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Is there job polarization at the firm level?

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Abstract

We perform decompositions and regression analyses that test for the routinization hypothesis and job polarization at the firm level, instead of the aggregate or industry level as in previous studies. Furthermore, we examine the technology-based explanations for routinization and job polarization at the firm level using firm-level R&D as an explanatory variable in the regressions. Our results for the intermediate education group and the routine occupation group are consistent with polarization at the firm level, i.e. disappearing middle due to technological change. These results are robust for accounting for dynamic selection effects.

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1. Introduction

An extensive literature exists that provides the theoretical and empirical grounds for the standard view that skill-biased technological change (SBTC), especially related to computer-based production technologies, has been the driving force behind increasing wage differentials, education premiums and skill-upgrading observed in many industrialized countries since the 1970s/1980s until recently (see Acemoglu and Autor (2010) and Acemoglu (2002) for recent reviews).

Autor, Levy and Murnane (2003), (henceforth ALM), however, raised the question *"… what it is that computers do – or what it is that people do with computers – that causes educated workers to be relatively more in demand?"* The answer provided by ALM has become known as the routinization hypothesis. Adoption of computers in the workplace changes the tasks performed by workers at their jobs. Computers are substitutes, especially for workers who perform routine tasks, but complement workers who carry out non-routine tasks. ALM present a theoretical model which predicts that industries and occupations that were initially intensive in routine tasks will invest more in computer capital as its price declines, and therefore reduce routine task inputs and increase non-routine task inputs. This increases the relative demand for educated workers, because they have a comparative advantage in non-routine tasks and computer usage. On the other hand, the demand for labour in intermediate wage and skill level occupations, which are often routine task intensive, declines because workers in them are substituted by computers.

This adjustment may lead to job polarization, where employment growth concentrates at the low and high skill (wage) occupations, whereas the jobs at the middle of the skill distribution are diminished, as suggested by Goos and Manning (2007) and Autor, Katz and Kearney (2006).[1] Acemoglu and Autor (2010) present a formal task-based model that makes this specific prediction. They also provide some empirical evidence for their model with aggregate economy regressions that predict changes in wages for different skill groups (defined by sex, education and experience) using variables that indicate the relative advantage of these skill groups in performing non-

[1] An early predecessor of current literature on polarization is by Jenkins (1995).

routine, routine or service tasks (i.e. the shares of each skill group in non-routine, routine, and service occupations prior to the computer era). The increase over decades in the coefficients for initial abstract and service shares compared to routine shares interacted with time (that proxy for technological change) is consistent with their models' predictions.[2]

ALM (2003) also presented empirical evidence for their model using industry-level regressions that explained the changes in the non-routine and routine task inputs (using the measures from the Dictionary of Occupation Titles, DOT) with industry-level computerization. They found that non-routine task input rises more, and routine task input declines more, within industries that invest more in computer capital. This observation is consistent with their theoretical model for routinization. Also, Michaels, Natraj and Van Reenen (2010) provided evidence, using country-industry panel data, that wage bill shares (and relative wages) for both high and low education levels are positively related to industry ICT capital, whereas those for the middle educated are negatively related to ICT. This pattern is consistent with job polarization.

In this paper we study the routinization hypothesis and the implied job polarization in the Finnish private sector using the new Harmonized Wage Structure Statistics (HWSS) data of Statistics Finland. Using this data we first confirm the patterns of employment and wage polarization development in the Finnish private sector labour market.[3] As Figure 1 shows, there has been considerable employment polarization at the aggregate level in the Finnish private sector employment. The structure of changes in the employment shares by initial occupational wage deciles is U-shaped, similar to the pattern documented for the UK in Goos and Manning (2007). On the other hand, there is no indication of wage polarization in Figure 2, which presents the change in real wages for each percentile of the wage distribution separately for men and women over the 1995-2008 period. Wage growth increases almost linearly with the wage level (percentile). This implies that wage differentials increase in both the upper and the lower tails of the wage distribution, which is consistent with the predictions of

[2] It should be noted that Acemoglu and Autor (2010) describe their empirical exercise as "…highly preliminary – indeed, it is intended as an example of an empirical approach rather than a test of the theory…".
[3] Earlier Finnish evidence on polarization at the aggregate level is provided in Asplund et. al. (2011), Asplund et. al. (2012) and Mitrunen (2013).

standard SBTC. In contrast, wage polarization predicts a U-shaped pattern, i.e. declining wage differentials at the lower part of the wage distribution, which is clearly absent from the pattern of wage growth in Finland.

Figures 1-2 here

The novelty of our paper is, however, in performing analyses for the changes in the structure of labour demand at the firm level, instead of at the aggregate or industry level as in Michaels, Natraj and Van Reenen (2010) and Acemoglu and Autor (2010). In this way we are able to study routinization and job polarization at the micro level, where the actual labour demand decisions are made, rather than at the more aggregate industry level as in Michaels et al. (2010). This minimizes any effects from the compositional changes in product demand (inter-firm shifts in production and employment) on the structure of employment or wages that may cause spurious relationships in aggregate studies to the extent that the main driver of employment changes are changes in relative demands for labour. Furthermore, we are able to examine the technology-based explanations for routinization and polarization at the firm level using firm-level R&D as an explanatory variable in the firm-level regressions. Using firm-level technology indicators allows us to avoid indirect reasoning in relating occupational changes to technical change based only on time effects as, for example, in Acemoglu and Autor (2010). We also perform decompositions of changes in educational and occupational employment (wage bill) shares into within firms, between firms, and entry-exit components to gain indicative information about the likely sources of these changes.

2. Data

Harmonized Wage Structure Statistics (HWSS) data of Statistics Finland combines the annual wage structure statistics data into a harmonized panel data, where all important wage measures and classifications, such as industry and occupation, are consistent across the years. The new harmonized data is currently available for the private sector and it covers the years 1995-2008. The annual wage structure statistics are based on the firm and individual level wage surveys of employer federations, which include their member firms, augmented by Statistics Finland with samples of non-member firms and sectors not covered by employer data.

Harmonization over time is needed because of the changes in collective wage contracts and classifications used. The annual harmonization across collective agreements takes into account the differences in wage concepts and compensation components used in different sectors, for example, hourly and monthly paid are made comparable. “Hourly wage for regular working time” is used as the wage measure. It includes basic pay and various supplements and performance-based pay paid regularly. But it does not include overtime pay or one-off items, such as holiday and performance bonuses. Regular working hours per month, the number of employed persons and the wage bill, which we use to measure the employment structure (by education or occupation), are available at the firm level from this data source.

In the new panel version of this data used in this paper the previous harmonization is also extended across time. Education, occupation and industry variables are harmonized using the latest versions of standard classifications of Statistics Finland. Formal education is available from a comprehensive register of completed degrees. The industry of firms is available at the 5-digit level but used in analyses at the 2-digit level. Occupation codes in the primary data are converted to the international ISCO 2001 codes at the 5-digit level and analyzed at the 3-digit level. It is not possible to completely harmonize some occupations for white-collar manufacturing workers over the break point 2001-2002 due to the classification change in the primary data. Hence, we perform all our estimations using separate data before and after this break point using the periods 1995-2001 and 2002-2008.

This longitudinal data for the years 1995-2008 contains some 600 000–750 000 employees per year and about 30 000 firms exist in the data for at least one year over the period 1995-2008. Using sampling weights, these data are representative of the whole private sector, except for the smallest firms, which are exempted from the wage surveys of employer associations and Statistics Finland. We augment these HWSS data with the firm-level variables for technology intensity from the R&D and ICT Surveys of Statistics Finland. Furthermore, we match task input measures at the 2-digit occupation level from Goos, Manning and Salomons (2010) into the wage data.

To examine firm-level technological changes, the R&D Surveys at the firm level for the years 1995-2008 are linked to the HWSS data. R&D surveys include all large firms and a sample of smaller firms, on average some 4000 firms per year. R&D intensity is defined as in-house R&D expenditures divided by a firm's sales. As our primary measure of technological change at the firm level, we use the change in its R&D intensity over the periods 1995-2001 and 2002-2008. Although there are substantial changes in the composition of firms over the survey years, R&D surveys are targeted by Statistics Finland to the firms that are most likely to conduct R&D. Therefore, the continuously operating firms that perform R&D are most likely included in the panel in all years.[4] We use sales from Financial Statement Statistics and the Business Register to measure firm-level output. Capital intensity is proxied by fixed assets from Financial Statement Statistics.

The dependent variables in our regressions are the shares in the total wage bill of educational and occupational groups at the firm level. From the individual level data for hourly wage and hours worked we construct the total monthly wage bill of each firm, as well as this wage bill divided into three education groups (low, intermediate and high) and into three occupation groups (abstract, routine and service occupations). Our main variables of interest are the changes in these wage bill shares over the periods 1995-2001 and 2002-2008. We have also constructed similar shares for hours worked and employed persons, but the results for these are similar to the wage bill, so we report only those. The low education group consists of those with basic compulsory education only. The high education group consists of those with a university level bachelor's degree or more. The intermediate group consists of all degrees in between these, i.e. from vocational to non-university higher degrees which usually involve two to four years of education. Our occupational grouping is an application of the grouping presented in Acemoglu and Autor (2010) to the Finnish ISCO occupations. The abstract group includes managers, professionals and

[4] However, we have experimented with measuring R&D intensity in various ways in order to increase the number of observations. We have also used the level of R&D intensity either in the initial years 1995 or 2001 or as the firm-level average R&D intensity over all existing observations for the firm in the R&D surveys. Furthermore, we defined an R&D dummy that indicates whether a firm has ever reported a positive amount of R&D expenditures in any year in the R&D surveys. This indicator obtains zero for those firms that report zero expenditures in the R&D surveys or do not exist in the R&D surveys at all. In most cases these alternative measures produced unexpected and imprecise estimates, so we consider them as inadequate indicators of technological change and therefore do not report results from these experiments.

technicians; the routine group includes occupations for sales, clerical, production and operator's work; and services include occupations involving work in protection, food preparation, building and grounds, cleaning and personal care and services.

We also match so-called task measures for the abstract, routine and service intensity of each occupation to the data. These measures are available from Goos, Manning and Salomons (2010), (henceforth GMS), for two-digit occupations. The measures are derived from the 2006 version of the Occupational Information Network (ONET) database, which provides the occupational attributes and characteristics of workers in 812 US SOC occupations. GMS (2010) manually convert these to the International Standard Classification of Occupations (ISCO), so we can match the GMS (2010) measures to our data at the 2-digit ISCO level. GMS (2010) use 96 ONET variables related to worker characteristics, worker requirements and work activities to create their measures for the Abstract, Routine and Service task intensities of different occupations. The task information is gathered from job incumbents, occupational analysts and occupational experts, who evaluate how important these task variables are in each occupation on a scale from 1 (not important at all) to 5 (extremely important). The 96 ONET variables are divided into one of three groups of Abstract, Routine and Service tasks. Abstract task variables measure things like critical thinking and complex problem solving. Routine task variables measure things like manual dexterity, finger dexterity and operation monitoring. Service task variables measure assisting and caring for others, service orientation, and establishing and maintaining interpersonal relationships. The actual task measures are averages of these variables for each SOC occupation, which are then converted to an ISCO occupation, using US employment in SOC cells as weights. Each task measure is normalized to have zero mean and unit standard deviation and they are available at the 2-digit ISCO level from GMS (2010).

Another variable we take from GMS (2010) is their offshorability measure. It is constructed from the information in the European Restructuring Monitor (ERM) of the European Monitoring Centre on Change, which collects fact sheets of actual offshoring cases. These include information, among other things, about what kind of jobs (occupations) are offshored. From these fact sheets GMS (2010) construct an index of the offshorability of different occupations, with mean zero and unit standard deviation across occupations. This is also available for 2-digit ISCO occupations.

3. Decompositions for employment and wage bill shares

To obtain preliminary information about the possible sources of the changes in the employment structure, we present firm-level decompositions for the changes in wage bill shares by education and occupation.[5] This decomposition augments the Berman, Bound and Griliches (1994) industry-level decomposition to an unbalanced panel of firms with entry and exit. Vainiomäki (1999) has shown that the aggregate change in the employment or wage bill share of a worker group defined by education or occupation (indexed by g) can be decomposed as follows

$$\Delta P^A = \sum_i \Delta S_i \overline{P}_i + \sum_i \Delta P_i \overline{S}_i + w_t^N \left(P_t^N - P_t^S \right) + w_{t-s}^D \left(P_{t-s}^S - P_{t-s}^D \right)$$

where $P = \dfrac{E^g}{E}$, $P_i = \dfrac{E_i^g}{E_i}$, $S_i = \dfrac{E_i}{E}$, $w_t^N = \dfrac{E_t^N}{E_t^A}$ and $w_{t-s}^D = \dfrac{E_{t-s}^D}{E_{t-s}^A}$.

P is the aggregate share of the skill group in total employment or wage bill (denoted by E), P_i is the corresponding share in firm *i* (*i* = 1,...,N), S_i is the share of firm *i* in aggregate employment or wage bill, Δ indicates change over the period (t-s, t), and bar an average over the period's initial (t-s) and final year (t) values. Superscripts indicate sums or shares for all firms (A), surviving firms (S), entering firms (N) and exiting firms (D). It can be shown (see Vainiomäki, 1999) that the entry and exit effects can also be written as

$$ENTRY = w_t^N \left(P_t^N - P_t^S \right) = \left(P_t^A - P_t^S \right)$$

$$EXIT = w_{t-s}^D \left(P_{t-s}^S - P_{t-s}^D \right) = \left(P_{t-s}^S - P_{t-s}^A \right).$$

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[5] We have also performed the decompositions for employment shares and working hour's shares, but the results are essentially similar to those for wage bill shares that we report.

These effects therefore depend on the deviation of the entering and exiting plant's average skill group shares from that of continuing plants. The entry effect is positive and greater the *higher the group's share in new plants* is compared to continuing plants ($P_t^N \geq P_t^S$). Similarly, the exit effect is positive and greater the *lower the group's share is in exiting plants* compared to continuing plants ($P_{t-s}^S \geq P_{t-s}^D$). But it is noteworthy that the entry effect is also given by the simple difference between the group's aggregate wage bill (or employment) share for all firms and continuing firms in the *final* year of the period. Similarly, the exit share is given by the simple difference in the shares for continuing firms and exiting firms in the *initial* year of the period.

The other two terms are standard from industry-level decompositions. The first sum is the *between firms effect*, which captures shifts of employment (wage bill) between firms with different average shares of skilled workers. It is positive if employment (the wage bill) shifts towards firms which have a high employment (wage bill) share of the skill group in question. The second sum is the *within firms effect,* which captures changes in a skilled worker's share within each firm, weighted by the firm's average share of the total employment (wage bill). It is a common interpretation that the within component captures technological change within firms, the between component captures product demand changes across firms, and the entry/exit components reflect structural change in firm population. The education groups in our decompositions are Basic, Intermediate and High, as explained previously. The occupation groups are Abstract, Routine, and Services, following Acemoglu and Autor (2010).

Table 1 reports the decomposition of changes in the wage bill shares by the education groups. All results are weighted by working hours and sampling weights. The changes in the period 1995-2001 are mostly driven by the within component. The between component is small except for the highest education group. In addition, the entry and exit effects are generally small. The total changes imply linear skill upgrading.

Table 1 here

The results for the period 2002-2008 are different. The within and total changes for the intermediate education group turn negative for this period. The changes for the highest educated are larger compared to the previous period. The entry component also becomes more important for the basic education group and the exit component for the highest educated. These changes imply faster skill upgrading at a higher education level during the 2000s compared to the late 1990s. They are also consistent with the implications from polarization in the sense that the intermediate education group loses in comparison to the low and high education groups during the 2000s compared to the 1990s, i.e. the intermediate group's change turns from positive to negative, whereas the development was "linear" with respect to education in the 1990s.

Table 2 shows the decompositions of change in the wage bill shares by the occupation groups. In contrast to education, both within and between components are important for occupational changes and affect the same direction. We find that the routine occupation share declines and the abstract occupation share increases, so that the total change is consistent with the routinization hypothesis. There is also evidence for polarization in the entry component as entering firms are non-routine intensive.

Table 2 here

Again there are changes in the contributions of individual components in the later period and the total change now clearly reflects polarization. The results show that the within component accelerates and the between component slows down, except for service occupations where it turns from negative to positive. Entry and exit effects are even smaller for the later period. These variations imply polarization for occupational employment changes at the firm level, because the routine share declines, and the abstract and service shares increase. The shifts in production between different firms, the between component, seem to be more important in explaining the polarization in the occupational shares than in the educational shares. The shifts in production towards service-intensive firms and the entry of new service-intensive firms, especially for the service occupations, is relatively more important during the 2000s than for the other occupation groups. This suggests that changes in product demand may have a role in explaining the increase in the service occupations. However, for the abstract and routine occupations the overwhelming majority of change occurs within existing firms, which is consistent with technological change being important in explaining the declining shares of routine occupations.

4. Specifications and results from firm-level regressions

In order to examine the importance of the technology explanation for shifts in the structure of labour demand we estimate, at the firm level, equations for the wage bill shares of the education groups (E=Low, Middle, High) as follows

$$\Delta SHR_{it}^{E} = c^{E} + \beta_1^{E} \Delta \left(\frac{R\&D}{Q} \right)_{it} + \beta_2^{E} \Delta \ln \left(\frac{K}{Q} \right)_{it} + \beta_3^{E} \Delta \ln Q_{it} + u_{it}^{E}$$

where K is capital, Q is output and R&D is expenditures on new technology at each firm. Berman, Bound and Griliches (1994) showed that such an equation can be derived from a short-run trans-log cost function to examine relative demand for different labour groups. Michaels, Natraj and Van Reenen (2010) derive similar equations from a three-input CES production function, which allows for ICT capital to substitute for the medium educated, and to complement for the highly educated. The polarization hypothesis implies that following technological change (increase in ICT capital) the wage bill share of the Highly educated (skilled) workers increases ($\beta_1^{High} > 0$) and the Middle level educated (skilled) declines ($\beta_1^{Middle} < 0$). Instead of ICT capital we use R&D intensity as our technology measure.

We also perform similar regressions for occupational groups, i.e. E=Abstract, Routine, Service occupations. Analogously with the treatment of education, the polarization hypothesis now implies that technological change increases the demand and therefore the wage bill share of the Abstract occupations ($\beta_1^{Abstract} > 0$), reduces the share of the Routine occupations ($\beta_1^{Routine} < 0$) and has an ambiguous effect on the Service occupations ($\beta_1^{Service} = ?$).

The results for educational shares are reported in Tables 3-4. When no other controls are included in Table 3, except the ones in the equation above, we find the results strongly supportive of the polarization hypothesis. The wage bill share of the highly educated increases 1.7% points faster in firms that have a 10% points higher R&D intensity growth over a six-year period. Conversely, the wage bill share of the medium educated *declines* by 3.5% points more for each 10% points increase in a firm's R&D intensity. The share of the lowest educated is not statistically significantly related to the changes in R&D intensity. This pattern, which is consistent with the polarization hypothesis as noted above, remains similar when we consecutively add two-digit industry and lagged level of the wage bill share as regressors. For the intermediate educated the coefficient for R&D intensity remains significant at the 5% level, but for the highly educated only at the 10% level or almost so with the lagged variable included. Despite the decrease in significance, the size of the coefficients remains almost as high as indicated above.

Tables 3-4 here

The decline in the association between R&D intensity and the employment structure, when adding industry, implies that a substantial share of the variation in the technology-employment relationship is across detailed (two-digit) industry, rather than within industries. The importance of the lagged level of the dependent variable indicates that the regressions-towards-mean phenomenon is detected, but it also implies that the educational employment structure changes quite slowly even over six-year periods. The coefficients for the lagged variable imply that the autoregressive parameter for the level of the wage bill share is about 0.8 for the highly and medium educated, and about 0.6 for the low education group.

The results for occupational shares are reported in Tables 5-6. Without accounting for the industry effects in Table 5, we find that the routine occupation share declines in R&D intensity at the 10% level. However, this effect becomes insignificant after adding the industry effects and lagged dependent variable. The changes in the abstract and service occupation shares are not statistically significantly related to R&D intensity in any of the models.

Tables 5-6 here

Unobserved differences may cause dynamic selection bias for our results if they are not taken into account in estimation. Our models are essentially first-differenced equations and they are estimated only for continuing firms, which may be different from all firms in unobserved ways that correlate with both a firm's technology and its skill demand. To give an example, firms with high-quality management could invest more in new technology and employ more higher-quality (more educated) workers. Such firms are likely to have higher labour productivity, which we use as our primary explanatory variable in the selection correction model. That is, we re-estimate our model using the Heckman selection model. Survival is explained by the firm's (log) labour productivity, firm size (log output), and indicators for the firm's two-digit industry. The latter indicators proxy for changes in industry sales that are likely to affect the firm's survival, as used in a similar selection correction in Abowd et al. (2007).

Firm size and productivity effects are allowed to vary across a firm's main industries, i.e. they are interacted with one-digit industry indicators. This allows for differences in production technology and product market competition condition across industries. The model is estimated with Maximum Likelihood and the results for the share equations are presented in Tables 4 and 6 for educational and occupational shares respectively. We include industry dummies and the lagged wage bill share as regressors in all models in Tables 4 and 6. In general these results are quite similar to uncorrected results in Tables 3 and 5 for models that include the same regressors, so there is no evidence of significant biases due to dynamic selection in our previous results. This is confirmed by the Wald tests for the independence of unobserved effects in the share equation and the selection model reported in Table 4 on line Test Rho=0. The p-values are not significant at conventional levels, so the null hypothesis of independence is not rejected. Regarding our main interest, the coefficients and statistical significance of R&D intensity remain almost intact in these results compared to those in Table 3, so our conclusion about weak support for polarization in educational shares stands the test of accounting for dynamic selection effects. The same is true for the wage bill share of routine occupations in Table 6, which remains negatively related to R&D intensity but with low statistical significance.

Unfortunately, the ML estimations for other occupations failed, but given the results for education and the routine occupation, we conjecture that there would be no evidence for dynamic selection effects for these either.

It should also be noted that since our estimating equations are essentially *first-differenced* versions of the levels equations for wage bill shares, any endogeneity issues related to the unobserved firm-fixed effects in the *levels* equations are eliminated from our results. There are still remaining issues of endogeneity bias in our models. First, measurement error in explanatory variables causes the standard attenuation bias. Second, there is the possibility of reverse causality, i.e. shocks to wage bill share changes causing firms to change investments in new technology (measured here by R&D intensity). It is usually difficult to find firm-level instruments to correct for these, but we have performed some estimations with potential instruments that we have access to. We report results using changes in R&D intensity at the three-digit industry level as instruments for firm-level changes in R&D intensity. Industry-level R&D intensity should be (more or less) exogenous with respect to idiosyncratic firm-level shocks to the wage bill. Any industry-level shocks are confined to the industry effects included in the model. F-statistics in Tables 4 and 6 indicate that it also passes or almost passes the weak instrument test in most cases. We also experimented with a number of other possible instruments, but they hardly ever passed the weak instruments test, so we do not report these results.[6]

The results from our instrumental variables estimations are also presented in Tables 4 and 6 for the education groups and the occupation groups respectively. For the educational groups the coefficient for R&D intensity considerably increases in absolute value compared to OLS results as expected due to measurement error bias. However, only the negative effect for the intermediate groups remains anywhere close to statistical significance at the 10% level. As for the other variables, the output effects decrease, again in absolute value, and lose significance for intermediate and high groups. This may be related to the fact that output also has an effect via the denominator in R&D intensity whose coefficient increases considerably in IV results.

[6] As alternative instruments we have used the lagged R&D intensity, either from the first year of the period or from the year 2001 for the 2002-2008 period, the task measures for routine intensity and offshorability as changes or lagged values, all either at the firm level or aggregated to the three-digit industry level. We also experimented with various combinations of these instruments.

The results for the occupational groups similarly indicate, in absolute value, larger R&D effects for the abstract and routine groups, but only the negative effect for the routine group is significant at the 5% level. All in all, our IV results for the intermediate education group and the routine occupation group are still consistent with polarization, i.e. a disappearing middle due to technological change. For the routine occupation groups this result remains statistically significant, but for the intermediate education group the effect is marginally insignificant at the 10% level. The increase in IV coefficients is reassuring in that the OLS results are not likely to be upward biased due to any reverse causality or unobserved effects.

5. Conclusions

Using the new Harmonized Wage Structure Statistics (HWSS) data of Statistics Finland we first document the patterns of employment and wage polarization in the Finnish private sector labour market. Our results show that there has been considerable employment polarization at the aggregate level. The structure of changes in the employment shares by initial occupational wage deciles is clearly U-shaped. In contrast, there is no indication of wage polarization over the period 1995-2008. Thus, wage growth increases almost linearly with the initial wage level. This pattern is consistent with the predictions of standard SBTC.

The novelty of our paper is, however, in performing regression analyses that test for the routinization hypothesis and job polarization at the firm level, instead of the aggregate or industry level as in previous studies. In this way, we are able to study routinization and job polarization at the micro level, where the actual labour demand decisions are made. Furthermore, we are able to examine the technology-based explanations for routinization and job polarization at the firm level using firm-level R&D as an explanatory variable in the firm-level regressions, instead of using proxies such as time trend or decade indicators.

Our decompositions show faster skill upgrading at the higher education level during the 2000s compared to the late 1990s. They are also consistent with the implications of polarization in the sense that the intermediate education group loses in comparison to the low and high education groups during the 2000s compared to the 1990s, i.e. the intermediate group’s change turns from positive to negative, whereas the development was “linear” with respect to education in the 1990s. Based on occupational decompositions, we also find that for the service occupations the shifts in production towards service-intensive firms and the entry of new service-intensive firms is relatively more important during the 2000s than for other occupation groups. This suggests that changes in product demand may have a role in explaining the increase in service occupations. However, for the abstract and routine occupations the overwhelming majority of change occurs within existing firms, which is consistent with technological change being important in explaining the declining shares of routine occupations.

Our main conclusion is that there is weak evidence for polarization in the educational and occupational employment structures from our firm-level regressions. These models capture technological change using firm-level R&D as an explanatory variable in the wage bill share regressions. The wage bill share of the highly educated increases faster in firms that have higher R&D intensity growth. Conversely, the wage bill share of the medium educated *declines* in firms with increasing R&D intensity. The share of the lowest educated is not significantly related to the changes in R&D intensity. This pattern is consistent with the polarization hypothesis. Regarding our results for occupational shares, we find that the changes in abstract and service occupation shares are not statistically significantly related to R&D intensity in any of the estimated models. However, we find that the routine occupation share is declining in R&D intensity without accounting for the industry effects in the OLS results. Furthermore, the IV results for the occupational groups obtain a negative and significant effect at the 5% level for the routine group. All in all, our IV results for the intermediate education group and the routine occupation group are consistent with polarization, i.e. a disappearing middle due to technological change. These results also seem to be robust in the specifications that account for dynamic selection effects.

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FIGURE 1

Employment Polarization.

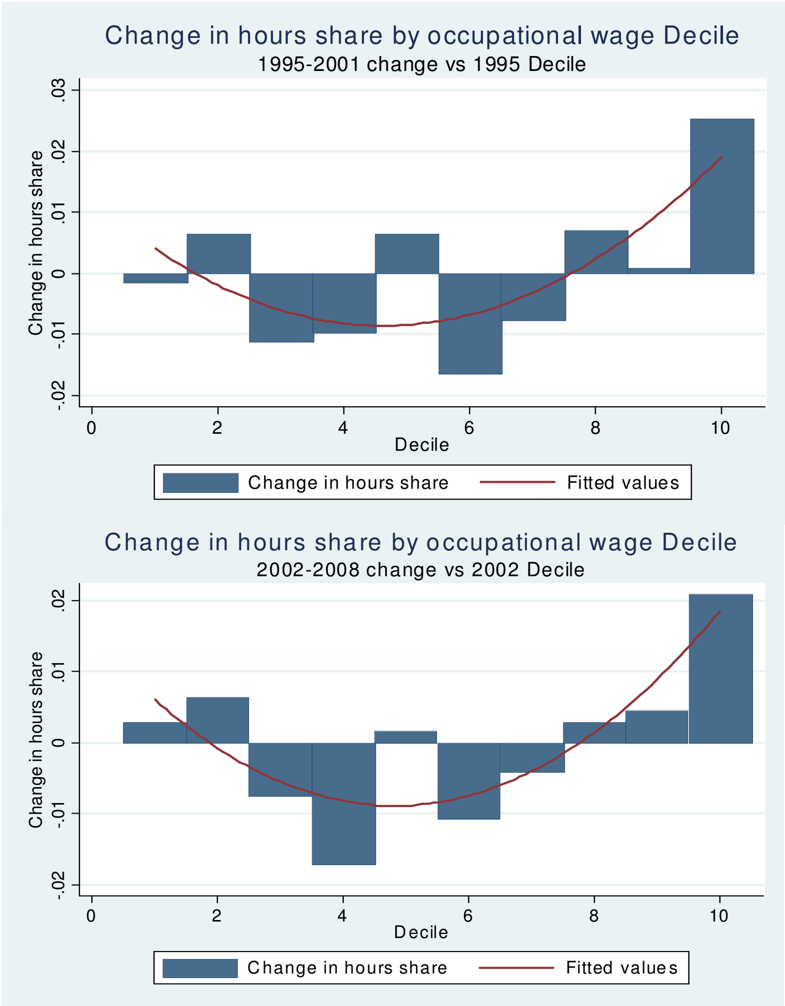

FIGURE 2.

Wage Polarization.

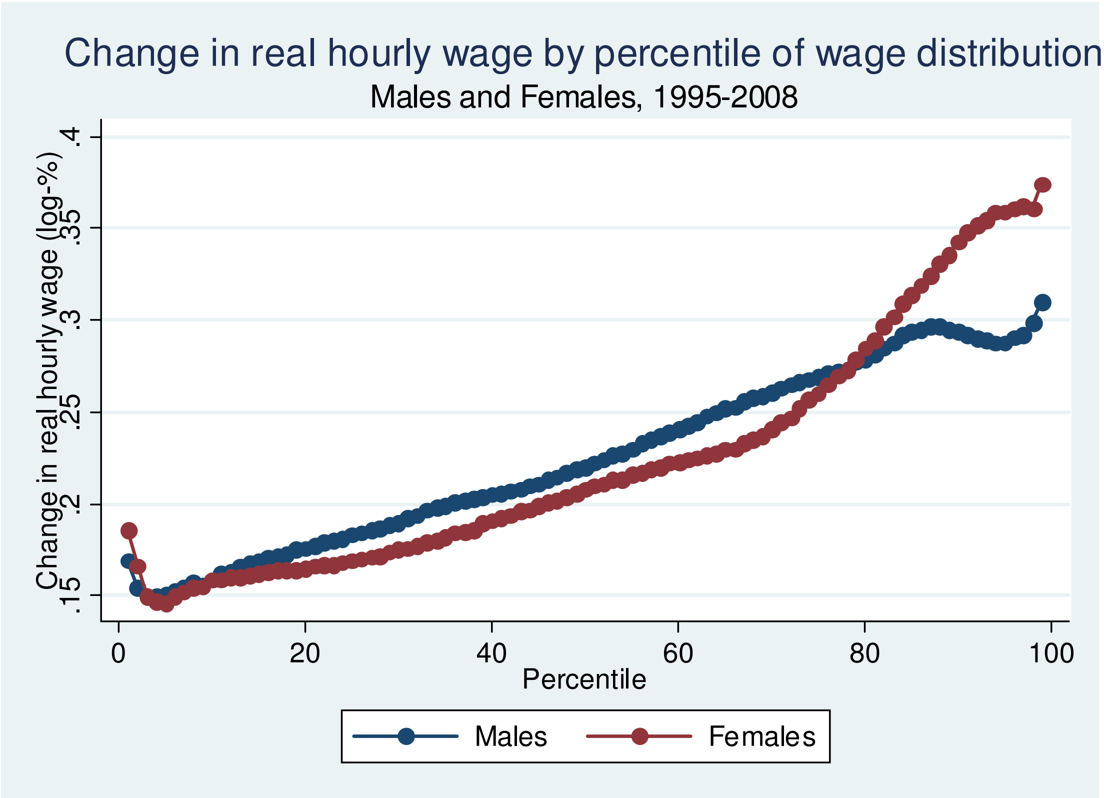

TABLE 1

Decompositions for Wage Bill Share by Education

Period	Education group	Within	Between	Entry	Exit	Total	Share (2001) / (2008)
1995-2001	Basic	-0.053	-0.014	0.007	-0.008	-0.068	0.200
1995-2001	Intermediate	0.026	-0.015	0.001	0.010	0.022	0.587
1995-2001	High	0.026	0.030	-0.008	-0.002	0.046	0.213
Period							
2002-2008	Basic	-0.051	-0.001	0.012	-0.006	-0.046	0.138
2002-2008	Intermediate	-0.018	0.001	-0.004	-0.007	-0.028	0.571
2002-2008	High	0.068	0.000	-0.007	0.013	0.074	0.291

TABLE 2

Decompositions for Wage Bill Share by Occupation

Period	Occupation group	Within	Between	Entry	Exit	Total	Share (2001) / (2008)
1995-2001	Abstract	0.029	0.036	0.005	-0.006	0.064	0.407
1995-2001	Routine	-0.024	-0.028	-0.014	0.008	-0.058	0.530
1995-2001	Service	-0.006	-0.007	0.009	-0.002	-0.006	0.063
Period							
2002-2008	Abstract	0.045	0.004	-0.004	0.000	0.045	0.464
2002-2008	Routine	-0.038	-0.019	-0.001	0.001	-0.057	0.450
2002-2008	Service	-0.007	0.015	0.005	-0.001	0.012	0.086

TABLE 3

Regressions for the Change in Wage Bill Shares by Education Group

	High			Intermediate			Basic		
Δ R&D/Q	0.173	0.153	0.126	-0.354	-0.313	-0.259	0.052	-0.097	-0.059
	(2.46)	(1.80)	(1.54)	(-2.66)	(-2.48)	(-2.20)	(0.40)	(-1.48)	(-0.95)
Δ ln(K/Q)	-0.012	-0.013	-0.013	-0.005	0.002	0.002	0.005	0.007	0.004
	(-1.73)	(-1.98)	(-1.87)	(-0.65)	(0.34)	(0.23)	(0.61)	(0.88)	(0.60)
Δ ln(Q)	-0.045	-0.055	-0.046	0.016	0.026	0.024	0.005	0.004	-0.004
	(-2.22)	(-2.50)	(-2.58)	(0.77)	(1.34)	(1.41)	(0.34)	(0.44)	(-0.46)
SHR(t-6)			-0.183			-0.179			-0.404
			(-3.21)			(-2.77)			(-5.61)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
N	774	774	774	857	857	857	822	822	822
R-sq	0.100	0.171	0.224	0.104	0.273	0.311	0.004	0.211	0.468

Notes: Weighted by hours worked multiplied by sampling weight. Robust t-values reported.
Δ means six-year difference over periods 1995-2001 or 2002-2008.

TABLE 4

Educational Share Regressions Correcting for Dynamic Selection and Endogeneity using Heckman and IV Estimation

	High		Intermediate		Low	
	ML	IV	ML	IV	ML	IV
Δ R&D/Q	0.122	1.29	-0.258	-1.28	-0.059	-0.029
	(1.55)	(0.85)	(-2.24)	(-1.60)	(-0.98)	(-0.07)
Δ ln(K/Q)	-0.013	-0.026	0.002	0.007	0.004	0.004
	(-1.98)	(-1.36)	(0.28)	(0.75)	(0.66)	(0.54)
Δ ln(Q)	-0.044	0.001	0.023	-0.002	-0.005	-0.004
	(-2.57)	(0.01)	(1.44)	(-0.12)	(-0.54)	(-0.40)
SHR(t-6)	-0.196	-0.139	-0.185	-0.127	-0.410	-0.405
	(-3.42)	(-1.62)	(-2.82)	(-2.29)	(-5.76)	(-5.61)
Test Rho=0	1.38		0.07		2.07	
	(p=0.24)		(p=0.32)		(p=0.15)	
F (weak inst.)		0.88		9.34		12.8
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	774	773	857	857	822	822
R-sq		0.226		0.100		0.468

Notes: Weighted by hours worked multiplied by sampling weight. Robust t-values reported.
Δ means six-year difference over periods 1995-2001 or 2002-2008.
Industry-level (3-digit) R&D intensity change as an additional instrument for firm’s R&D intensity change.
The explanatory variables of the selection equation in the ML model are described in the text.

TABLE 5

Regressions for the Change in Wage Bill Shares by Occupation Group

	Abstract			Routine			Service		
Δ R&D/Q	0.035	-0.070	-0.085	-0.540	-0.431	-0.365	0.053	0.080	0.085
	(-0.26)	(-0.53)	(-0.66)	(1.87)	(-1.67)	(-1.45)	(0.63)	(1.26)	(1.39)
Δ ln(K/Q)	-0.014	-0.018	-0.020	0.001	0.011	0.011	0.006	0.001	0.005
	(-1.87)	(-2.29)	(-2.67)	(-0.12)	(1.15)	(1.15)	(0.38)	(0.16)	(0.46)
Δ ln(Q)	-0.053	-0.061	-0.053	0.026	0.042	0.039	0.012	-0.002	0.004
	(-2.53)	(-2.65)	(-2.74)	(1.05)	(1.64)	(1.58)	(0.64)	(-0.15)	(0.27)
SHR(t-6)			-0.177			-0.164			-0.231
			(-3.42)			(-3.42)			(-1.32)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
N	809	809	809	857	857	857	400	400	400
R-sq	0.045	0.116	0.166	0.062	0.173	0.199	0.023	0.613	0.648

Notes: Weighted by hours worked multiplied by sampling weight. Robust t-values reported.
Δ means six-year difference over periods 1995-2001 or 2002-2008.

TABLE 6

Occupational Share Regressions Correcting for Dynamic Selection and Endogeneity using Heckman and IV Estimation

	Abstract		Routine		Service	
	ML	IV	ML	IV	ML	IV
Δ R&D/Q		4.58	-0.365	-1.91		-0.153
		(0.69)	(-1.48)	(-2.10)		(-0.69)
Δ ln(K/Q)		-0.072	0.011	0.016		0.006
		(-0.95)	(1.21)	(1.36)		(0.66)
Δ ln(Q)		0.122	0038	0.007		0.003
		(0.46)	(1.62)	(0.30)		(0.20)
SHR(t-6)		-0.124	-0.167	-0.129		-0.230)
		(-0.97)	(-3.46)	(-3.10)		-1.38
Test Rho=0			0.56			
			(P=0.45)			
F (weak inst.)		0.75		16.1		5.04
Year		Yes	Yes	Yes		Yes
Industry		Yes	Yes	Yes		Yes
N		809	857	857		395
R-sq		..		0.069		0.639

Notes: Weighted by hours worked multiplied by sampling weight. Robust t-values reported.
Δ means six-year difference over periods 1995-2001 or 2002-2008.
Industry-level (3-digit) R&D intensity change as an additional instrument for firm's R&D intensity change.
The explanatory variables of the selection equation in the ML model are described in the text.
ML model did not converge for Abstract and Service groups.