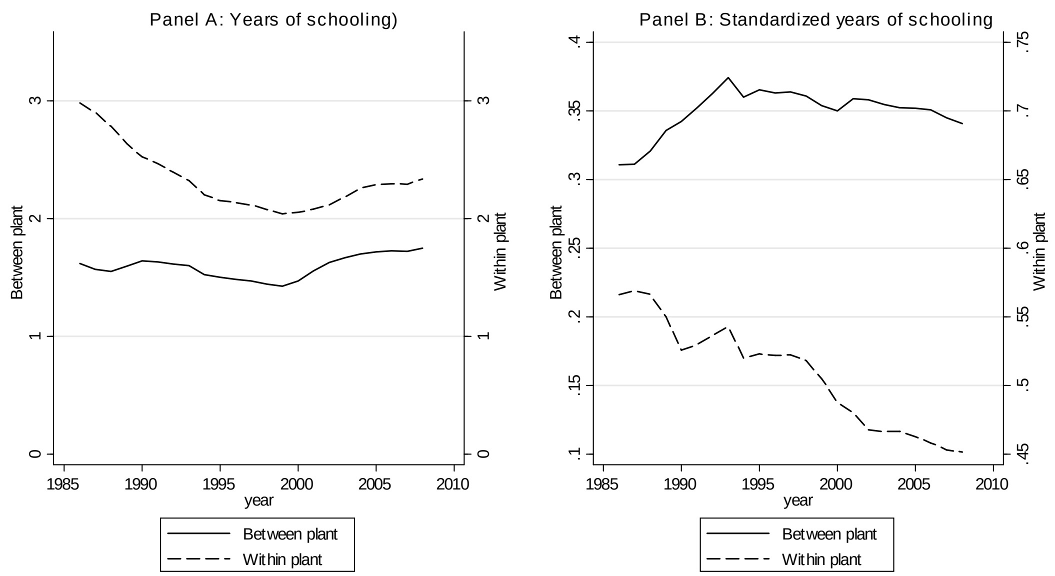
Figure C1.2 Distribution of plant average skills



Note: Kernel density plots for average plant level skills, weighted by the number of observed workers at each plant. The sample includes 30-35 year-old men employed at plants belonging to firms with at least 10 employees. Bandwidths are .0701 for cognitive skills and .0418 for non-cognitive skills.

Figure C1.3 shows the decomposition of years of schooling (Panel A) and standardized years of schooling (Panel B) in between- and within-plant components.

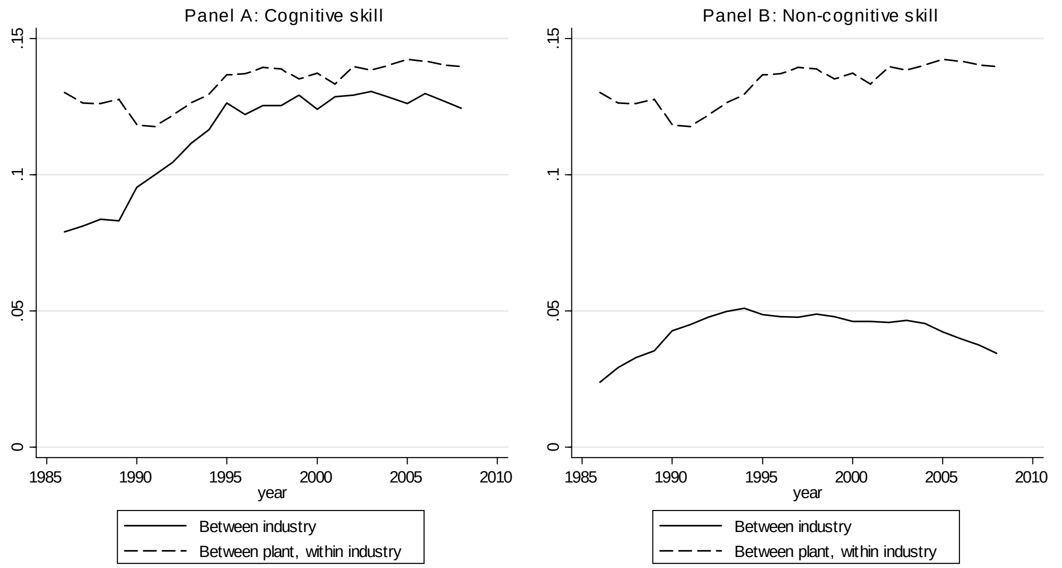
Figure C1.3 Schooling



Note: Between and within-plant variances in educational attainment expressed in years of schooling (Panel A) and years of schooling standardized by cohort (Panel B). The sample includes 30-35 year-old men employed at firms with at least 10 employees. Variances corrected for plant-level sample size.

In Figure C1.4, we decompose the between plant skill variance. As in the firm-level analysis (Figure 4), the bulk of the increase in sorting is due to increasing skill differences across industries.

Figure C1.4 Decomposing the between-plan variance



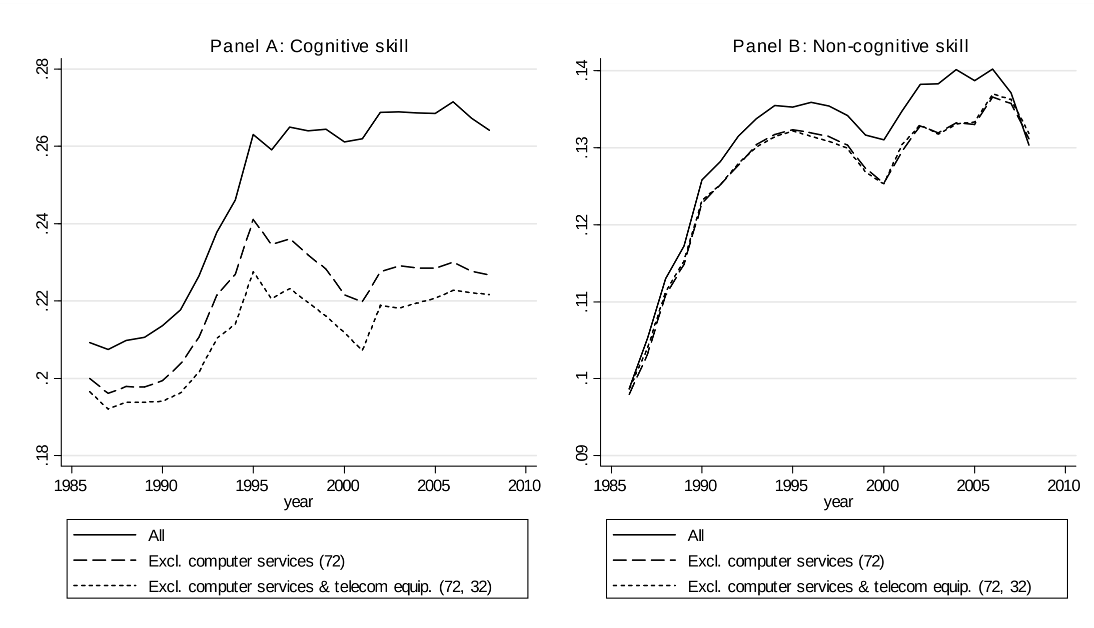
Note: Between industry and between-plant within-industry skill variances. The sample includes 30-35 year-old men employed at firms with at least 10 employees. Variances corrected for plant-level sample size.

Table C1.1 shows the average cognitive and non-cognitive skills by industry (based on plants). As for industries defined by firms (see Table 1), the IT-industry grows dramatically in size while keeping almost the same high average of cognitive skill.

[TABLE C1.1 HERE]

Figure C1.5 shows the "counterfactual" between-plant variance when the ICT sector (computer services and manufacturing of telecom equipment) are taken out from the sample. As in the corresponding decomposition for firms (Figure 5), the ICT sector plays an important role in the increasing sorting according to cognitive skill.

Figure C1.5 Counterfactual between-plant variance



Note: Between-plant skill variances including and excluding Computer services and Telecom equipment. The sample consists of 30-35 year-old men employed at firms with at least 10 employees. Variances are corrected for plant-level sample size.

Table C1.2 shows the average within-firm variance by industry (based on plants). The pattern is similar compared to the corresponding table for firms (Table 2): firms in manufacturing industries had the highest average within-firm variance in 1986, and almost all industries saw a shift toward internally more homogeneous firms between 1986 and 2008.

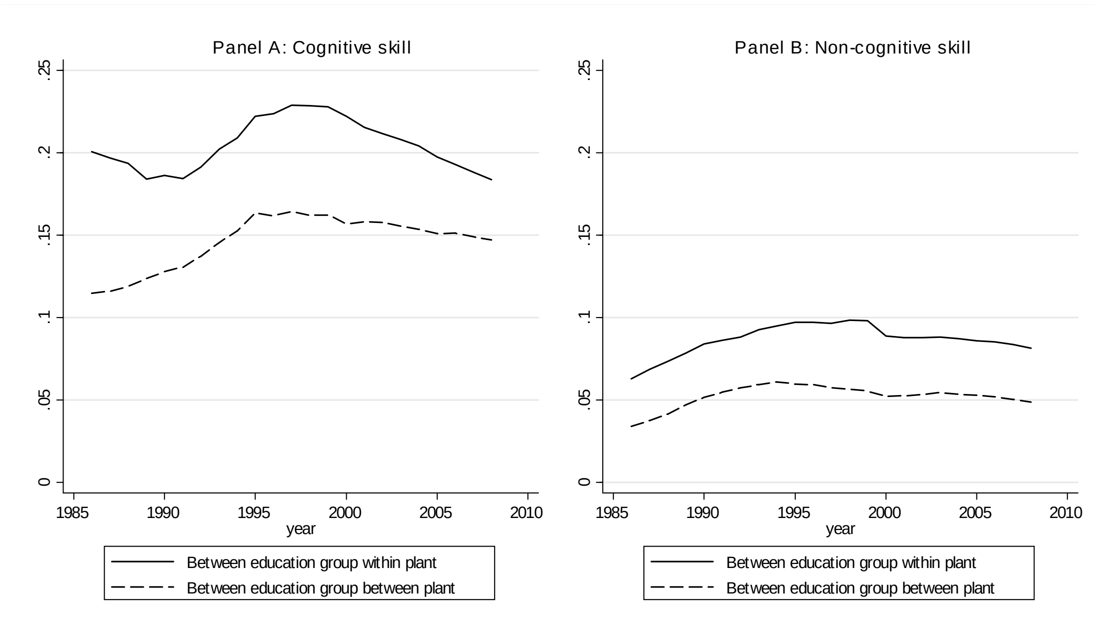
[TABLE C1.2 HERE]

Table C1.3 shows the results when we regress the change (1986-2008) or level of the industry-average within-firm variances on a set of covariates. The results in Table C1.3 are very similar to Table 3, which shows the corresponding results for industries based on firms. In paerticular, Table C1.3 shows that industries converged in terms of average within-firm variance between 1986 and 2008.

[TABLE C1.3 HERE]

Figure C1.6 shows the decomposition of the variance in skill between-educational groups. As for firms (Figure 7), the between-plan component increase in relation to the within-plant component for cognitive skill.

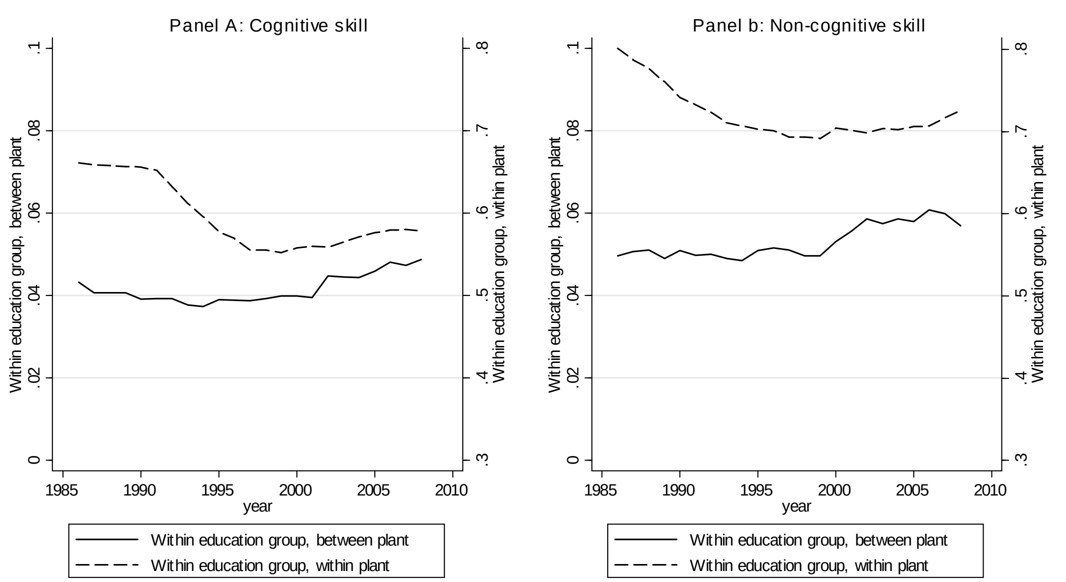
Figure C1.6 Decomposing the variance between educational groups



Note: The figure shows the within- and between-plant components of the variance in skills between educational groups. The sample consists of 30-35 year-old men employed at firms with at least 10 employees. Variances corrected for plant-level sample size.

Figure C1.7 shows the decomposition of the variance in skill within educational groups. As for firms, the between-plant share of the within-group variance increases, reflecting a higher degree of assortative matching of skills.

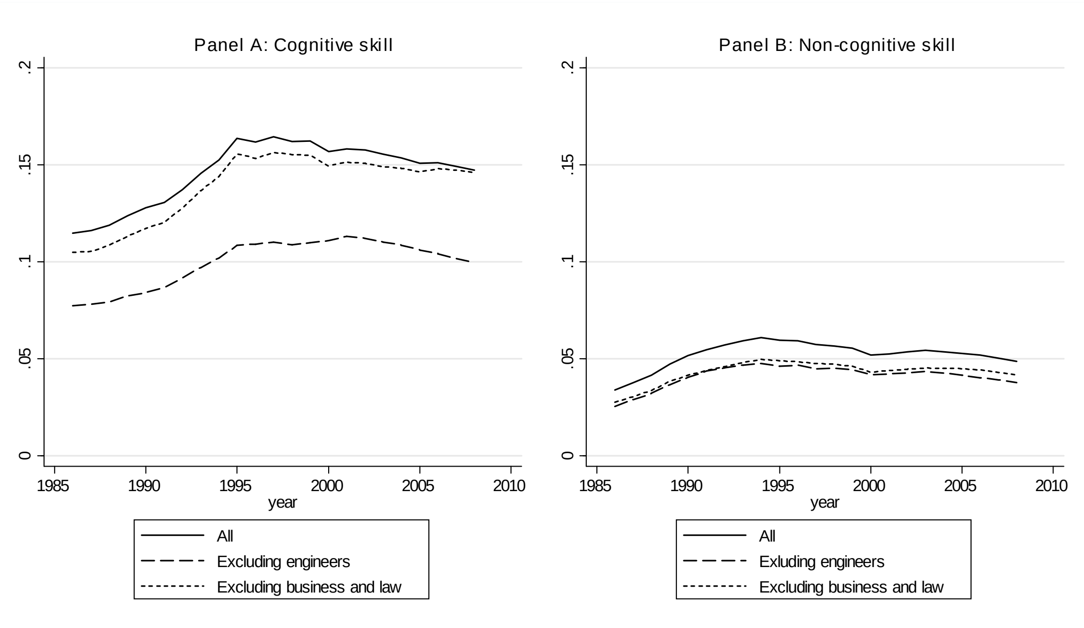
Figure C1.7 Decomposing the variance within educational groups



Note: The figure shows the within- and between-plant components of the variance in skills within educational groups. Skill variances within educational groups in their within and between-plant components. The sample consists of 30-35 year-old men employed at firms with at least 10 employees. Variances corrected for plant-level sample size.

Figure C1.8 shows the "counterfactual" evolution of the between-plan component of the between-group variance when majors in a) engineering or b) business and law are removed from the sample. As for firms (Figure 9), excluding engineering majors has a stark effect on the evolution of the variance in cognitive skill between educational groups and plants.

Figure C1.8 Counterfactual between-group between-plan variance



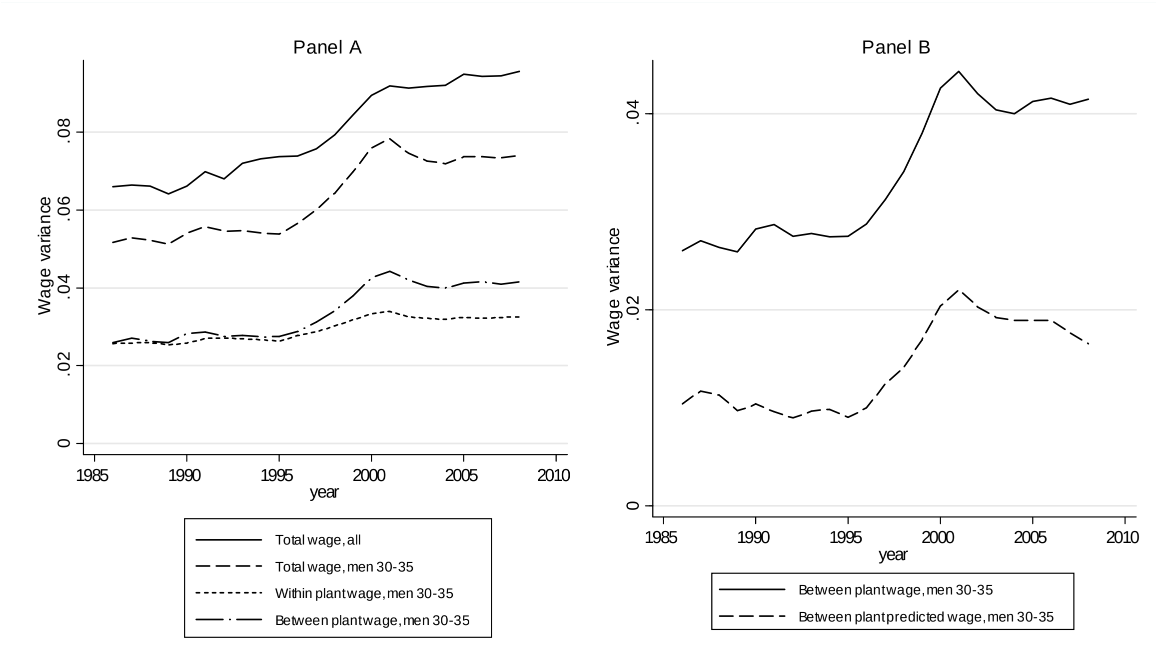
Note: Between-occupation between-plant skill variances, including and excluding employees with Engineering, Business, and Law degrees. The sample consists of 30-35 year-old men employed at firms with at least 10 employees. Variances corrected for plant-level sample size.

Table C1.4 shows the results when the within-education group within-plant variances of cognitive and non-cognitive skills are regressed on a set of covariates (the corresponding estimates for firms are reported in Table 4). Overall, the results for plants are similar to the results for firms. The coefficients for skills (both actual minus predicted and predicted) are generally negative, implying that skill upgrading is positively correlated with assortative matching. This pattern is stronger for assortative matching by cognitive skill, but upgrading of non-cognitive skill is a stronger predictor than upgrading of cognitive skill. Yet the coefficients for skills are hard to interpret when both types of skill are controlled for simultaneously due to multicollinearity.

[TABLE C1.4 HERE]

Figures C1.9 shows how the variance in wages has evolved when we use plants rather than firms is the unit of analysis. Again, the patterns are close to identical as in the main analysis.

Figure C1.9 Decomposing the variance in wages



Note: Panel A shows the variance of log wages for all workers age 20-64 and 30-35 year-old men. Both samples restricted to firms with at least 10 employees. Panel B shows the between-plant variance in (log) wages and predicted (log) wages from regression (5). All variances corrected for plant-level sample size.

Table C1.5 shows the decomposition of the explained wage variance into sorting and skill gradients. The decomposition is similar to that based on firms (Table 5): both gradients and sorting contribute to the increase in the explained wage variance, although gradients are slightly more important.

[TABLE C1.5 HERE]

Appendix D: Measuring Sorting

D.1 Alternative decompositions

Let C_{jk} denote the average cognitive skills of firm j in industry k and N_{jk} is the number of workers in this firm, while C_k and N_k are the corresponding variables at the industry level. The between-firm variance in cognitive skill can then be decomposed as:

$$\underbrace{\frac{1}{N}\sum_k\sum_j N_{jk}\left(C_{jk}-C_k\right)^2}_{\text{variance between firms within industries}} + \underbrace{\frac{1}{N}\sum_k N_k\left(C_k-\overline{C}\right)^2}_{\text{variance between industries}}. \tag{D1}$$

In addition to quantify sorting in each skill measure separately, we also decompose the covariance of cognitive and non-cognitive into between- and within-firm components. Let C_{ij} and NCS_{ij} denote cognitive and non-cognitive skills of worker i in firm j and C_j and NCS_j the corresponding averages for firm j. We can then decompose the covariance between cognitive and non-cognitive skill as

$$\underbrace{\frac{1}{n}\sum_j\sum_i\left(C_{ij}-C_j\right)\left(NCS_{ij}-NCS_j\right)}_{\text{within-firm covariance}} + \underbrace{\frac{1}{n}\sum_j N_j\left(C_j-\overline{C}\right)\left(NCS_j-\overline{NCS}\right)}_{\text{between-firm covariance}}. \tag{D2}$$

The between-firm covariance tells us whether firms that employ workers with high cognitive skill also employ workers with high non-cognitive skills. Since cognitive and non-cognitive skills are positively correlated at the level of the individual, the sum of the within- and between-firm components is positive. However, depending on how skills are valued across firms, the between-firm covariance could in principle be negative. For example, if cognitive and non-cognitive skills are substitutes in the firm-level production function, we expect firms to focus on hiring workers with either high cognitive or high non-cognitive skill.

D.2 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

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

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).[39] 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

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

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

$$\underbrace{\frac{1}{n}\sum_j n_j \left(\frac{N_j - 1}{N_j}\right)\left(\frac{1}{n_j - 1}\right)\sum_i \left(C_{ij} - C_j\right)^2}_{\text{within-firm variance}} \tag{D3}$$
$$+\underbrace{\frac{1}{n}\sum_j n_j \left[\left(C_j - \overline{C}\right)^2 - \frac{N_j - n_j}{N_j n_j}\left(\frac{1}{n_j - 1}\right)\sum_i \left(C_{ij} - C_j\right)^2\right]}_{\text{between-firm variance}}.$$

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

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

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

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

We now turn to the covariance between cognitive and non-cognitive skills. Let N_j denote the number of workers in firm j and n_j the number of observations in the same firm. The

[39] 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.

adjustment for sample size is the same as in the case of standard variance. That is, we get

$$\underbrace{\frac{1}{n}\sum_j n_j\left(\frac{N_j-1}{N_j}\right)\left(\frac{1}{n_j-1}\right)\sum_i\left(C_{ij}-C_j\right)\left(NC_{ij}-NC_j\right)}_{\text{within-firm covariance weighted by } n_j}+ \tag{D4}$$

$$\underbrace{\frac{1}{n}\sum_k\sum_j n_j\left[\left[\left(C_j-\overline{C}\right)\left(NC_j-\overline{NC}\right)\right]-\frac{N_j-n_j}{N_jn_j}\left(\frac{1}{n_j-1}\right)\sum_i\left(C_{ij}-C_j\right)\left(NC_{ij}-NC_j\right)\right]}_{\text{between-firm covariance weighted by } n_j}$$

D.3 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 $N\left(0,\sigma_{\varepsilon_C}^2\right)$. 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:

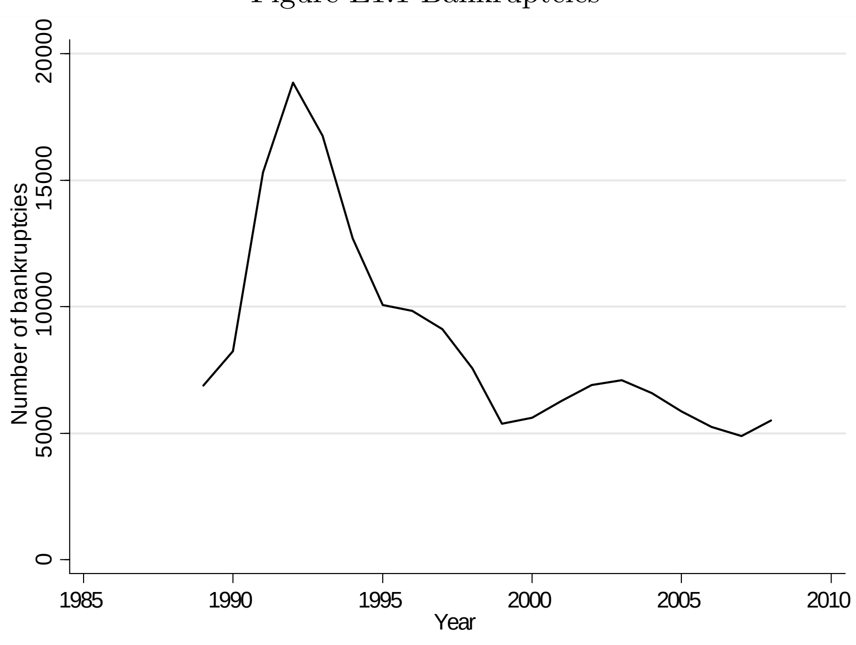
$$
\begin{aligned}
BF\_VAR\_CS_{ADJ,t} &= \frac{BF\_VAR\_CS_{UNADJ,t} - VI_{BF,CS}}{1 - 0.1325/TOT\_VAR\_CS_{UNADJ,t}} \\
WF\_VAR\_CS_{ADJ,t} &= \frac{WF\_VAR\_CS_{UNADJ,t} - VI_{WF,CS}}{1 - 0.1325/TOT\_VAR\_CS_{UNADJ,t}} \\
BF\_VAR\_NCS_{ADJ,t} &= \frac{BF\_VAR\_NCS_{UNADJ,t} - VI_{BF,NCS}}{1 - 0.297/TOT\_VAR\_NCS_{UNADJ,t}}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

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 E: The Swedish economy 1986-2008

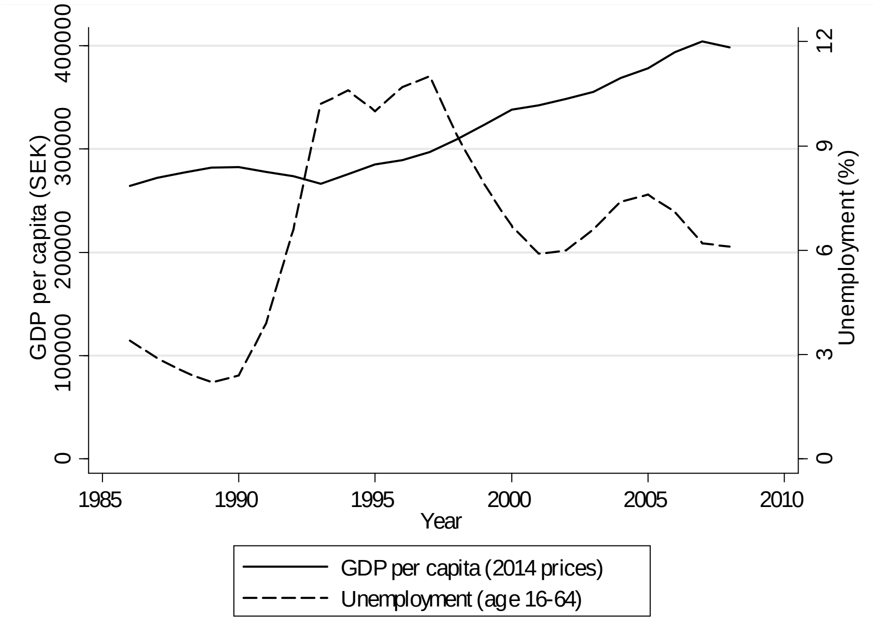
This section provides a short summary of the macroeconomic development in Sweden over the course of our study period (1986-2008). The main macroeconomic event during this period was the Swedish banking crisis of the early 1990's. The crisis had several causes (**?**): deregulation of financial markets 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 E1.1). GDP per capita fell three years in a row (1991-1993) while the unemployment rate quadrupled between 1990 and 1993 (Figure E1.2). 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 A5.1, 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 E1.1 Bankruptcies



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

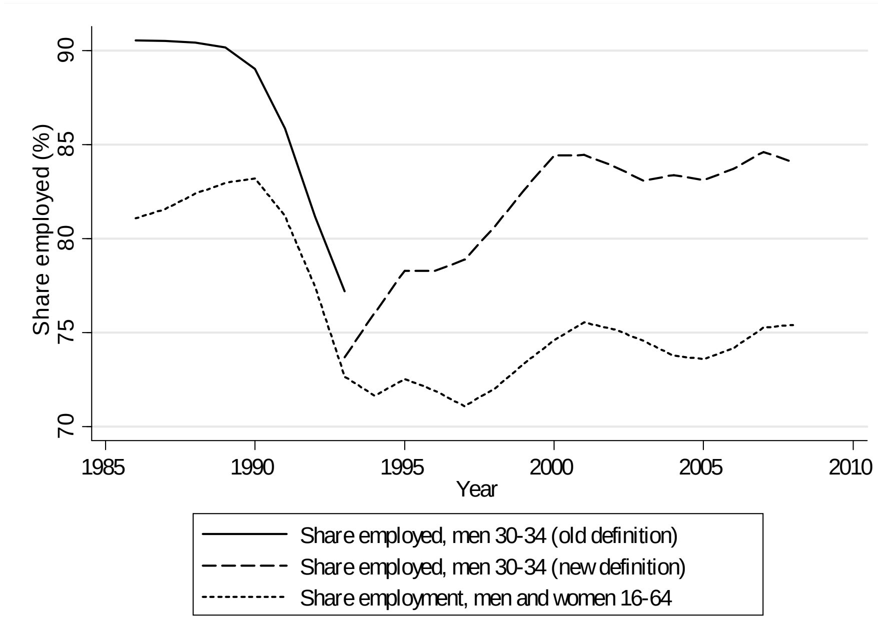
Figure E1.2 GDP per capita and unemployment



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 E1.3 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 E1.3



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.

As we explain in the paper, the crisis of the early 1990's coincides with the most dramatic increase in sorting over the course of our study period. It is an open question to what extent the restructuring of the economy that was induced by the crisis caused sorting to increase. However, there are a number of reasons as to why the increase in sorting is unlikely to be solely due to the economic crisis. First, sorting increased already in the late 1980's and continued to increase for cognitive skill in the 2000's, up to 15 years after the height of the crisis in 1993. Second, the main driving force behind the increase in sorting according to cognitive skill is the secular expansion of the ICT sector, which appears uncorrelated with the crisis (see Figure B2.1). Third, the economic crisis may have sped up a restructuring of the economy that would have taken place anyhow, albeit more slowly.

Table 1. Average skills by industry

		Cognitive skill		Non-cognitive skill		Share workers (%)	
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
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

The table shows the mean of skills and relative sizes of industries in 1986, and the changes between 1986 and 2008. Only industries with at least 1.5 % of the workforce in 1986 or 2008 are included. The sample is restricted to 30-35 year old men employed at firms with at least 10 employees. The description of some industries have been abbreviated.

Table 2. Average within-firm variance by industry

		Cognitive skill		Non-cognitive 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
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

The table shows the average within-firm variance of skills and relative sizes of industries in 1986, and the changes between 1986 and 2008. Only industries with at least 1.5% of the workforce in 1986 or 2008 are included. The sample is restricted to 30-35 year old men employed at firms with at least 10 employees. The description of some industries have been abbreviated.

Table 3. Industry-average within-firm variance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Cognitive skill (CS)				Non-cognitive skill (NCS)				CS	NCS
	Average within-firm variance								*Average skill*	
	Change 1986-2008		Level (per year)		Change 1986-2008		Level (per year)		Level (per year)	
Average CS (1986/per year)	0.0029	-0.0003	-0.0851**	0.0659				0.0572		
	(0.0458)	(0.0438)	(0.0392)	(0.0479)				(0.0588)		
Average NCS (1986/per year)				-0.252***		-0.1020	-0.0375	-0.0857		
				(0.062)		(0.0816)	(0.0544)	(0.0682)		
Average within-firm variance (CS) 1986	-0.538***	-0.476***								
	(0.122)	(0.100)								
Average within-firm variance (NCS) 1986					-0.613***	-0.506***				
					(0.111)	(0.103)				
Average Log(Capital) (1986/per year)	0.0050		0.00683*	0.00642**	0.0070		-0.0020	-0.0022	0.0043	0.0009
	(0.0141)		(0.00342)	(0.00314)	(0.0128)		(0.0026)	(0.0026)	(0.0049)	(0.0056)
World trade (1986/per year)	0.0049		0.0010	0.0012	-0.0046		0.0050	0.0053	-0.0094	-0.0048
	(0.0106)		(0.0041)	(0.0040)	(0.0081)		(0.0055)	(0.0055)	(0.0147)	(0.0205)
China imports (1986/per year)	-1.044		-0.103	-0.086	0.497		0.002	-0.010	0.535**	0.389*
	(1.071)		(0.154)	(0.167)	(1.690)		(0.155)	(0.161)	(0.261)	(0.227)
Manufacturing (1986/per year)	0.0625**	0.0678**			0.0169	-0.0086				
	(0.0265)	(0.0252)			(0.0208)	(0.0251)				
Change in average CS 1986-2008		0.053				0.233				
		(0.114)				(0.144)				
Change in average NCS 1986-2008		-0.214				-0.283				
		(0.147)				(0.169)				
Change in average log(Capital) 1986-2008		0.0169*				0.0003				
		(0.0084)				(0.0076)				
Change in World trade 1986-2008		0.0203***				0.0099				
		(0.0066)				(0.0095)				
Change in China imports 1986-2008		-0.1410				-0.056				
		(0.0963)				(0.181)				
Observations	50	50	1229	1229	50	50	1229	1229	1229	1229
Adjusted R-squared	0.279	0.385	0.941	0.944	0.379	0.467	0.799	0.800	0.979	0.958
Industry FE			Yes	Yes			Yes	Yes	Yes	Yes
Year FE			Yes	Yes			Yes	Yes	Yes	Yes

All variables are measured at the 2-digit industry level. Missing information on World trade or China imports have been imputed to zero. The dependent variable in column 1-8 is the change (1986-2008) or level of the average within-firm variance of skills. The dependent variable in column 9-10 is average skills. All regressions are estimated using OLS. Standard errors are clustered at the industry level. 1/2/3 stars denote statistical significance at the 10/5/1 percent level in a two-sided test.

Table 4. Within-education group within-firm variance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cognitive skill (CS)				Non-cognitive skill (NCS)			
Log(Capital)	0.00153	0.00155	0.00143	0.00139	0.00111	0.00104	0.00109	0.00100
	(0.00118)	(0.00116)	(0.00119)	(0.00121)	(0.00189)	(0.00194)	(0.00188)	(0.00192)
Log(Number of employees)	0.0262***	0.0220***	0.0202***	0.0202***	0.0104**	0.00870**	0.00990**	0.00887**
	(0.0026)	(0.0023)	(0.0024)	(0.0026)	(0.0041)	(0.00416)	(0.00398)	(0.00412)
World trade	-0.00019	-0.00097	-0.00084	-0.0009	0.0061	0.00597	0.00596	0.00602
	(0.00412)	(0.00405)	(0.00388)	(0.0039)	(0.0044)	(0.00439)	(0.00443)	(0.00438)
China imports	-0.0442	-0.0418	-0.0341	-0.0328	-0.0134	-0.0070	-0.0118	-0.0063
	(0.0926)	(0.0913)	(0.0937)	(0.0950)	(0.0540)	(0.0532)	(0.0532)	(0.0520)
Actual CS - Predicted CS		-0.0343***		-0.0150			-0.0170**	-0.00489
		(0.0109)		(0.0121)			(0.0067)	(0.00870)
Predicted NCS		-0.0703***		0.0470**			-0.0027	0.0497*
		(0.0187)		(0.0224)			(0.0143)	(0.0261)
Actual NCS - Predicted NCS			-0.0714***	-0.0682***		-0.0442**		-0.0431**
			(0.0040)	(0.0050)		(0.0184)		(0.0197)
Predicted NCS			-0.132***	-0.196***		-0.0204		-0.0878*
			(0.026)	(0.020)		(0.024)		(0.0439)
Observations	273,517	273,517	273,517	273,517	273,517	273,517	273,517	273,517
Adjusted R-squared	0.326	0.327	0.33	0.33	0.322	0.323	0.323	0.323
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is the within-education group within-firm variance at each firm. All explanatory variables are measured at the firm level, except for World trade and China imports which are the same for all firms in the same 2-digit industry. Missing information on World trade or China imports have been imputed to zero. All regressions are estimated using OLS. Standard errors are clustered at the industry level. 1/2/3 stars denote statistical significance at the 10/5/1 percent level in a two-sided test.

Table 5. Counterfactual predicted wage variance

	2008 sorting	1986 sorting
2008 gradients	0.0144	0.0115
1986 gradients	0.0106	0.0085

The table shows the predicted between-firm variance of wages when sorting and estimated between-firm skill gradients are set at the 1986 and 2008 level, respectively.

Table B1.1 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
Between group, between firm	0.093	0.003	0.004	0.005
Between group, within firm	0.218	0.306	0.307	0.308
Within group, between firm	0.035	0.008	0.010	0.012
Within group, within firm	0.667	0.690	0.692	0.695
Non-cognitive skills 1986				
Within-firm	0.872	0.935	0.939	0.942
Between-firm	0.081	0.010	0.013	0.017
Between group, within firm	0.071	0.097	0.098	0.098
Between group, between firm	0.029	0.001	0.001	0.002
Within group, within firm	0.814	0.838	0.841	0.844
Within group, between firm	0.039	0.009	0.012	0.015
Covariance 1986				
Between-firm covariance	0.088	0.002	0.005	0.007
Within-firm covariance	0.262	0.343	0.345	0.348
Cognitive skills 2008				
Within-firm	0.721	0.931	0.935	0.938
Between-firm	0.229	0.012	0.015	0.019
Between group, between firm	0.127	0.004	0.005	0.006
Between group, within firm	0.198	0.318	0.319	0.320
Within group, within firm	0.587	0.613	0.616	0.618
Within group, between firm	0.038	0.008	0.010	0.012
Non-cognitive skills 2008				
Within-firm	0.801	0.893	0.896	0.899
Between-firm	0.110	0.011	0.015	0.018
Between group, within firm	0.086	0.125	0.126	0.126
Between group, between firm	0.041	0.002	0.002	0.003
Within group, within firm	0.736	0.768	0.770	0.773
Within group, between firm	0.047	0.010	0.013	0.015
Covariance 2008				
Between-firm covariance	0.116	0.003	0.006	0.008
Within-firm covariance	0.234	0.342	0.344	0.347

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 B1.2 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 B3.1 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

The table shows the components in the decomposition of the change of the within-firm variance, described in Appendix B3.

Table C1.1 Average skills by plant-industry

NACE	Industry	Cognitive skill 1986	Cognitive skill Change 1986-2008	Non-cognitive skill 1986	Non-cognitive skill Change 1986-2008	Share workers (%) 1986	Share workers (%) Change 1986-2008
72	Computer and related activities	0.74	0.02	0.29	-0.02	1.66	6.98
74	Other business activities	0.48	-0.16	0.23	-0.05	4.36	7.88
32	Manufacture of radio, television and communication equipment	0.40	0.17	0.03	0.18	1.66	0.28
24	Manufacture of chemicals and chemical products	0.15	0.00	0.03	0.10	2.20	-0.55
51	Wholesale trade and commission trade	0.13	-0.13	0.13	0.00	8.87	-0.11
31	Manufacture of electrical machinery and apparatus n.e.c.	0.12	0.01	-0.03	0.05	2.02	-0.77
22	Publishing, printing and reproduction of recorded media	0.09	0.04	-0.10	0.07	2.80	-1.33
55	Hotels and restaurants	-0.02	-0.19	-0.08	0.01	1.06	0.69
63	Supporting and auxiliary transport activities	-0.02	-0.15	-0.03	-0.05	1.20	0.76
52	Retail trade, repair of personal and household goods	-0.04	-0.04	-0.02	0.00	2.03	1.83
64	Post and telecommunications	-0.08	0.36	-0.23	0.39	0.09	1.48
29	Manufacture of machinery and equipment n.e.c.	-0.11	0.10	-0.10	0.10	8.35	-2.31
65	Financial intermediation, except insurance and pension funding	-0.12	0.57	0.03	0.46	5.35	-3.28
34	Manufacture of motor vehicles, trailers and semitrailers	-0.14	0.08	-0.12	0.05	5.27	0.36
50	Sale, maintenance and repair of motor vehicles and motorcycles	-0.16	-0.15	-0.04	-0.11	3.15	-0.31
45	Construction	-0.22	-0.07	-0.03	-0.01	8.59	1.11
21	Manufacture of paper and paper products	-0.28	0.14	-0.17	0.17	3.93	-2.40
28	Manufacture of fabricated metal products, except machinery and equipment	-0.31	0.01	-0.22	-0.02	4.67	-1.03
15	Manufacture of food products and beverages	-0.32	-0.05	-0.21	0.02	3.06	-0.77
60	Land transport, transport via pipelines	-0.36	-0.09	-0.29	-0.05	3.09	-0.12
27	Manufacture of basic metals	-0.36	0.11	-0.22	0.08	2.62	-0.76
20	Manufacture of wood and of products of wood and cork	-0.47	0.05	-0.22	0.06	2.87	-1.17

The table shows the mean of skills and relative sizes of industries in 1986, and the changes between 1986 and 2008. Only industries with at least 1.5 % of the workforce in 1986 or 2008 are included. The sample is restricted to 30-35 year old men employed at firms with at least 10 employees. The description of some industries have been abbreviated.

Table C1.2 Average within-firm variance by plant-industry

NACE	Industry	Cognitive skill 1986	Cognitive skill Change 1986-2008	Non-cognitive skill 1986	Non-cognitive skill Change 1986-2008	Share workers (%) 1986	Share workers (%) Change 1986-2008
34	Manufacture of motor vehicles, trailers and semitrailers	0.99	-0.14	0.89	-0.10	5.27	0.36
24	Manufacture of chemicals and chemical products	0.99	-0.17	0.92	-0.13	2.20	-0.55
15	Manufacture of food products and beverages	0.93	-0.11	0.91	-0.09	3.06	-0.77
21	Manufacture of paper and paper products	0.92	-0.19	0.86	-0.05	3.93	-2.40
31	Manufacture of electrical machinery and apparatus n.e.c.	0.92	-0.09	0.81	0.03	2.02	-0.77
29	Manufacture of machinery and equipment n.e.c.	0.91	-0.10	0.81	-0.03	8.35	-2.31
27	Manufacture of basic metals	0.91	-0.09	0.80	0.10	2.62	-0.76
20	Manufacture of wood and of products of wood and cork	0.90	-0.15	0.78	-0.04	2.87	-1.17
28	Manufacture of fabricated metal products, except machinery	0.87	-0.08	0.84	-0.04	4.67	-1.03
55	Hotels and restaurants	0.85	-0.15	1.04	-0.15	1.06	0.69
22	Publishing, printing and reproduction of recorded media	0.83	-0.12	0.99	-0.11	2.80	-1.33
32	Manufacture of radio, television and communication equipment	0.83	-0.16	0.82	-0.10	1.66	0.28
64	Post and telecommunications	0.81	-0.10	0.97	-0.16	0.09	1.48
63	Supporting and auxiliary transport activities, activities of travel agencies	0.78	-0.06	1.03	-0.23	1.20	0.76
60	Land transport, transport via pipelines	0.78	-0.04	0.83	-0.08	3.09	-0.12
52	Retail trade, repair of personal and household goods	0.75	-0.07	0.85	-0.02	2.03	1.83
51	Wholesale trade and commission trade	0.75	-0.10	0.86	-0.11	8.87	-0.11
50	Sale, maintenance and repair of motor vehicles and motorcycles	0.74	-0.12	0.77	-0.02	3.15	-0.31
45	Construction	0.70	-0.12	0.77	-0.04	8.59	1.11
65	Financial intermediation, except insurance and pension funding	0.65	-0.05	0.82	-0.11	5.35	-3.28
74	Other business activities	0.63	0.02	0.82	-0.04	4.36	7.88
72	Computer and related activities	0.55	0.02	0.80	-0.02	1.66	6.98

The table shows the average within-firm variance of skills and relative sizes of industries in 1986, and the changes between 1986 and 2008. Only industries with at least 1.5% of the workforce in 1986 or 2008 are included. The sample is restricted to 30-35 year old men employed at firms with at least 10 employees. The description of some industries have been abbreviated.

Table C1.3 Industry-average within-plant variance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Cognitive skill (CS)				Non-cognitive skill (NCS)				CS	NCS
	Average within-firm variance								*Average skill*	
	Change 1986-2008		Level (per year)		Change 1986-2008		Level (per year)		Level (per year)	
Average CS (1986/per year)	0.0425	0.0483	-0.0799**	0.0339				0.0173		
	(0.0383)	(0.0349)	(0.032)	(0.0517)				(0.060)		
Average NCS (1986/per year)				-0.168***		-0.0485	-0.0534	-0.0713		
				(0.0573)		(0.0519)	(0.0411)	(0.0714)		
Average within-plant variance (CS) 1986	-0.451***	-0.400***								
	(0.103)	(0.120)								
Average within-plant variance (NCS) 1986					-0.724***	-0.678***				
					(0.116)	(0.120)				
Average Log(Capital) (1986/per year)	-0.0058		0.00692	0.00648	0.00112		-0.0014	-0.0015	0.0189	0.0102
	(0.0129)		(0.00416)	(0.00392)	(0.00997)		(0.00277	(0.00282	(0.0157	(0.0125
World trade (1986/per year)	0.00708		-0.00455	-0.00327	-0.00511		0.00184	0.00196	0.0014	0.0085
	(0.00844)		(0.0044)	(0.0043)	(0.00717)		(0.00615	(0.00625	(0.0131	(0.0152
China imports (1986/per year)	-0.434		-0.0465	-0.0404	1.184		0.0491	0.0478	0.372*	0.288
	(1.436)		(0.112)	(0.120)	(1.526)		(0.142)	(0.143)	(0.218)	(0.210)
Manufacturing (1986/per year)	0.0493*	0.0665**			0.0380**	0.0253				
	(0.0263)	(0.0256)			(0.0158)	(0.0205)				
Change in average CS 1986-2008		-0.0184				0.0956				
		(0.119)				(0.171)				
Change in average NCS 1986-2008		-0.158				-0.199				
		(0.153)				(0.206)				
Change in average log(Capital) 1986-2008		0.0266**				-0.000973				
		(0.011)				(0.0113)				
Change in World trade 1986-2008		0.0123**				0.00125				
		(0.00587)				(0.00855)				
Change in China imports 1986-2008		-0.0779				0.00967				
		(0.0929)				(0.154)				
Observations	50	50	1,227	1,227	50	50	1,227	1,227	1,227	1,227
Adjusted R-squared	0.381	0.457	0.941	0.943	0.488	0.506	0.795	0.795	0.965	0.938
Industry FE			Yes	Yes			Yes	Yes	Yes	Yes
Year FE			Yes	Yes			Yes	Yes	Yes	Yes

All variables are measured at the 2-digit industry level. Missing information on World trade or China imports have been imputed to zero. The dependent variable in column 1-8 is the change (1986-2008) or level of the average within-plant variance of skills. The dependent variable in column 9-10 is average skills. All regressions are estimated using OLS. Standard errors are clustered at the industry level. 1/2/3 stars denote statistical significance at the 10/5/1 percent level in a two-sided test.

Table C1.4 Within-education group within-plant variance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cognitive skill (CS)				Non-cognitive skill (NCS)			
Log(Capital)	0.00144	0.00167	0.0016	0.0016	0.000429	0.00042	0.000438	0.000404
	(0.00157)	(0.00156)	(0.00156)	(0.00155)	(0.00243)	(0.00245)	(0.00241)	(0.00245)
Log(Number of employees)	0.0259***	0.0233***	0.0219***	0.0217***	0.0258***	0.0245***	0.0255***	0.0246***
	(0.00428)	(0.00428)	(0.00451)	(0.0045)	(0.00569)	(0.00556)	(0.00555)	(0.00557)
World trade	-0.001	-0.000979	-0.000597	-0.000627	0.00515	0.00523	0.00509	0.00528
	(0.00372)	(0.00377)	(0.00367)	(0.00365)	(0.00511)	(0.00512)	(0.00512)	(0.00506)
China imports	0.00368	0.0122	0.0198	0.020	0.0252	0.0325	0.0269	0.031
	(0.0797)	(0.0821)	(0.0862)	(0.0872)	(0.0992)	(0.101)	(0.0993)	(0.101)
Actual CS - Predicted CS		-0.0348***		-0.0176			-0.0147**	-0.00545
		(0.0117)		(0.0129)			(0.00685)	(0.00925)
Predicted NCS		-0.0766***		0.0346			-0.000985	0.0619**
		(0.0208)		(0.0261)			(0.0119)	(0.0248)
Actual NCS - Predicted NCS			-0.0670***	-0.0632***		-0.0351**		-0.0339*
			(0.00404)	(0.00517)		(0.0172)		(0.0186)
Predicted NCS			-0.138***	-0.188***		-0.0214		-0.106**
			(0.028)	(0.0232)		(0.0222)		(0.0455)
Observations	367,592	367,592	367,592	367,592	367,592	367,592	367,592	367,592
Adjusted R-squared	0.317	0.318	0.321	0.321	0.317	0.318	0.317	0.318
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is the within-education group within-plant variance at each firm. All explanatory variables are measured at the plant level, except for World trade and China imports which are the same for all plants in the same 2-digit industry. Missing information on World trade or China imports have been imputed to zero. All regressions are estimated using OLS. Standard errors are clustered at the industry level. 1/2/3 stars denote statistical significance at the 10/5/1 percent level in a two-sided test.

Table C1.5 Counterfactual predicted wage variance

	2008 sorting	1986 sorting
2008 gradients	0.0165	0.0141
1986 gradients	0.0122	0.0104

The table shows the predicted between-plant variance of wages when sorting and estimated between-firm skill gradients are set at the 1986 and 2008 level, respectively.