Does ICT Usage Erode Routine Occupations at the Firm Level?

Petri Böckerman[1] — Seppo Laaksonen[2] — Jari Vainiomäki[3]

Abstract. We show that disappearing routine work can be linked to firm-level ICT usage. Our results for the increasing abstract and declining routine occupation shares of total wage bill are consistent with job polarization at the firm level. The observed changes coincide with the usage of ICT in firms. These results are based on decompositions and regression analyses that evaluate the hollowing-out of routine occupations and job polarization at the firm level.

1. Introduction

Occupational structures in Europe are in turmoil (Fernández-Macías, 2012). This paper examines the routinization hypothesis and occupational polarization using rich firm-level data. We contribute to the relatively thin but growing empirical literature that has used firm-level data to explore the sources of polarization (Akerman *et al.*, 2015; Bartel *et al.*, 2007; Cortes and Salvatori, 2015; Crino, 2010; Gaggl and Wright, 2017; Harrigan *et al.*, 2016). The use of firm-level data is a natural extension of the literature, which has focused on changes at the aggregate, industry, or local labour market levels.[1]

We analyse changes in the occupational structure of labour demand at the firm level. This allows us to examine heterogeneity in job polarization and the technology explanation for routinization at the micro level, where actual labour demand decisions are made. The literature has documented a large amount of heterogeneity between firms in terms of productivity and wages (Card *et al.*, 2013; Syverson, 2011).

We evaluate an important aspect of routine-biased technical change, i.e., employment polarization. The results show that the wage bill shares of (non-routine) abstract and service occupations have increased, whereas the share of routine occupations have decreased. The aggregate polarization of the employment distribution is decomposed into between- and within-firm effects, in addition to the influence of entry and exit. The changes for abstract and routine occupations are driven by within-firm employment reallocation, but the changes for manual/service occupations reflect mostly reallocation of employment

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Declarations: The data used in this study are confidential but other researchers can independently obtain access to the data for replication purposes with the permission of Statistics Finland. The authors will provide guidance about acquiring the data upon request. The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

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between firms. The pattern is consistent with the Autor and Dorn (2013) model's general equilibrium explanation for the rising service employment.[2]

Second, we estimate models that utilize specific measures for the usage of information and communication technologies (ICT) at the firm level. The aim is to identify whether ICT at a firm leads to decreasing shares of routine occupations and increasing shares of non-routine abstract occupations. The use of comprehensive firm-level ICT indicators allows us to establish a more direct link between observed occupational or educational changes and computer-based technological change than aggregate studies based on time effects or industry-level aggregates. We concentrate on firm-level regressions for changes in employment shares because our decompositions show that the changes in wage bill shares are predominantly within-firm phenomena. Our results show that the usage of ICT coincides with the growth in abstract occupation wage bills and the decline in routine occupation wage bills at the firm level. We provide a parallel focus on educational and occupational shares in order to consider the possible differences in the effects of routinization on the demand for skills and tasks.

Michaels *et al.* (2014) used country-industry panel data and showed 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 education levels are negatively related to ICT. In the previous firm-level literature Bartel *et al.* (2007) focus on a narrow manufacturing sector; Akerman *et al.* (2015) use a very specific ICT technology (broadband Internet); Cortes and Salvatori (2015) use computer share and an indicator for adoption of new technology from a management survey; Gaggl and Wright (2017) use ICT investments rather than detailed ICT technologies; Harrigan *et al.* (2016) use the share of 'techies' (ICT-related personnel) as a proxy for ICT services; and Pekkala Kerr *et al.* (2016) use one indicator for the share of employees using ICT from 1 year. In contrast to these either narrow or very broad ICT measures used in the contemporary literature, we utilize detailed information about a broad set of specific ICT technologies used by firms in all sectors of the economy, which more comprehensively captures the penetration of new technology into the organization of tasks within firms.

Traditionally, the driving force behind the increase in wage differentials, education premiums, and skill-upgrading in industrialized countries has been seen to be skill-biased technological change (SBTC) (see, e.g., Acemoglu, 2002; Bound and Johnson, 1992; Machin, 2008; for reviews). To address the observed anomalies that are difficult to explain with the standard SBTC model (Acemoglu and Autor, 2011; Card and DiNardo, 2002), Autor *et al.* (ALM) (2003) noted the differences between the tasks that workers do in their jobs and the skills they use to perform these tasks in different occupations. Computers replace routine tasks but complement non-routine analytical and interactive tasks. Reduction in routine tasks is dubbed the routinization hypothesis (or routine-biased technological change).[3]

Autor *et al.* (2006) and Goos and Manning (2007) argued that the routinization process may lead to occupational polarization, where employment growth is concentrated in low and high skill (wage) occupations, whereas jobs in the middle of the skill continuum are diminished.[4] Low-wage (education), non-routine manual, and service jobs are unlikely to be directly affected by computerization, but non-homothetic preferences in product demand may lead to increasing demand for low-paid services and non-routine manual jobs.

The article is structured as follows. We first describe the data and present the aggregate patterns and the results from decompositions. Firm-level regressions of employment structure on ICT usage are then presented and the estimates are reported. A summary concludes the article.

2. Data

We use linked data that match wage structure statistics to firm-level technology indicators. The Harmonized Structure of Earnings Survey (HSES) data from Statistics Finland combine annual earnings structure statistics data into harmonized panel data, where all wage measures and classifications, such as industry and occupation, are consistent across years and sectors. The core of the annual earnings structure statistics is the set of firm- and individual-level payroll record data of employer federations for their member firms. Statistics Finland conducts an augmenting survey for the non-member firms and sectors that are not covered by the Confederation of Finnish Industries (EK). Statistics Finland has calibrated weights to the payroll record data that further improve the representativeness of the data.[5] We use these weights in all our analyses. The harmonized data are available for the private sector for every year from 1995 onwards. In our analysis, the recession years following the financial crisis after 2008 are excluded, because our interest is the structural effects of new technology.

Harmonization over time is needed because of the differences and changes in both collective wage contracts and classifications used over time and across sectors. The annual harmonization across different sectors takes into account the differences in wage concepts and compensation components used in different collective agreements. For example, hourly and monthly pay schedules are made comparable.

In the panel data, education, occupation, and industry variables are harmonized over time to the latest versions of standard classifications of Statistics Finland. Formal education is available from a comprehensive register of completed degrees. The industry classifications of firms are available at the five-digit level but used in the analyses at the two-digit level. Occupation codes in the primary data are converted into international ISCO 2001 codes at the 5-digit level but used in the analyses at the three-digit level. Unfortunately, it is not possible to completely harmonize some occupations for white-collar manufacturing workers over the break point of 2001–2002 due to a classification change in the primary employer payroll record data. Hence, we either perform all our estimations using separate data before and after this break point using the periods of 1995–2001 and 2002–2008 or focus only on the latter period.

This longitudinal HSES data for the years from 1995–2008 contain some 600,000–750,000 employees per year. Approximately 28,000 firms exist in the data for at least 1 year during the period of 1995–2008. Using sampling weights, these data are representative of the total private sector (with the exception of the smallest firms, which are exempt from the construction of payroll record data gathered by employer associations and Statistics Finland).

Our wage concept, the 'hourly wage for regular working time' includes basic pay and various supplements for working conditions and performance-based pay that is paid on a regular basis. It does not include overtime pay or one-off items, such as holiday and annual performance bonuses. In addition to wages, we observe regular working hours per month for each worker in these wage statistics. Because the employer of each person is known, we are able to calculate the total number of employed persons and their total monthly wage bill for each firm in these statistics. Finally, we observe the education level and the occupation of each person, so we can disaggregate these measures according to education and occupation in order to examine the employment structure at the firm level.

The wage bill is divided into three education groups (low, intermediate, and high) and three occupation groups (abstract, routine, and service occupations). 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 the latter. 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 higher. The intermediate group consists of all degrees in between, i.e., from vocational to non-university higher degrees that usually involve 2–4 years of education.

The occupational grouping is an application of the classification presented in Acemoglu and Autor (2011) to the Finnish ISCO occupations. The abstract group includes managers, professionals, and technicians; the routine group includes sales, clerical, production, and operator's work; and services include occupations in protection, food preparation, building and grounds, cleaning, and personal care and services. The idea here is that although each occupation can be thought as a bundle of different tasks, each occupation is dominated by a main task, that can be characterized as abstract (non-routine cognitive), routine, or service (non-routine manual) task. Thus, the routine content is measured at the occupational level following Acemoglu and Autor (2011).

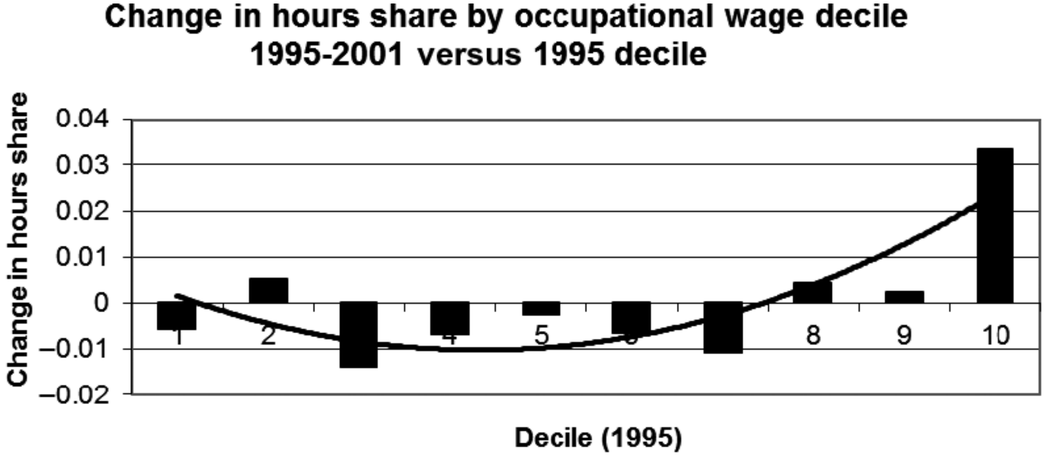
We augment wage and employment structure data (HSES) with comprehensive firm-level variables quantifying the use of ICT. Our data regarding the use of information technology and electronic commerce in firms originate from the Statistics Finland survey 'Use of Information Technology in Enterprises' (ICT survey). The survey is a stratified random sample of firms in the sampling frame of the Business Register of Statistics Finland. It covers all large firms (100 employees or more) and a random sample of smaller firms with more than five employees. Matching these two data sources reduces the number of firms in the linked data substantially due to the sampling in ICT surveys. To partially address this issue, we use all panel years to create indicators of whether a firm in any year during the period of 2002–2008 reported having certain ICT technology. This retains in the data all firms surveyed even once during the period.[6] The variables in this survey describe the usage of ICT in firms, including Internet, intranet, broadband, home pages, services offered via home pages, electronic commerce, and electronic data interchange (EDI). The full list and explanations of variables are provided in Appendix A.

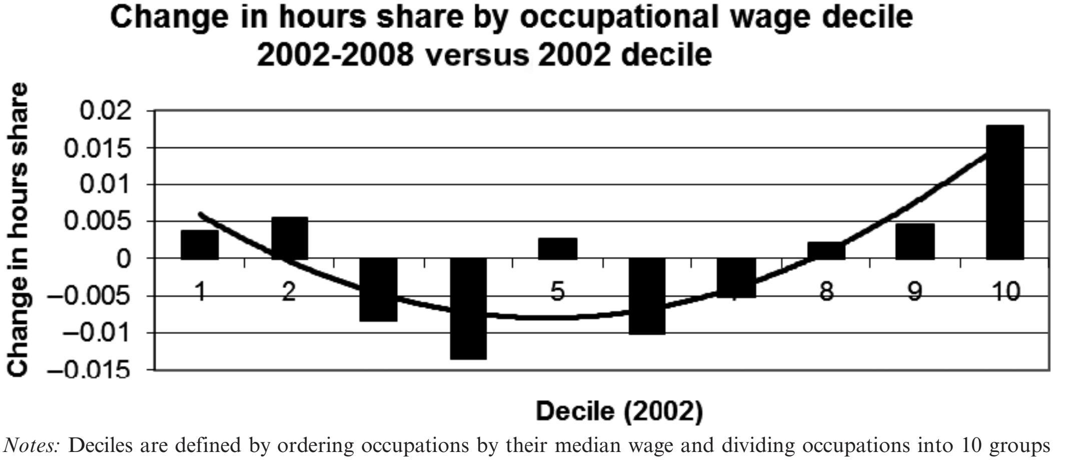
The variables that describe various aspects of ICT are highly correlated because they measure the underlying characteristics of firms that affect the adoption of new technologies.[7] For this reason, we use factor analysis to compress this information into latent factors, which we use as explanatory variables in our regressions. This alleviates multi-collinearity and variance inflation in the estimated models because the factors are orthogonal. We use the principal factors method and based on the eigenvalues, three factors are adequate to describe the common variance of the ICT indicators. The cumulative variance explained is 71%. The factor loadings are documented in Appendix B. We call Factor 1 EDI because it loads on variables related to the usage of EDI by the firm for various purposes (sending and receiving invoices, orders, or sending transport documents). Factor 2 loads on a large number of variables related to broadband or mobile access to the Internet, the firm having a website, and whether the firm orders or sells through computer networks. This factor also loads on the firm having enterprise resource planning, but we call this the Internet factor for short. The third factor loads on two variables indicating whether the firm shares supply chain management (SCM) data with suppliers or customers, so we call it the SCM factor.

3. Aggregate patterns of job polarization

Figure 1 illustrates the aggregate pattern of job polarization in the Finnish private sector.[8] It shows that changes in employment shares by initial occupational wage deciles have been U-shaped in both the 1995–2001 and 2002–2008 periods, similarly to the polarization pattern documented for the UK in Goos and Manning (2007). On the other hand, we find no indication of wage polarization in Finland in Böckerman *et al.* (2013), where it is shown that wage growth increases almost linearly with initial wage levels.

Figure 1. Employment polarization





Notes: Deciles are defined by ordering occupations by their median wage and dividing occupations into 10 groups with equal share of total hours. The line shows the quadratic fit.

Figure 2. Development of employment shares of Abstract, Routine, and Service occupations, 1995–2013 [Colour figure can be viewed at wileyonlinelibrary.com]

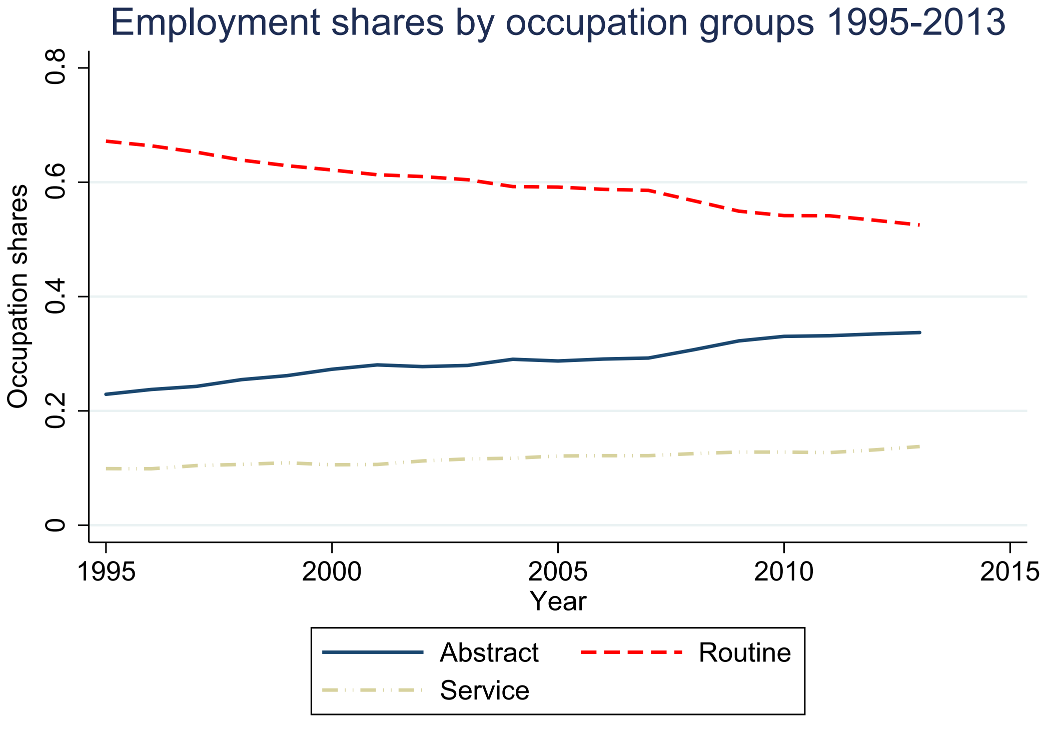


Figure 2 documents the development of the employment (hours) shares of occupation groups over the period of 1995–2013. The figure shows that employment in routine-intensive occupations has decreased steadily over the years. We also find increasing employment in both abstract and service task-intensive occupations. These patterns are consistent with the routinization hypothesis of ALM (2003).

4. Changes in routine and non-routine occupation's shares

The main variables of interest in our examinations are the shares of the total wage bill by education and occupation groups at the firm level and their changes over time. To obtain information about the possible sources of changes in labour demand structure, we present firm-level decompositions for the changes in wage bill shares. This decomposition augments the Berman *et al.* (1994) industry-level decomposition to an unbalanced panel of firms with entry and exit.[9] The aggregate change in the wage bill share of a worker group defined by education or occupation (indexed by g) can be decomposed as follows:

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

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

P^g is the aggregate share of the skill group g in the total wage bill for all firms (denoted by E^A), P_i is the corresponding share in continuing firm i (i = 1, …, N), S_i is the share of firm i in the aggregate wage bill, Δ indicates change over the period ($t{-}s$, t), and bars denote averages over the period's initial-year ($t{-}s$) and final-year (t) values. Superscripts indicate the sums or shares for all firms (A), surviving firms (S), entering firms (N), and exiting firms (D). It can be shown that the entry and exit effects can also be written as

$$ENTRY = w_t^N (P_t^N - P_t^S) = (P_t^A - P_t^S),$$

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

These effects therefore depend on the deviation of the entering and exiting plant's average skill group shares with that of continuing plants. The more positive the entry effect is, the *higher the group's share in new plants* is compared with continuing plants ($P_t^N \geq P_t^S$). Similarly, the more positive the exit effect is, *the lower the group's share is in exiting plants* compared with continuing plants ($P_{t-s}^S \geq P_{t-s}^D$). However, it is noteworthy that the entry effect is also given by the simple difference between the group's aggregate wage bill 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 in industry-level decompositions. The first sum is the *between-firm effect*, which captures the shifts of employment (wage bill) between firms with different average wage bill shares. It is positive if the wage bill shifts towards firms that have a high wage bill share of the skill group in question. The second sum is the *within-firm effect,* which captures changes in the wage bill share within each firm, weighted by the firm's average share of the total wage bill. The conventional interpretation in the literature is that the within component captures technological change within firms, the between component captures product demand changes across firms, and the entry/exit components reflect demographic changes in the firm population (Goos *et al.*, 2014). It should be noted that technology could also lead to between-firm changes by forcing certain firms to downsize or close while enabling other firms to grow faster. Similarly, product demand changes could lead to within-firm changes if firms adjust their production towards different goods. However, in our empirical application the within component dominates and as usual, our data do not contain information about the product composition of firms' output to study potential demand effects in practice.

We use the wage bill shares as indicators for the relative demand of different skill groups defined by education or occupation. The main justification for this is that relative labour demand equations with wage bill shares as the dependent variables, can be derived from a translog cost function (see Berman *et al.*, 1994), which is a flexible, second-order approximation to a general cost function. However, it is clear, that an increase in the demand for a worker group may lead to an increase in its wage bill share either because the employment share of the group rises, or because the relative wage of the group rises, or both. As a general indicator for rising demand, the wage bill captures both effects, but it is also of interest to know how the rising demand is divided between wages and employment.

To examine this issue more closely, we use a (novel)[10] version of the wage bill decomposition, in which both the within-firm and the between-firm components for continuing firms are further divided into terms that capture only changes in relative wages (respectively relative employment) of different skill groups, as follows (superscript g denotes the skill group of interest, and u denotes all other groups; e.g., g is highly educated and u indicates the sums/averages for medium- and low- educated):

$$\Delta P^g = \sum_i \Delta SW_i \bar{P}_i^g + \sum_i \Delta SE_i \bar{P}_i^g + \sum_i \Delta PW_i^g \bar{S}_i + \sum_i \Delta PE_i^g \bar{S}_i$$

where $\Delta SW_i = \left(\frac{W_{i,t}E_{i,t}}{W_t E_t} - \frac{W_{i,t-s}E_{i,t}}{W_{t-s}E_t}\right)$, $\Delta SE_i = \left(\frac{W_{i,t-s}E_{i,t}}{W_{t-s}E_t} - \frac{W_{i,t-s}E_{i,t-s}}{W_{t-s}E_{t-s}}\right)$,

$$\Delta PW_i^g = \left(\frac{W_{i,t}^g E_{i,t}^g}{W_{i,t}^g E_{i,t}^g + W_{i,t}^u E_{i,t}^u} - \frac{W_{i,t-s}^g E_{i,t}^g}{W_{i,t-s}^g E_{i,t}^g + W_{i,t-s}^u E_{i,t}^u}\right), \text{ and}$$

$$\Delta PE_i^g = \left(\frac{W_{i,t-s}^g E_{i,t}^g}{W_{i,t-s}^g E_{i,t}^g + W_{i,t-s}^u E_{i,t}^u} - \frac{W_{i,t-s}^g E_{i,t-s}^g}{W_{i,t-s}^g E_{i,t-s}^g + W_{i,t-s}^u E_{i,t-s}^u}\right).$$

The ΔSW_i and ΔSE_i terms divide the between-firm change in a plant's share of total wage bill ΔS_i into components reflecting only wage or employment changes. The ΔPW_i^g and ΔPE_i^g do the same for the within-firm change in the skill group's share of the wage bill ΔP_i^g. A particular firm's ΔPW_i^g is positive only if the relative wage of the skill group g compared with all other groups u, $(W_{i,t}^g / W_{i,t}^u)$, increases in the firm from period t-s to period t. The third term therefore reflects only the effect of within-firm changes in relative wage of the skill group on the aggregate change in the skill groups' wage bill share. Similarly, ΔPE_i^g is positive only if skill group's relative employment $(E_{i,t}^g / E_{i,t}^u)$ increases in firm i, so that the last term reflects changes only in the relative employment within firms. The first two between effects, on the other hand, reflect changes only in the wage structure across firms, and shifts only in employment across firms towards firms with higher wage bill shares for the skill groups of interest. This more detailed decomposition is valuable for identifying both the sources of increasing skilled wage share (between and within components) and whether the effects of such changes are channelled into relative wages or employment.

Table 1 reports the decomposition of changes in wage bill shares by education groups for the period 2002–2008.[11] We find that the within and total changes for the low- and intermediate-education groups are negative for this period. The respective changes for the highest educated are large and positive. The entry component for the basic education group and the exit component for the highest educated are also positive. This means that exiting firms used relatively less high-educated workers than continuing firms, because their exit increased the high-education share in the remaining firms in aggregate. However, the positive entry effect for the low educated means that also new firms were disproportionately intensive in low-skilled workers. Together these results imply that at least to some extent the entering firms rehire those low educated that were made redundant by the exiting firms. The between components for all education groups are minimal. These results imply a rapid skill upgrading at the highest educational level during the 2000s, which overwhelmingly occurs within firms. The patterns are broadly consistent with job polarization in the sense that the intermediate education group loses shares, but in general, these results show that the development has been 'linear' with respect to education. The largest decline in shares occurs for the lowest educated and the largest increase for the highest educated.

Wage bill share changes can further be decomposed into relative wage and employment changes (Table 1). We find that in the within components for education, the employment changes clearly dominate the overall change. In the between component for education, the

Table 1. Decompositions of wage bill share by education group, 2002–2008 change

Education group	Within	Between	Entry	Exit	Total change	Group's share in 2008
Basic	−0.051	−0.001	0.012	−0.006	−0.046	0.138
Wage/Employment	−0.002/−0.048	0.003/−0.004				
Intermediate	−0.018	0.001	−0.004	−0.007	−0.028	0.571
Wage/Employment	0.003/−0.021	−0.001/0.002				
High	0.068	0.000	−0.007	0.013	0.074	0.291
Wage/Employment	−0.001/0.069	−0.002/0.002				

wage and employment changes are more balanced, but their contribution to the overall change is minuscule. These results show that the main margin of adjustment is employment rather than wages. Furthermore, we observe no major decline in wages for groups with increasing employment, which would be required for the pure supply explanation to be valid.

Table 2 reports the decompositions of change in wage bill shares by occupation groups. In contrast to education, both within and between components are important for occupational changes, and their effects have the same direction, except for the service occupations. We find that in total the routine occupation share declines and the abstract and service occupation shares increase, such that the total change is clearly consistent both with the routinization hypothesis and with job polarization. The entry and exit effects are small in general, but the entering firms are mildly service intensive and less intensive in abstract occupations.[12] The shifts in production between different firms (the between component) seems to be more important in explaining polarization in the occupational shares than in educational shares. The shifts in production towards service-intensive firms and away from routine-intensive firms clearly contribute to the polarized pattern of total change. This finding suggests that changes in product demand or outsourcing 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.

To gain further insight into the extent to which between-firm changes are driven by industry composition versus between-firm, within-industry reallocations, we have performed also industry-level decompositions (not reported in detail). For occupations, the firm-level between component for the routine group is −0.018 and for the service group it is 0.013. In comparison, they are −0.012 and 0.016 at the industry level. These results

Table 2. Decompositions of wage bill share by occupation group, 2002–2008 change

Occupation group	Within	Between	Entry	Exit	Total change	Group's share in 2008
Abstract	0.046	0.005	−0.004	0.000	0.047	0.464
Wage/Employment	0.011/0.035	−0.005/0.010				
Routine	−0.038	−0.018	−0.001	0.001	−0.056	0.450
Wage/Employment	−0.010/−0.028	0.001/−0.019				
Service	−0.008	0.013	0.005	−0.001	0.009	0.086
Wage/Employment	−0.001/−0.007	0.004/0.009				

reveal that the demand shifts for routine and service groups occur mainly between industries rather than between firms within industries.

Using decomposition of wage bill share changes further to wage and employment changes (Table 2), we find that for occupations the changes in wages make a slightly larger contribution compared with education in Table 1. The contribution of wage changes is approximately one-fourth for the within component. For the between component, the results vary more but still the contribution of the between component to the total change is small. Therefore, the main adjustment channel also for occupations is the employment change within firms.

As a preliminary analysis of the effect of new technology on wage shares, we depict in Figure 3 the distributions of the within contributions for each occupation and education group partitioned by the median of each ICT factor. First, the distributions confirm substantial heterogeneity in changes of occupation and education groups. Second, for each factor, we find that a decrease in the routine share and an increase in the abstract share are more likely when the factor score is greater than the median. In contrast, the service share is not affected. For education groups the pattern is distinctly different. The distributions tend to tilt towards increasing shares for the highly educated and towards declining shares for both the intermediate and the low educated. In the next section we quantify these effects using regressions.

5. ICT usage as driver of disappearing routine work

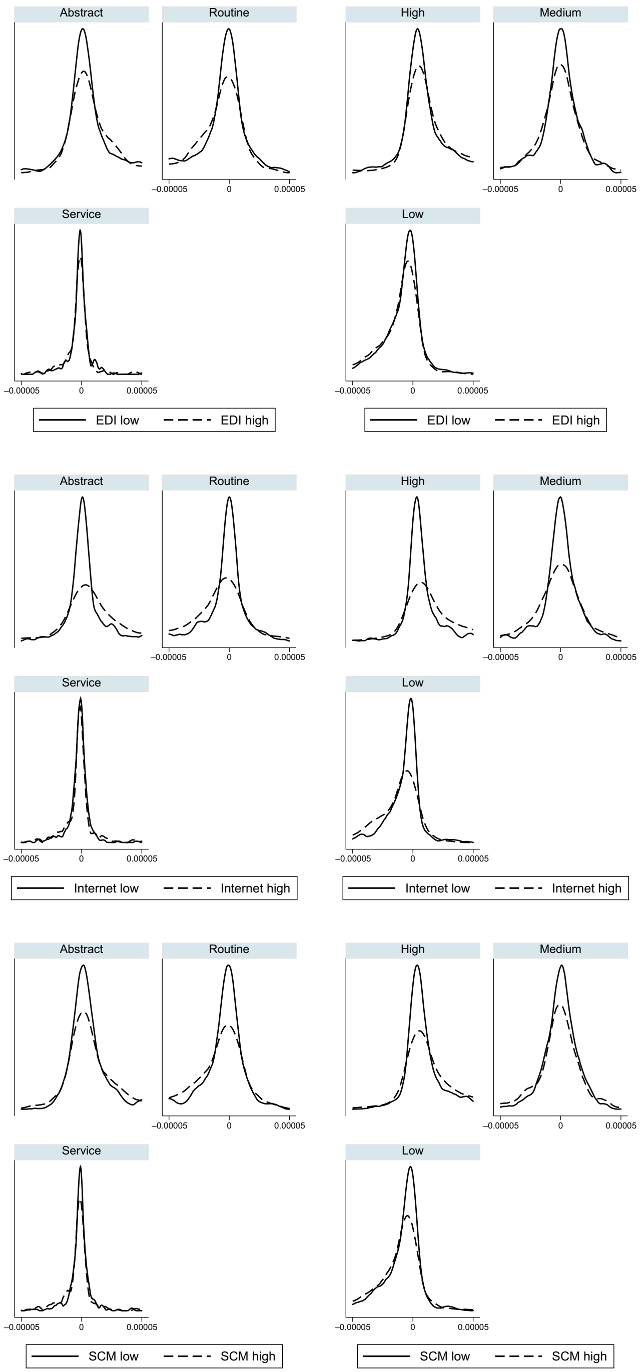
To examine the importance of the technology explanation to the shifts in the structure of labour demand, we estimate the following equations, at the firm level, for the wage bill shares of the education groups (g = Low, Middle, High) and occupation groups (g = Abstract, Routine, Service):

$$\Delta SHR_{it}^{g} = c^{g} + \beta_1^{g} ICT_{it} + \beta_2^{g} X_{it} + u_{it}^{g}$$

where ΔSHR_{it}^{g} denotes the change in wage bill share over the period of 2002–2008, ICT denotes the adoption of new technology in each firm, and X denotes a vector of other control variables. Berman *et al.* (1994) showed that this type of share equation can be derived from a short-run translog cost function to examine the relative demand for different labour groups. However, this specification omits relative wages, which we control with the use of two-digit industry indicators. Michaels *et al.* (2014) derive similar equations from a three-input CES production function, which allows for the ICT capital to substitute for the medium educated and to complement the highly educated. Note that the constant that is incorporated in all models captures the changes in time effects (including the potential trends in the variables) between two years.

Autor *et al.* (2003) presented a model with computer capital and imperfectly substitutable routine and non-routine labour inputs. They demonstrated that sectors that invest relatively more in computer capital exhibit a greater increase in the usage of non-routine labour input and a larger decline in the usage of routine labour input. Acemoglu and Autor (2011) further developed a task-based theoretical model with endogenous assignment of skills to tasks (occupations). They showed that exogenous technological change (machines replacing workers in routine tasks) leads to employment polarization, where the

Figure 3. Distributions of within contributions by ICT factors [Colour figure can be viewed at wileyonlinelibrary.com]



Note: The figure depicts the distributions of the within contributions for each occupation and education group partitioned by the median of each ICT factor. The contribution is the change in each group's wage bill share in each firm multiplied by the firm's share of total employment.

low-skilled tasks and highly skilled tasks increase, whereas the medium-skilled tasks decline. Also, the relative wage in routine tasks declines compared with both high-skilled (abstract) tasks and low-skilled (service) tasks. This polarization result therefore implies that following the use of ICT (increase in ICT capital), the wage bill share of the Abstract occupations increases ($\beta_1^{Abstract} > 0$), the share of the Routine occupations decreases ($\beta_1^{Routine} < 0$), and the share of Service occupations increases ($\beta_1^{Service} > 0$). There are two caveats regarding the effect on the Service occupations. If the non-routine manual service occupations are technologically independent of ICT, then the effect of ICT on their share may be ambiguous. Furthermore, the product demand effects are general equilibrium effects, which are not manifest at the firm level in those exact firms that adopt new technologies. The decompositions above on the other hand incorporate the demand effects in all other firms. They indicated that the shifts in production between firms and the entry of new service-intensive firms do play some role in explaining the rise in service occupations.

We also perform similar regressions for education groups. Analogous to the treatment of occupations, the polarization hypothesis now implies that technological change increases the demand and therefore the wage bill share of the highly educated (skilled) workers ($\beta_1^{High} > 0$) and decreases the share of the middle educated (skilled) ($\beta_1^{Middle} < 0$), and the change in the share of the lowest educated is either negative or ambiguous. As explained in Section 2, we performed a factor analysis on a large number of ICT indicators at the firm level to create underlying ICT factors, which we use as explanatory variables in our regressions instead of ICT capital, which is not available at the firm level.

We begin our analysis with OLS results for educational shares in Table 3. The explanatory variables for the change in the wage bill share of each education group include the three ICT factors (our main interest) and the lagged level of the dependent (to control for the regression-towards-mean phenomenon), log firm size, log capital-output ratio, and two-digit industries as control variables. Firm size controls for the fact that the adoption of ICT technologies correlates positively with the size of the firms.[13] To the extent that firm size itself or omitted factors that are correlated with size (e.g. the quality of firm management) have effects on the structure of labour demand, omitting firm size would obscure the results for ICT factors.[14] Our results are based on comparing similar sized 'ICT and non-ICT firms' (different levels of ICT factors). Similarly, we include capital-output ratio as a control for possibly differential effect of capital-skill complementarity on wage growth and employment development of different education and occupation groups. Our first-differenced equations already account for all firm fixed effects in levels,[15] but here, we attempt to control for the possibly differential effects of capital intensity on the wage growth (e.g. increasing skill premiums) or on employment growth by education or occupation. We use the firm's average capital-output ratio over the whole period of 2002–2008 to measure its capital intensity. The two-digit industry indicators control for all other differences among industries, including differences in wage and employment growth from overall technological progress between industries. It should be noted that any association between a firm's ICT factors and employment structure that we find prevails across firms within two-digit industries.

The pattern of results for education groups in Table 3 is consistent with SBTC. All the ICT factors are positively associated with the increase in high-skilled wage bills and negatively associated with the share of both medium and basic education groups, without much difference between these latter groups. The regression coefficients are also numerically significant. We find that the wage bill share of the highly educated increases 1.7%-points faster in firms that have a one standard deviation (0.43) higher score for the EDI factor, 1.3%-points faster for the Internet factor (s.d. 0.25), and 0.9%-points faster for the SCM

Table 3. Regressions for the change in wage bill shares by education group

Variable	High	Medium	Low
ICT Factors			
EDI	0.040***	−0.020*	−0.024***
	(0.011)	(0.011)	(0.006)
Internet	0.050***	−0.029*	−0.031**
	(0.018)	(0.016)	(0.012)
SCM	0.019*	−0.008	−0.013**
	(0.011)	(0.009)	(0.006)
Lagged dependent (level)	−0.215***	−0.260***	−0.431***
	(0.045)	(0.052)	(0.068)
ln(Size)	−0.004	−0.001	0.004**
	(0.003)	(0.003)	(0.002)
ln(Capital-output) ratio	0.004	−0.0004	−0.005*
	(0.004)	(0.003)	(0.003)
F-test/χ^2 (industry)	23.0	8.65	85.4
	(0.000)	(0.000)	(0.000)
N	1,110	1,110	1,110
Dependent mean (weighted)	0.052	−0.003	−0.049

Notes: Weighted by the product of sampling weight and total working hours of the firm. Robust t-values reported. The dependent variable is a 6-year difference over the period of 2002–2008.
The OLS estimates of the coefficients do not sum to zero because the models include a different lagged dependent variable in each equation.

factor (s.d. 0.46). These effects and their sum, 3.6%, are economically large compared with the total increase of 7.4% of the high-educated wage bill share over the 2002–2008 period, as reported in Table 1. The sum of the one-standard-deviation effects of ICT factors (and the total change) for Intermediate education is −2.0% (−2.8%), and for Basic education −2.4% (−4.6%). The ICT factors together explain approximately half of the increase in the high-education share and the decrease in the low-education share. These results are different from those in Michaels *et al.* (2014), who found that ICT capital affected education groups in a U-shaped pattern, i.e., reduced the demand for the middle educated most. Note that the OLS estimates of the coefficients do not sum to zero because the models include a different lagged dependent variable in each equation.

The results for occupational shares, reported in Table 4, are supportive of the occupational routinization hypothesis that is associated with the ICT factors. The EDI and Internet factors are positively and significantly related to the change in the share of Abstract occupations, and they are negatively and significantly related to the share of routine occupations. The pattern is similar for the SCM factor but all SCM coefficients are insignificant. The service share is mostly independent of ICT at the firm level, with only the EDI factor gaining significance in regressions. The magnitude of the coefficients is again economically significant compared with the mean of the dependent variable, or to the total change in shares in Table 2. A one-standard-deviation increase in the EDI factor increases the abstract occupation share by 2.4%-points and reduces the routine occupation share by 1.8%-points. Corresponding effects for the Internet factor are 2.1%-points and −1.9%-points. One-standard-deviation changes in ICT factors would explain essentially all of the observed changes in occupational wage bill shares. The sum and total changes are 5.4% (4.5%) for the abstract group, −4.5% (−5.7%) for the routine group, and −1.0% (1.2) for the service occupations.

Our results highlight that educational upgrading and occupational polarization reflect routinization from different angles because there is no one-to-one mapping between education groups and tasks performed within them. The shares of education groups in different occupations explain the observed pattern for education groups. We find that the low educated are concentrated in routine occupations (72%), and the highly educated are concentrated in abstract occupations (81%); see Table A2 of Appendix C. However, the occupation structure of the medium educated is more varied: 60% work in routine occupations, but more than a quarter (26%) are found in abstract occupations. Taking into account the fact that the number of intermediate-educated workers is more than three times the number of highly educated workers, there is approximately the same absolute number of medium and highly educated workers in abstract occupations. The fact that the medium-educated work to a substantial extent in abstract occupations provides an explanation for our different pattern of results for education and occupation groups. To illustrate the importance of the occupational distribution of different education groups on our results, we compute predicted educational effects based on occupational effects. Table A3 documents the predicted values for the within contributions and the effect of ICT for each education group using the within contributions in Table 2 and the estimated coefficients for ICT factors for each occupational group in Table 4 (and the shares in Table A2). The structure of these predicted effects is similar to the estimated effects for education groups. These back-of-envelope calculations show that the results for education and occupation groups are consistent with each other, as the educational results reflect the occupational effects and occupational distribution of each education group. Overall, our interpretation is that our results support the routinization hypothesis and that ICT contributes to routinization. Our educational results reflect the fact that a substantial share of the medium-educated work in abstract occupations, which mitigates the effect of routinization on the intermediate educated as a group.

Table 4. Regressions for the change in wage bill shares by occupation group

ICT Factors	Abstract	Routine	Service
EDI	0.056***	−0.043*	−0.011***
	(0.017)	(0.016)	(0.004)
Internet	0.083***	−0.075**	−0.009
	(0.029)	(0.030)	(0.010)
SCM	0.021	−0.016	−0.006
	(0.016)	(0.016)	(0.004)
Lagged dependent (level)	−0.243***	−0.267***	−0.166
	(0.048)	(0.042)	(0.136)
ln(Size)	−0.015***	0.010**	0.004***
	(0.005)	(0.005)	(0.002)
ln(Capital-output) ratio	0.021***	−0.019***	−0.003*
	(0.007)	(0.007)	(0.002)
F-test/χ^2 (industry)	21.9	5.2	5.0
	(0.000)	(0.000)	(0.000)
N	1,110	1,110	1,110
Dependent mean (weighted)	0.031	−0.030	−0.002

Notes: Weighted by the product of sampling weight and total working hours of the firm. Robust t-values reported. The dependent variable is a 6-year difference over the period of 2002–2008.
The OLS estimates of the coefficients do not sum to zero because the models include a different lagged dependent variable in each equation.

Instead of factor scores, we have used summary indicators of ICT variables that resemble the factors used in our analyses. We created three summary variables as the means of individual ICT items that have the largest loadings on each of the three factors. The results (not reported in detail) for these summary indicators are qualitatively similar (including statistical significance) to the results for the factor scores. We have also included all ICT indicators both individually and jointly, as explanatory variables without summarizing them. Individually, many ICT indicators are significant in abstract (high education) and routine (low education) share equations, but only a few items are statistically significant at the 10% level when they are included jointly. The strongest and most consistent effects relate to the firm using EDI in receiving invoices. This increases the shares of abstract occupations and of the highly educated and reduces the shares of routine occupations and of the intermediate- and low educated, with the changes being statistically significant at the 1% level. In addition, the existence of a firm website and broadband connection increase the abstract occupation share and reduce the routine occupation share significantly at least at 10% level.

As already noted above, our estimating equations are essentially first-differenced versions of the levels equations for wage bill shares, so any endogeneity related to the unobserved firm fixed effects in the levels equations is eliminated from our results. Other sources of endogeneity bias, however, remain in our models. First, measurement error in explanatory variables causes the standard attenuation bias. Second, the lagged level of a wage bill correlates by definition with its change. Third, there is the possibility of reverse causality in ICT, i.e., shocks to the firm's wage bill shares causing firms to change their investments in new technology (adoption of ICT).

We have performed instrumental variables (IV) estimations to account for these endogeneity and reverse causality issues. Our attempts to find valid instruments at the firm level were not completely successful so the IV results are not reported here.[16] Although we cannot claim causal relationships between ICT and wage bill shares, our IV estimation results are not in contradiction to our main result, namely, that the routinization and polarization of employment is related to the adoption of new ICT technologies by firms.

6. Conclusions

Using the Harmonized Structure of Earnings Survey (HSES) data of Statistics Finland, we first document patterns of employment polarization in the Finnish private sector labour market. We establish that there has been considerable job polarization at the aggregate level. The structure of changes in the employment shares by initial occupational wage deciles is distinctly U-shaped. We also find that the changes in aggregate occupational structure are consistent with the routinization hypothesis, i.e., the routine intensity of employment declines in a trend-like manner over the period of 1995–2013.

Our paper uses decompositions and regression analyses that test for the routinization hypothesis and job polarization at the firm level, instead of the aggregate, industry or local levels as in most prior studies. Using a firm-level approach, we are able to study routinization and job polarization at the micro level, where actual labour demand decisions are made. In this manner, we account for the effects of the compositional changes in product demand on the structure of employment and/or wages more thoroughly than in industry- or aggregate-level studies. The compositional changes in production confound aggregate studies if they are driven by factors other than technology (e.g. by offshoring or consumer preferences).

Our firm-level decompositions for the changes in wage bill shares indicate likely reasons behind these changes. The decompositions for education groups show that changes in education shares are towards more-educated groups in a 'linear' fashion with respect to education level. This pattern is consistent with the standard SBTC model. The total change occurs overwhelmingly within firms, which is suggestive of a technological cause of these changes. For changes in occupational shares, we find that the increase in abstract and the decrease in routine occupations also occur substantively within existing firms.

Our decompositions also show that for service occupations, the shifts in production towards service-intensive firms and the entry of new service-intensive firms is relatively more important than for other occupation groups. This pattern indicates that changes in product demand or outsourcing may have a role in explaining the increase in service occupations, which produces a polarized pattern of total changes for occupation groups, i.e., increasing abstract and service shares and decreasing routine share. Autor and Dorn (2013) propose a theory that assumes that love for variety rationalizes the increase in demand for service jobs by highly paid abstract workers. There is scant empirical evidence for this general equilibrium effect in the previous literature. Our decompositions are consistent with this explanation because we find that the increasing service share is driven by between-firm reallocation.

We further examine the contributions of the changes in employment and wages to wage bill changes using a new decomposition method. We find that the main adjustment channel for both education and occupation groups is the employment change within firms rather than relative wages.

Furthermore, we examined the technology-based explanations for routinization and job polarization at the firm level by using firm-level indicators of ICT usage as explanatory variables in the firm-level regressions. We first perform a factor analysis on a large number of indicators for ICT adoption at the firm level to obtain factor scores for three ICT factors. We then use these factor scores as explanatory variables in regressions for changes in the wage bill shares of different education and occupation groups.

The OLS regressions show that the ICT factors are associated with increases in the demand for highly educated workers and reductions in the demand for the low educated, whereas the intermediate education group is independent of ICT. In regressions for occupation groups, we find that ICT factors are associated with increases in abstract occupation shares and decreases in routine occupation shares. These occupational patterns support the routinization hypothesis at the firm level. Since routinization is the main mechanism producing polarization, these results are also consistent with job polarization. The service occupation share is independent of ICT at the firm level, and the increasing aggregate share of services is related to demand effects, as noted above.

We find that a substantial share of the medium-educated work in abstract occupations. As there is no one-to-one mapping between education groups and tasks performed within them, the effect of routinization on the intermediate educated as a group is mitigated. The results highlight that educational upgrading and occupational polarization reflect different aspects of routinization. These results stand in contrast with those in Michaels *et al.* (2014), who found that ICT capital reduced the demand for the middle-educated most.

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Appendix A Variables and definitions for terms used in the ICT survey

Variables	
PC	Firm uses computers
INTER	Firm has Internet connection
WEB	Firm has a website
EPURCH	Firm orders through computer networks (websites or EDI)
ESALES	Firm sells through computer networks (websites or EDI; not email orders)
BROAD	Firm has broadband (ADSL, SDSL, cable modem; faster than ISDN)
MOB	Firm has mobile access to Internet (laptop, mobile phone; 3G, 4G, or slower)
ERP	Firm has Enterprise Resource Planning system (ERP programme); 2006 onwards
SCMT	Sharing Supply Chain Management (SCM) data with suppliers using computer networks (inc. Internet); regular exchange of information on demand forecasts, inventories, production plans, delivery progress, product planning; available 2006–2009
SCMA	Sharing SCM data with customers; see above; available 2006–2009
CRMINF	Management and sharing of customer information with other business functions within firms; 2006 onwards
CRMANA	Firm analyses customer information for marketing purposes (price setting, promoting sales, choosing delivery channels); 2006 onwards
AUTTIED	Electronic data interchange used
AUTLASVA	Receiving e-invoices using electronic data interchange; available 2007–2009
AUTLASLA	Sending e-invoices using electronic data interchange; available 2007–2009
AUTKULJ	Using electronic data interchange in sending transport documents; available 2007–2009
Definitions of some terms	
Broadband	Broadband is a telecommunications connection with a capacity of at least 256 Kbps. In the statistics on the use of information technology in enterprises, broadband has in practice been defined through the type of technology used in the connection as either DSL (e.g. ADSL) or other broadband connection (faster than a traditional telephone modem or ISDN)
E-invoice	An e-invoice is an electronic invoice constructed according to a generally used message format, whose data can be handled and interpreted automatically. E-invoices are transmitted via a telecommunications service provider or a bank, e.g., Finvoice, eInvoice, TEAPPSXML, PostiXML
E-mail invoice	An e-mail invoice is an invoice sent as a pdf-file attached to an e-mail
EDI	EDI (Electronic Data Interchange) is a procedure by which information located in an enterprise's data system is used to produce a specified data flow that is transmitted electronically to a receiving enterprise, where it is directly incorporated into the data system (e.g. order, payment order for invoice, price list or product catalogue)

EDI commerce	EDI commerce is electronic commerce that occurs between enterprises through the medium of EDI
EDI invoice	An EDI invoice is an electronic invoice in machine code according to the EDI structure standards. EDI invoices are often sent via a telecommunications service provider
Electronic invoice	An electronic invoice is an invoice transmitted in electronic form: an EDI invoice, an e-invoice, an e-mail invoice or some other electronic invoice. Payments entered by a customer into an online banking system or direct debit are not electronic invoices
Homepage	A homepage here is defined as an enterprise's own Internet homepages or its section in the homepages of a group. Homepages do not refer, for example, to publication of an enterprise's contact details on various company and address lists
Internet sales	Internet sales are communications between a person and a data system. Online shopping, as defined here, is an order placed by completing and sending a ready-made electronic form on the Internet and shopping in actual Internet shops. Orders placed with a standard email message are not defined as online shopping. Purchases made on an extranet subject to the same conditions are also counted as Internet sales
Online shopping	Online shopping is the ordering of goods and services via a computer network, regardless of payment or delivery method

Source: Statistics Finland.

Appendix B Factor analysis of ICT variables

Factor analysis describes variability among observed variables in terms of a lower number of latent variables that are called factors. The variables in the ICT survey are (mostly) binary indicators. Factor analysis assumes that the observed variables are continuous (or at least ordinal), because they are modelled as linear combinations of continuous latent factors. One could proceed with a factor analysis for binary variables, which specifies a logistic link function between observed indicators and latent factors. Alternatively, one can continue to use ordinary factor analysis but base it on a tetrachoric correlation matrix. Tetrachoric correlations are estimates for the correlation coefficient of latent bivariate normal distribution based on observed binary variables. The results of factor analysis using tetrachoric correlations are usually similar to those obtained with the binary factor analysis. The difference is mainly that tetrachoric correlations treat binary variables as incompletely observed underlying variables rather than observed items of latent factors.

We used tetrachoric correlations for the 16 binary indicators of the usage of different aspects of ICT in the firms in the ICT survey. Using orthogonal rotation and the principal factors method yielded the following rotated factor loadings for three factors with eigenvalues greater than one (Table A1).

Table A1 Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor 1	Factor 2	Factor 3	Uniqueness
Firm has website	0.1322	0.8854	−0.1564	0.1742
Firm has broadband	0.1354	0.7020	0.3243	0.3837
Firm has mobile access to Internet	0.2011	0.7382	0.2517	0.3513

Table A1. Continued

Variable	Factor 1	Factor 2	Factor 3	Uniqueness
Firm orders through computer networks	0.2590	0.5490	0.3133	0.5333
Firm sells through computer networks	0.4405	0.5793	0.1155	0.4570
Firm has Enterprise Resource Planning	0.2516	0.6405	0.3845	0.3786
Shares SCM data with suppliers	0.3013	0.0714	0.8988	0.0963
Shares SCM data with customers	0.2640	0.2855	0.8003	0.2083
Shares customer information (within firms)	0.1774	0.6967	0.3841	0.3356
Analyses customer information for marketing	0.1907	0.6689	0.4096	0.3484
Receives e-invoices via electronic data exchange	0.7500	0.3795	0.0792	0.2872
Sending e-invoices via electronic data exchange	0.7880	0.4563	0.0414	0.1692
Electronic data interchange used	0.9605	0.1052	0.2008	0.0260
Receiving orders	0.7872	0.2495	0.2425	0.2593
To suppliers	0.7729	-0.1093	0.3617	0.2598
Sending transport documents	0.7375	0.1138	0.3758	0.3020

Source: ICT panel 2001–2009 (information refers to the end of previous year, i.e., 2000–2008). Variables are indicators that the firm has or utilizes the technology indicated by the variable name.

Factor 1: Loads on using automated data exchange for sending and receiving invoices and orders and sending transport documents. We call this factor EDI (for electronic data interchange). Factor 2: Loads on firm having a website and access to Internet, selling, and placing orders via computer networks (website or EDI). It also loads on the firm having a special programme (CRM) for sharing and analysing customer information within the firm and on the firm having Enterprise Resource Planning (ERP). We call this a general Internet factor. Factor 3: Loads on sharing supply chain management (SCM) data with suppliers or customers via computers (demand forecasts, inventory levels, production plans, deliveries, product planning information); we call this factor SCM.

Appendix C Information on education and occupation groups

Table A2 Occupational composition of education groups

	Low	Medium	High
Abstract	0.14	0.26	0.81
Routine	0.72	0.60	0.15
Service	0.15	0.13	0.04
	1	1	1

Note: Based on the average distribution for the years 2002 and 2008.

Table A3 Predicted and observed values for the within contributions and ICT effects

	Low	Medium	High
Pred. within contr.	−0.022	−0.012	0.030
Observed	−0.051	−0.018	0.068
Pred. EDI	−0.025	−0.013	0.038

Table A3. Continued

	Low	Medium	High
Obs. EDI (OLS)	−0.024	−0.020	0.040
Pred. Internet	−0.044	−0.025	0.055
Obs. Internet (OLS)	−0.031	−0.029	0.050
Pred. SCM	−0.010	−0.005	0.014
Obs. SCM (OLS)	−0.013	−0.008	0.019

Notes: Predicted values for the within contributions and the effect of ICT for each education group are obtained by weighting the within contributions in Table 2 and the estimated OLS coefficients for ICT factors for each occupational group in Table 4 by the occupational employment shares in Table A2 for each education group. The observed values for education groups are from Tables 1 and 3.

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Notes

[1] This paper is a substantially revised version of our earlier working paper Böckerman *et al.* (2013), in which we first presented the firm-level decompositions and regressions on technology explanations for polarization, which have also been used in other papers concurrently or later.

[2] Cortes *et al.* (2017) shows that the changes in the demographic composition of the economy do not explain the job polarization in the US context.

[3] ALM (2003) provided industry-level evidence using the task measures derived from the Dictionary of Occupation Titles and showed that analytical and interactive non-routine task inputs increase more and routine task inputs decrease more in industries that invest more heavily in computer capital. Acemoglu and Autor (2011) presented a complete task-based model of technological change to explain the anomalies related to SBTC model.

[4] Jenkins (1995) precedes the current literature on job polarization.

[5]There is a size threshold of at least five persons for the firm to be included in the Structure of Earnings Survey data. The size limit of five persons applies also for the Statistics Finland's survey of non-member firms included in the data, which are often small. The data also excludes the following industries: agriculture, forestry and fisheries, household employers, as well as international organizations employment. Furthermore, the company's top managers and owners and their family members and the employment spells beginning or ending during the reference month are also excluded. After these exclusions the data cover 70% of the total private sector employment. These data are therefore representative for the population of firms with more than five persons, other than the excluded industries and top managers and owners, when the survey weights are used.

[6]The non-panel nature of ICT surveys prevent us from estimating fully differenced models with ICT variables also measured as changes. Because ICT items relate to fairly new technologies, their usage may in practice reflect changes.

[7]For the 16 ICT indicators only two pairwise correlations are not statistically significant at the 5% level. The correlations are usually in the interval of 0.30–0.50 (max 0.64) and statistically significant at the 1% level.

[8]Earlier Finnish evidence regarding job polarization at the aggregate level is provided in Asplund *et al.* (2011), Mitrunen (2013), and Böckerman *et al.* (2013). Polarization is documented for a large set of industrialized countries (Goos *et al.*, 2014; Ikenaga and Kambayashi, 2016). The aggregate pattern of employment changes for three occupation groups reported in Goos *et al.* (2014) is consistent with job polarization in Finland, so we maintain that the omission of smallest firms in our data does not crucially affect our results.

[9]See Vainiomäki (1999a,b) for a detailed derivation of this decomposition augmented to include entry and exit effects.

[10]This decomposition was first presented in Vainiomäki (1999a), but it has gone unnoticed in the literature. Vainiomäki (1999b) includes a more detailed derivation and justification for the decomposition.

[11]We present these decompositions here as background for the regressions below only for the 2002–2008 period, because the ICT variables in regressions are available only for the 2000s.

[12]There are 5,327 continuing firms over the period of 2002–2008; 5,716 enter and 5,746 exit during this period. Thus, the small entry/exit effects imply that the employment structures of entering and exiting firms do not differ much from those of continuing firms, rather than small amounts of entry and exit.

[13]The (weighted) correlations of individual ICT indicators with log firm size are all statistically significant at the 1% level and in the interval from 0.10 to 0.44.

[14]The effects for both ICT factors or for the original ICT indicators (not reported) are essentially similar, but the coefficients are smaller and less significant if firm size is not included in the equation as a control variable.

[15]Our estimating equation can be interpreted as a first-differences version of a level equation for wage bill shares. Then, firm fixed effects in the levels of these shares are controlled by differencing.

[16]The IV results are reported in the working paper version (Böckerman *et al.*, 2016).