WORK ORGANIZATION AND JOB POLARIZATION*

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Abstract  
This paper contributes to the literature on the effects of technical change on occupational and wage structure, whereby mid-skill jobs disappear because of increased mechanization and digitization of routine tasks. While the recent empirical literature on job polarization has estimated the relative importance of technical change and globalization as key drivers of the process, the role of organizational change has remained unexplored. Unlike previous studies, we do not focus on changes in the task content of occupations but rather on the changes in work organization and managerial practice within firms. To this end we merge two firm level surveys from Denmark and add registry data to gain detailed knowledge of changes in the firms’ occupational structure. We construct measures of work organization in line with previous research, describe how work organization evolves over the period 2006-2010, and show that changes in work organization affect polarization even in the absence of technological change and changes in offshoring. The results show not only that the organizational level is central to understanding possible trends towards job polarization, but also demonstrate that changes in work organization often co-occur with changes in technology and in offshoring behavior, thus mediating the effects of technology and offshoring on job polarization.

JEL Codes  
L23; O33; J26

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I. Introduction

An important literature has developed over the last several decades on the effects of technical change on occupational and wage structure. A starting point of this literature has been the evidence that the returns to skills as measured by the relative wages of persons with a higher-level education has increased despite the secular increase in the supply of highly educated labor.\(^1\) The main technology centered hypothesis developed to explain this until recently was the skill-biased technical change (SBTC) hypothesis, which focused on the effects of computerization and automation in the so-called third industrial revolution on the demand for skills. The basic hypothesis, supported by a variety of survey-based and case study evidence, is that computerization and related capital investments have had both a substitution effect and a complementarity effect favoring the employment of skilled labor. The substitution effect comes from the observation that simple repetitive tasks characteristic of low skill workers have proven more amenable to computerization and automation than the relatively complex tasks of high skill workers such as managers and professionals requiring judgment and interaction. The complementarity effect emphasized in the work of authors like Bresnahan, Bynjolfsson and Hitt (2002) refers to the way computerization changes data use and information processing within the firm leading to greater decentralization of decision making and an increase in the need for worker flexibility and discretion in coordinating work processes, both of which increase the demand for skilled labor. A further implication is that the positive productivity effects of the introduction of these new technologies will be greater in more highly skill intensive firms.

A more recent literature, while not questioning the hypothesis in the SBTC literature that technical change has led to an increase in the demand for skilled labor, argues for a more nuanced view, taking into account how the tasks and skills of the lowest skilled groups (mainly sales and service workers and the elementary trades) differ from those of the middling groups composed of clerks and skilled and semi-skilled manual workers. A basic hypothesis of this literature is that technical change since the 1990s, based on the increasing use of such technologies as robotics, the internet of things and artificial intelligence, has led to a hallowing out of the middling categories. The underlying premise is that these new technologies are complements to the skills of technicians and managers while substituting for the skills of such middle-level skill categories as clerks and skilled manual workers whose work is increasingly open to routinization. The lower categories due to the importance of people skills for sales worker or the non-routine though low-skilled nature of many of the tasks carried out by the elementary trades is assumed impervious to the recent wave of technological change. The result is a trend towards job polarization seen in an increase in the employment shares of both the

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\(^1\) See Acemoglu and Autor (2011) for a survey of the literature on the returns to skills.

While the recent empirical literature on job polarization has estimated the relative importance of technical change and globalization as key drivers of the process, the role of organizational change has remained unexplored. Our contribution to the analysis of the changes observed in the distribution of jobs is to distinguish between organizational changes that create polarization on their own and organizational changes that contribute to polarization by moderating the effects of technological change or globalization. We accomplish this by adding an unparalleled level of detail to the analysis of organizational changes that contribute to job polarization. In order to do this we draw on a data set consisting of a panel of 532 Danish firms created by merging two surveys. The surveys provide information on the firms’ organizational practices including HRM practices, on priorities and outcomes of their innovation activities and on the impact of the 2008 financial crisis. By merging this panel with registry data for the entire Danish economy we add detailed data on the composition of firms’ workforce in terms of occupations. The sample displays a strong polarization tendency with the low skill group employment share increasing by 2.60 percent, the middle skill group share declining by 8.03 percent and the high skill group share increasing by 5.43 percent.

In section II we discuss previous work on job polarization, and we discuss the theoretical links between work organization within firms and job polarization. On the basis of this we introduce the standard model for job polarization studies: the translog cost function. In section III we describe the data sources, construct indicators of work organization, and provide descriptive statistics. In section IV we present the trends in job polarization and work organization changes in our data, and in section V we present the econometric model and the results. In Section VI we draw out the main conclusions.

II. Theory

II.A. Organizational Change, Technology and Job Polarization

The effect of technological change on the structure of wages and the occupational structure is a perspective on structural transformation that takes the labor market as the point of departure. Structural change is traditionally operationalized as a change in the distribution of economic activity over industries measured by employment or production, which of course yield quite different results. More recently there has also been focus on the change in export portfolio, which is argued to proxy changes in the activities and available capabilities within a country (Hidalgo et al. 2007; Hausmann and Hidalgo 2011), and a focus on studying structural change as a change in the distribution of wages (Férandez-Macia 2012; Autor 2015). The wage distribution is interpreted as a proxy for the skill distribution and a general result is that a polarizing pattern is observed over time, where the highest
and lowest skill/wage jobs are expanding at the expense of middling wage/skill jobs, as described in the introduction.

There are in principle four different channels of job polarization (Autor, Levy and Murnane 2003; Goos, Manning and Salomons 2014; Heyman 2016): 1) For a given occupational composition within industries polarization is the relative growth of industries where high and/or low skill occupations are relatively common at the expense of industries where medium level occupations are relatively common. 2) For a given occupational composition within firms, inter-firm competition leading to differences in firm growth rates may similarly cause polarization. 3) Changes within the firm such as technological change, outsourcing or organizational change may cause a polarizing change in the firm’s occupational composition and finally 4) such changes may entail that the definition or task-wise content of occupations change. Empirical results imply that processes at all four levels are important for the aggregate polarization pattern (Autor, Levy and Murnane 2003; Goos, Manning and Salomons 2014; Heyman 2016), and the focus has to a large extent been at the aggregate polarization resulting from changes at all four levels. Our analysis explicitly focuses on within firm changes but this does not mean that our paper accounts for polarization in terms of the quality of jobs. The quality of a job clearly depends on many other factors than just the wage level (Greenan, Kalugina and Walkowiak 2014).

Our analysis focuses on the changes within firms that contribute to structural change as observed in the wage distribution. An enduring feature of structural change, since at least Adam Smith’s famous example of the pin factory, is increasing division of labor and hence increasing specialization through routinization, with more routinized activities being more susceptible to automation (Bresnahan, Brynjolfson and Hitt 2003). Automation by means of mechanization or computerization depends on the codification of the skills or, more precisely, the codification of the knowledge applied in the routine activity, if sufficient incentives are in place. The RBTC hypothesis for explaining structural transformation in the wage distribution is based on the premise that routine jobs are also mid-skill and mid-wage jobs, and these jobs tend to become automated (Autor 2015, Goos, Maning and Salomons 2014; Autor, Levy and Murnane 2003). In a relatively high wage economy there is also an incentive to outsource such jobs and offshore outsourcing has also been studied as a driver of changes in the wage distribution (Goos, Manning and Salomon 2014). A further nuance to the model suggests that even if the proportion of workers in each occupation were fixed there would still be polarization in aggregate wage data arising from a shift in relative wages (Deming 2017). This is very similar to the mechanisms suggested by Baumol (1967), “Baumol’s cost disease”: Labor intensity in some tasks is more or less fixed, often because of a requirement for direct human interaction. In as much as the demand for such tasks is relatively income elastic and price inelastic, the share of labor allocated towards such tasks will increase as average income expands. However, while Baumol (1967) concludes that the cost disease will lead to downward pressure on wages in afflicted (i.e. routine)
occupations, Deming (2017) argues that changes in work organization accompanying technological change may necessitate increased interaction among workers leading to a wage premium for social skills. In terms of the taxonomy of tasks applied in Autor, Levy and Murnane (2003), Deming (2017) focusses on the growth in interactive non-routine tasks while Baumol’s cost disease applies to non-routine manual and analytical tasks. While Autor, Levy and Murnane (2003) argues that non-routine analytical tasks are a complement to technological change, the model by Deming (2017) implies that technological change will tend to make tasks either routine and hence substitutable, or that accompanying organizational changes will make tasks interactive. It is necessary to distinguish between the effects of technological change in the absence of organizational change, and the effect of technological change with accompanying organizational changes, as accompanying organizational change may make the task interactive though it is not necessarily observed in all cases.

Technological change and outsourcing thus contribute to a general increase in average wage, as observed in some countries, while the polarizing tendency is arguably caused by technological change and outsourcing together with a share of the economy suffering from Baumol’s cost disease (Férandez-Macia 2012; Autor 2015). The effects of technological change and outsourcing are thus relatively clear, while it is not clear how organizational changes contribute to the changes in the wage distribution. Earlier studies focusing on the skill-biased effects of organizational change tend to use relatively simple measures and do not offer detailed explanations for the hypothesized effects (Caroli and Van Reenen 2001; Piva, Santarelli and Vivarelli 2005). Important exceptions are Bresnahan, Brynjolfson and Hitt (2002) and the above discussed Deming (2017). Bresnahan, Brynjolfson and Hitt (2002) argue that changes in IT capital, work organization and products tend to co-occur within firms. Such change decreases routine tasks and increases the use of discretion and autonomy among workers. It also increases the availability of data and faced with potential problems of data overload one response is to decentralize decision-making meaning that workers are faced with more problem solving, which often takes place in groups. As a result, managers are pushed to rely more on people skills than formal monitoring for assessing the productivity of individual workers. Thus, the hierarchy is arguably flattened. It may also be argued that the increased use of quantitative data associated with increased computerization can lead to increased use of standards, norms and formal requirements to facilitate quantification. Bresnahan, Brynjolfson and Hitt (2002) still apply a relatively crude approach by summing a number of work organization indicators into a single factor in their analyses, and they do not study the effect on the composition of employment but instead focus on potential skill bias. A related study is Acemoglu et al. (2007) which studies the relationship between flattening of hierarchies and technological change. The authors argue that such decentralization is a necessary consequence of the fragmentation of information accompanying rapid technological change, whereas more hierarchical structures are better suited for organizations where information is generally public.
Contrary to the above-mentioned studies, Green (2012) argues that organizational change and new management practices should not be considered solely as an intermediary link between technology change and task distribution. Organizational change may have independent effects on the distribution between non-routine and routine tasks and thus on polarization tendencies. Among the new management practices, a main track has abandoned the Taylorist principles of tight vertical control of narrow routine tasks and delegated autonomy to the operational employee level, promoting discretion and functional flexibility in the organization. This development has been known as high-involvement or high-commitment practices. It often implies horizontal collaboration and integration of functions. This has supported problem solving and discretionary learning practices (Lorenz and Valeyre 2007) on an operational level, which also is important for innovative capabilities in the organization. Green (2012) argues that the practices enhancing involvement and horizontal integrative collaboration should be regarded as “potential independent sources of change in the content of tasks” and his results indicate strong effects of employee involvement and task discretion on generic skills in job requirements.

II.B. Model

Our modelling framework relies on the translog cost function, and follows related studies as, for example, Caroli and Van Reenen (2001). The starting point is a firm level short run production function of general form taking only technology and labor as inputs. Upper case letters denote vectors and lower case letters denote elements of the vectors.

\[ y_i = f(L_i, A_i) \]

Equation 1 specifies output of firm \( i \) as a function of labor input \( L \) and technology \( A \). \( L \) is a vector of \( J \) skill groups indexed by \( j \). Given output, technology and wages the firm minimizes costs. This is stated in equation 2 and equation 3 is thus the total costs for firm \( i \).

\[ l_j, i = l_{j,i}(y_i, A_i, W_i) \]
\[ c_i = \sum_j w_j l_j, i(y_i, A_i, W_i) = C(y_i, A_i, W_i) \]

\( J \) wage cost share equations can be derived from equation 3 by first constructing the second order Taylor polynomial at the expansion point 1, and secondly computing the \( J \) partial derivatives associated with the elements of the wage vector facing firm \( i \), \( w_i \). This process is completely standard and need not be repeated here.\(^2\) If it is assumed that the cost function is homogenous of degree 1 in

\(^2\) See e.g. Holm, Timmermans and Østergaard (2017) or Sanders and ter Weel (2000) for more detailed derivations.
wages, meaning that a proportional increase in all wages leads to an also proportional increase in total costs, the resulting wage cost share equations can be written as equation 4.

\[
\frac{w_{j,i}}{c_i} = s_{j,i} = \alpha_j + \sum_k \beta_{j,k} \ln w_{k,i} + \theta_j \ln y_i + \gamma_j \ln A_i + u_j
\]

In equation 4 \( k \) is used as an alternative index of skill groups and \( u_j \) is the remainder from the Taylor expansion. Equation 4 says that the cost share in firm \( i \) of skill groups \( j \) depends on the wages for each skill group, the output level of the firm and the firm’s technology.

Equation 4 lends itself directly to econometric analysis but we add a number of modifications to adapt the equation to our research interest. First, we estimate labor shares rather than wage cost shares as our interest is in the structural change in the labor market, as evident in the change in composition of jobs by skill group. Second, we do not include the wage schedule facing firm \( i \), \( (W_i = w_{1,i} \ldots w_{k,i} \ldots w_{J,i}) \) as regressors since we have no particular interest in the estimates of the \( \beta \) and the wage schedule might arguably be endogenous to the skill composition of the firm’s workforce. It is still necessary to control for the wage schedule and, following Caroli and Van Reenen (2001), we do so with wage instruments. The customary reason for estimating the \( \beta \) parameters is that they allow for estimating the elasticities of substitution among the skill groups and the own price elasticity when \( k = j \). Finally, we extend the technology variable and the associated parameter, \( \gamma_j \), to vectors describing not only the technology of firm \( i \) but also its work organization and off-shoring behavior.

III. Data

III.A. Data sources

Our dataset is based on merging data from three different sources: The DISKO4 survey from 2006, the GOPA survey from 2010 and registry data on the populations of firms, workplaces and working age people in Denmark. Our sample is the overlap of the DISKO4 and GOPA surveys. GOPA is our source for firms’ organization of work in 2010, their offshoring use in 2010, their innovation effort in 2007-2009 and the impact of the 2008 financial crisis on the firms. DISKO4 is our source for firms’ organization of work and offshoring use in 2006. In the registry data each employed person is linked to at least one workplace through employment relations and each employment relation has an occupation code. We describe the structural composition of jobs at a given firm by aggregating all employment relations over workplaces within the firm. This is done for 2006 and 2010. The registry data is also the source for sales data and for data on firm age, industry and region.
GOPA has a linked survey design covering both employers and employees, designed to investigate the effects of external exposure and internal firm practices on employees’ psychosocial work environment. Previous research based on GOPA has primarily focused on health outcomes among employees (e.g. Bamberger et al. [2015]) while we utilize the employer level GOPA data which includes a number of the questions used in previous waves of the DISKO survey. The DISKO4 survey conducted in 2006 by Statistics Denmark, like previous waves of the survey, collected information from private sector employers on innovation, organizational change, managerial practices, employee relations and collaboration. The DISKO surveys have been used extensively in combination with registry data for analyses on the relationships between labor market dynamics, firm performance and innovation, work organization, and firms’ collaboration strategies (e.g. Lundvall and Nielsen 1999; Foss and Laursen 2005; Jensen et al. 2007; Østergaard, Timmermans and Kristinsson 2011).

The DISKO4 survey resulted in a sample of 1775 employer responses, which were used as a basic sampling frame for the GOPA survey thus establishing a panel to the DISKO4 survey. 20 out of the 47 questions from DISKO4 were used in the GOPA employer level survey and supplemented with 27 questions specific to GOPA inquiries. This survey resulted in 601 usable firm responses constituting the panel of the two surveys. Firms with less than 10 employees in either year are excluded as our focus is on organizational practices, which require a minimum firm size to be meaningful and hence the data available for regressions includes 532 firms. This study is the first to exploit the panel structure between GOPA and DISKO4.

The dataset created from merging GOPA, DISKO4 and the registry data has a number of missing responses including “Don’t know” responses in the two surveys. We therefore impute the missing values and use multiple imputation with 25 imputations to complete the data\(^3\). We assume that the missing variables are missing at random and apply fully conditional specification methods to produce estimates.\(^4\)

III.B. Weights

The panel of firms that are on both the GOPA survey and the DISKO4 survey is not representative of the Danish economy, as DISKO4 oversampled firms in previous DISKO waves and GOPA is a

\(^3\) Single-imputation methods treat imputed values as known in the analysis and this underestimates the variance of the estimates resulting in overly optimistic significance tests. Multiple-imputation rectifies this by creating multiple imputations and taking into account the sampling variability due to missing data. See Little & Rubin (2002).

\(^4\) See the supplementary material for further details regarding the imputation procedure.
subsample of DISKO4 as explained above. Therefore, we construct post-stratification weights based on registry data to mend the selection bias.

Table I shows the representativeness of the firms in our data compared to the entire economy in 2006. The table documents the distribution of firms across sectors and firm size groups. As can be seen “Primary, manufacturing and utilities”, and medium and large firms are overrepresented in our data while “Construction, “Other services” and small firms are underrepresented. This is corrected by weighting the data in the econometric analysis. Public sector including education and health are excluded since they were not included in DISKO4 and GOPA.

**Table I**

**Size and industry distribution**

<table>
<thead>
<tr>
<th>Sector</th>
<th>NACE 2</th>
<th>DISKO4-GOPA</th>
<th>Danish economy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1: Primary, manufacturing and utilities</td>
<td>ABCDE</td>
<td>34.77</td>
<td>22.02</td>
</tr>
<tr>
<td>2: Construction</td>
<td>F</td>
<td>10.53</td>
<td>16.21</td>
</tr>
<tr>
<td>3: Other services</td>
<td>GHILNRS</td>
<td>38.72</td>
<td>48.21</td>
</tr>
<tr>
<td>4: KIBS</td>
<td>JKM</td>
<td>15.98</td>
<td>13.56</td>
</tr>
</tbody>
</table>

Size

<table>
<thead>
<tr>
<th>Size</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1: 10-49 employees</td>
<td>41.92</td>
<td>83.05</td>
</tr>
<tr>
<td>2: 50-249 employees</td>
<td>46.05</td>
<td>14.22</td>
</tr>
<tr>
<td>3: 250-500 employees</td>
<td>6.20</td>
<td>2.27</td>
</tr>
<tr>
<td>4: 500+ employees</td>
<td>5.83</td>
<td>0.46</td>
</tr>
</tbody>
</table>

Source: Computed from registry data for 2006. Pct. of total employment excluding public administration, health and education.

NACE (Nomenclature Statistique des Activités Economiques dans la Communauté Européenne) is the industry standard classification system used in the European Union.

An attempt at explaining the observed aggregate polarization in jobs would necessarily entail also weighting the data by firms’ employment as larger firms have a higher impact on the aggregate job
structure but our emphasis is on identifying the within firm effects that lead to changes in the job structure and therefore we do not add employment weights.

III.C. Dependent variable

Our dependent variables are the shares of employment within each of three categories High, Middling and Low. This approach follows recent contributions, as discussed above, but in our econometric analysis we also provide separate results for managers as the shares for managers are found to evolve idiosyncratically. The analysis by Goos, Manning and Salomons (2014) is undertaken at the sub-major group (2 digit) level of ISCO codes but the result perfectly separates occupations at the major group (1 digit) level in the following pattern of ISCO-88 codes:

- High-paid occupations
  - ISCO-22 = 1: Managers
  - ISCO-88 = 2: Professionals
  - ISCO-88 = 3: Technicians and associate professionals
- Middling occupations
  - ISCO-88 = 4: Clerks
  - ISCO-88 = 7: Craft and related trades workers
  - ISCO-88 = 8: Plant and machine operators and assemblers
- Low-paid occupations
  - ISCO-88 = 5: Service workers and shop and market sales workers
  - ISCO-88 = 9: Elementary occupations

ISCO-88 = 6 “Skilled agricultural and fishery workers” and ISCO-88 = 0 “Armed forces” are very small occupational groups that are not included in the study by Goos and colleagues and are not observed in our data. As a control for validity we have confirmed that the wage level for each occupation corresponds to the hierarchy established by Goos, Manning and Salomons (2014).

For each firm we compute the share of the workforce in each occupational group in 2006 and 2010. If a worker has is missing occupational code for 2006 and works at the same firm in 2005 he/she is given the occupation from 2005. If this is also missing the 2007 occupation is used. In the Danish

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5 ISCO: International Standard Classification of Occupations
data ISCO-88 is used until 2009 while ISCO-08 is used from 2010. Thus, all workers in 2010 receive the 2009 occupation code if they worked at the same firm, and 2008 is used if 2009 is missing. Following this procedure, of the 127,371 combined employees of the original 601 firms in 2006, 2.43 percent still have missing occupations, and 9.52 percent have missing occupations of the 121,323 employees in 2010. In order to attribute employees with missing occupation to one of the three groups, the average wage for High, Middling and Low occupations is computed for the entire sample and those with a missing occupational code are grouped into high, middling or low depending on their own wage level. This is done separately for 2006 and 2010, and at the same time we also identify managers among the High skill group, in order to separate them out at a later stage.

After all employees at each firm in 2006 and 2010 are thus classified as High, Middling or Low we compute employment shares for each of the three categories as full time equivalent employment. The registry data contains information on the form of employment contract distinguishing between full time and six levels of part time work. This information is used to transform the firm level occupational groups into full-time equivalent and hence to compute the total employment of the firm.

Goos, Manning and Salomons (2014) document labor market polarization over a range of European countries, including Denmark, for the period 1993-2010. In their data the share of Low goes up by 1.73 percentage points and the share of High goes up by 8.56 percentage points, while the share of Middling goes down by 10.30 percentage points. This is based on the European Union Labour Force Survey but fits well with the polarizing pattern observed in Denmark after 2010 as documented in Holm, Timmermans and Østergaard (2017), which relies on the same registry data used in this paper.

In the DISKO4-GOPA panel there is also a clear polarization tendency. In our sample, the shares of High and Low increase by 5.43 and 2.60 percentage points respectively. Correspondingly, the share of Middling jobs decreases by 8.04 percentage points. This is illustrated in figure I. The proportion of employees in each category in our sample also corresponds very well to the data used by Goos and colleagues.

Figure I

Polarization in our sample
III.D. Work organization variables

Our regressions are to identify the within firm changes associated with the observed job polarization. Previous studies have in particular emphasized technological change and off-shoring as the factors responsible for the disappearance of middling occupations and the growth of high- and low-skill occupations. Relatively few studies have focused on the effect of organizational change, which is our primary focus. To this end we exploit that firms were asked a number of identical questions on the DISKO4 and GOPA surveys: “Does the firm make use of some of the following ways of organizing the work?”.

1. Autonomous groups
2. Systems for collecting proposals from employees
3. Quality circles/groups (Formal delegation of quality control)
4. Delegation of responsibility
5. Interdisciplinary workgroups
6. Integration of functions (e.g. sales, production)

For each question, the respondent was asked to assess the share of employees involved and we thus have seven categorical variables taking four values: 1) No/None, 2) Less than 25%, 3) 25-50%, 4)
over 50%. We pool both surveys and run a principle components analysis (PCA) on the resulting 1064 observations.6

Table II

Frequencies for work organization variables

<table>
<thead>
<tr>
<th>Year</th>
<th>No/None</th>
<th>&lt;25%</th>
<th>25%-50%</th>
<th>&gt;50%</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autonomous groups</td>
<td>2006</td>
<td>38</td>
<td>20</td>
<td>20</td>
<td>23</td>
</tr>
<tr>
<td></td>
<td>2010</td>
<td>37</td>
<td>24</td>
<td>20</td>
<td>19</td>
</tr>
<tr>
<td>System for collecting proposals</td>
<td>2006</td>
<td>36</td>
<td>27</td>
<td>13</td>
<td>24</td>
</tr>
<tr>
<td></td>
<td>2010</td>
<td>32</td>
<td>39</td>
<td>12</td>
<td>17</td>
</tr>
<tr>
<td>Quality circles</td>
<td>2006</td>
<td>40</td>
<td>21</td>
<td>16</td>
<td>23</td>
</tr>
<tr>
<td></td>
<td>2010</td>
<td>40</td>
<td>27</td>
<td>17</td>
<td>16</td>
</tr>
<tr>
<td>Cross functional groups</td>
<td>2006</td>
<td>31</td>
<td>28</td>
<td>17</td>
<td>24</td>
</tr>
<tr>
<td></td>
<td>2010</td>
<td>30</td>
<td>29</td>
<td>25</td>
<td>15</td>
</tr>
<tr>
<td>Integration of functions</td>
<td>2006</td>
<td>37</td>
<td>22</td>
<td>19</td>
<td>22</td>
</tr>
<tr>
<td></td>
<td>2010</td>
<td>33</td>
<td>32</td>
<td>21</td>
<td>14</td>
</tr>
<tr>
<td>Delegation of responsibility</td>
<td>2006</td>
<td>7</td>
<td>12</td>
<td>24</td>
<td>58</td>
</tr>
<tr>
<td></td>
<td>2010</td>
<td>6</td>
<td>16</td>
<td>29</td>
<td>49</td>
</tr>
</tbody>
</table>

Reponses on the 2006/DISKO4 and 2010/GOPA surveys on work organization questions. Row pct.

Table II shows the frequencies for the four different responses for each of the six variables in both surveys describing organizational practices. The distributions are quite similar with the exception that delegation of responsibility appears to be a relatively intensively used practice with about half of the enterprises reporting penetration rates of over 50% in 2010. The data indicate two opposing trends: from 2006 to 2010 systems for collective proposals, integration of functions and the delegation of responsibility tended to diffuse among Danish firms in the sense that fewer firms report not using such practices at all, while the intensity of use of the practices within firms contracted in the sense that the share of firms reporting that more than 50 percent of the workforce is involved decreased.

6 The matrix of correlations underlying the PCA is constructed from weighted polychoric correlations. For robustness we compared to a PCA based on regular Pearson correlations and to results without weights. There are only marginal differences in the results.
The six variables, coded with values from 1 to 4 (4 = over 50%), are all correlated with p<0.0001 and correlation coefficients ranging from 0.256 to 0.531. The first two factors resulting from the PCA and accounting for 66.54 of the total variance are selected for oblique rotation. After factor rotation the eigenvalues recalculated on the assumption that the other factors are ignored are 2.94 and 2.24. The resulting correlations between the factors and the original variables are shown in table III.

Table III

<table>
<thead>
<tr>
<th>Correlations after rotation</th>
<th>Factor1</th>
<th>Factor2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Systems for proposals</td>
<td>0.442</td>
<td>0.881</td>
</tr>
<tr>
<td>Quality circles</td>
<td>0.498</td>
<td>0.837</td>
</tr>
<tr>
<td>Auton. groups</td>
<td>0.699</td>
<td>0.380</td>
</tr>
<tr>
<td>Interd. Workgroups</td>
<td>0.849</td>
<td>0.475</td>
</tr>
<tr>
<td>Integration</td>
<td>0.774</td>
<td>0.507</td>
</tr>
<tr>
<td>Delegation</td>
<td>0.827</td>
<td>0.371</td>
</tr>
</tbody>
</table>

Delegation and Integration (DI) and Involvement (INV)

The first factor loads positively on autonomous teams, delegation of responsibility, interdisciplinary workgroups and integration of functions. Firms scoring high on this factor have a relatively flat organizational structure where responsibility is delegated from higher to lower levels of the hierarchy in part through the use of autonomous team organization and with interdisciplinary workgroups and other methods being used to increase the horizontal integration of different specialized functions. These methods are often associated with practices of large knowledge-intensive Japanese firms or with what Mintzberg (1979) refers to as the operating adhocracy. We refer to this factor in terms of the combined practices of delegation and integration (DI). The second factor captures employee involvement based on the use of quality circles, and systems for collecting proposals from employees. We refer to this factor as involvement (INV). The inter-factor correlation is 0.535 meaning that firms will tend to score high or low on both factors though this is not necessarily the case. Indeed the first factor captures what in some case are quite profound changes in the firm’s coordination mechanisms involving major changes in the definition of tasks and responsibilities and their allocation. The use of employee involvement practices might be complimentary to this sort of structural change. It is also
true that such practices and in particular suggestion schemes might be adopted or intensified in their use with little basic change in the firm’s coordination mechanisms.

III.E. Other variables in the model

The translog model includes variables for firm output, for input prices (wages) and for technology. We do not include wages as input prices but instead include instruments that are factors well known to correlate with wage. These are firm age, firm size, firm industry and the geographical location of the firm. In addition, as the period spans the 2008 financial crisis, we add controls for the effects of the financial crisis. The financial crisis may have affected the job structure through an effect on the wage structure but the economic conjuncture has also been shown to affect work organization (Holm and Lorenz 2015). The size and industry instruments each have four categories and they are delimited in the manner illustrated in table I. The geographical location is the NUTS3 region of the firm’s main address meaning that there are 11 categories. There are four age categories defined by the number of years since the firm was first registered: 1) less than five years, 2) five-nine years, 3) 10-19 years, 4) more than 19 years. Firm output is measured by sales. GOPA includes a number of questions pertaining to the effect of the financial crisis but there is a relatively high proportion replying “Not relevant” or “Don’t know” to most of the questions. We use two questions on GOPA, both of which most firms reply to, and which arguably reflects immediate and more long-term problems respectively: the effects on national sales and on liquidity. The effects on national sales and liquidity are two dummies taking the value 1 for some/high deterioration.

The variables for technology include the continuous variables for organizational practices described above as well as variables for changes in production technology and changes in offshoring behavior. Both the DISKO4 and GOPA surveys include detailed questions on off-shoring behavior but the questions are not identical. Hence we can only construct binary indicators for whether the firms uses off-shoring or not in each year, and then include variables in the regressions for whether the firm has begun or ceased to off-shore in the period between the surveys. In DISKO4 firms are asked whether and to which location they have outsourced a number of activities. If a firm indicates to have outsourced any activity to a country other than Denmark then it is registered as having engaged in off-shoring in 2006 in our data. The corresponding question on GOPA contains a different range of activities and has a different range of possible responses so the binary indicator for whether off-shoring was used in 2010 is 1 if the firm has outsourced internationally or not. We do not have a direct indicator of technological change within firms for the 2006-2010 period. Instead we construct
an indicator for the firm’s innovation effort. In GOPA firms are asked to indicate the priority given in the innovation effort to five different areas over 2007-2009, one of which is technological change, on a five-level Likert scale. We distinguish between firms that have prioritized technological change or not. If the firm has responded High or Very high it has prioritized technological change.\(^7\)

In our regressions focus is on the effects of organizational change, technological change and off-shoring behavior, and we therefore do not report the estimates for the wage instruments.

III.F. Descriptive statistics

Table IV presents correlations and summary data for the variables used in the regressions with post-stratification weights except for the control variables for wage. As elaborated below the regression equation is expressed in first differences and therefore the variables in table IV are first differences. Correlations where at least one variable is imputed or based on imputed data are estimated using Fisher’s z transformation. For these variables, the variances are split into within and between imputation variance. The correlations between the variables are generally weak and mostly insignificant, except for the correlations between the three dependent variables: the change in share of, high, middling and low respectively. These three variables generally have negative correlation, which is quite natural as they sum to zero. The correlations indicate that increases in involvement coincides with substituting mid workers for high workers, while technological change tends to coincide with substitution for low workers for mid workers. In addition, starting to offshore seems to coincide with technological change and with increased Involvement.

### Table IV

**Descriptive statistics**

<table>
<thead>
<tr>
<th>Variable</th>
<th>ΔShare high 1</th>
<th>ΔShare middling 2</th>
<th>ΔShare low 3</th>
<th>ΔDI 4</th>
<th>ΔINV 5</th>
<th>ΔTechnology 6</th>
<th>Add Offshoring 7</th>
<th>Remove Offshoring 8</th>
<th>Δln(Sales) 9</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>-0.467***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>-0.507***</td>
<td>-0.523***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.056</td>
<td>0.012</td>
<td>-0.066</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.109**</td>
<td>-0.170***</td>
<td>0.060</td>
<td>0.383***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(^7\) We also tried using the Likert scale as continuous and tried using it as a relative priority where it was standardized relative to the mean of all 5 questions pertaining to priorities in the innovation effort but these more complicated variables showed the same result in the regression analyses as the binary variable that we use.
As reported above, the two factors (DI and INV) have positive correlation and table IV shows that they also have quite strong positive correlation in differenced form. That is, firms tend to increase or decrease along both dimensions in tandem. The change in the two factors do not correlate strongly with the variables for technological change, adding off-shoring and ceasing to offshore, suggesting that there is not a simple uniform organizational change associated with technological change or changes in offshoring.

The mean of both factors is negative indicating that the average firm decreased both DI and INV over the period. Even though the data presented in table IV are firm level data, and not employee level as the data in figure I, the means presented in table IV show a polarization pattern that differs only slightly from figure I as firms with less than 10 employees are excluded here. 38% of firms had technical change over the period while only 7.6% started offshoring and 4.3% ceased offshoring. The effect of the crisis is clearly seen as the average firm saw a 6.6% decrease in sales.

IV. Trends

In this section we provide more detail on the aggregate employment trends observed in our data. Figure II shows the polarization trend across a number of subsamples. The first group of bars are for the entire dataset and hence corresponds to the data reported in figure I. The following four subsamples divide the data by industry. It is clearly seen that polarization is a general pattern but it can also be seen that it takes different forms. Among the knowledge intensive business services (KIBS) there is a polarization trend but also a very strong upgrading trend, entailing a shift towards High jobs.
In the final two subsamples the data are split into firms with technological change and firms without. The data show polarization in both groups indicating that technological change by itself cannot account for polarization. The main difference is that in the subsample of firms with technological change there is a stronger tendency for upgrading in addition to the polarization trend.

Figure III shows the average change in work organization by subsample. The average change is a slight decrease in both DI, and in Involvement. The trends presented figure III are in terms of total subsample employment and this means that the average employee experienced a decrease along both dimensions rather than meaning that the average firm decreased along both dimension.
Subsample average change in work organization

Employees that saw their employer introduce new technology experienced a greater decrease in Involvement than the average, while employees at firms that did not introduce new technology saw no change in Involvement. The decrease in DI does not appear to be affected by the introduction of new technology.

Employees in Construction faced on average a relatively large decrease along both dimensions while employees in the primary, manufacturing and utilities industries saw almost no change along both dimensions on average. The change in DI among both KIBS and Other Services is close to the overall average but while Other services saw no change in Involvement, Involvement decreased relatively much for employees in KIBS. The differences in group means for changes in work organization illustrated in figure III are not easy to rationalize with reference to economic theory but compared to the employment weighted distribution of the changes in DI and in INV the means are all very close to the grand mean.

V. Econometric specification and results

V.A. Econometric model

The translog cost model described in section II.B. is the basis for our econometric model. Putting labor shares \( (L_{S,ij}) \) rather than cost share on the left side of equation 4, explicating that technology is a vector of \( M \) elements, and specifying the equation in differences to eliminate firm fixed effects yields equation 5.

\[
\Delta L_{S,ij} = \sum_k \beta_{j,k} \Delta \ln w_{k,i} + \theta_j \Delta \ln y_i + \sum_m \gamma_{j,m} \Delta \ln A_{m,i} + \Delta u_j
\]

The \( J \) equations of the type in equation 5 all have identical regressors. This means that there is no difference between estimating each equation separately with ordinary least squares and estimating them jointly using Seeming Unrelated Regression (SUR), or the Zellner estimator (see Berndt [1990] chapter 9 for details). In our econometric specification we replace the wage regressors with instruments while we expand the vector of variables for technology to include organizational change, technological change and the use of offshore outsourcing.

Our basic occupational share equation is:

\[
\Delta L_{S,ij} = \alpha_{j} + \gamma_{j,1} \Delta DI_i + \gamma_{j,2} \Delta INV_i
\]
\[ + \gamma_{j,3} \Delta Tech_i + \gamma_{j,4} AddOffs_i + \gamma_{j,5} RmvOffs_i + \theta_j \Delta \ln Sales_i \] 

(6) + controls for region, age, industry, size and financial crisis + \epsilon_{j,i} \]

Equation 6 will be referred to as model 2. The main interest will be in the estimates of the gamma parameters, as these will reveal which firm level changes complement and substitute the different skill groups. Model 1 is model 2 without the control variables, and Model 3 is model 2 with interactions between the two variables describing work organization on the one hand, and the variables for technology and offshoring on the other hand. Model 3 will allow us to evaluate complementarity and substitutability conditional on the accompanying changes to work organization which has two components, \( \Delta DI \) and \( \Delta INV \).

V.B. Results

Table V shows the results with controls for changes in the log of sales but without the instruments for wage controls. In Table VI we include all the control variables, and in Table VII we add interaction effects between the technological change variable and the two organizational change variables, and between the two organizational change variables and the variables measuring the initiation and cessation of off-shoring.

**Table V**

Model 1 results

<table>
<thead>
<tr>
<th></th>
<th>Mangers</th>
<th>Profs/Techs</th>
<th>High</th>
<th>Middling</th>
<th>Low</th>
</tr>
</thead>
<tbody>
<tr>
<td>dDI</td>
<td>-0.002</td>
<td>0.007</td>
<td>0.005</td>
<td>0.013*</td>
<td>-0.017**</td>
</tr>
<tr>
<td>S.E.</td>
<td>0.003</td>
<td>0.007</td>
<td>0.007</td>
<td>0.007</td>
<td>0.007</td>
</tr>
<tr>
<td>dINV</td>
<td>0.003</td>
<td>0.011*</td>
<td>0.014**</td>
<td>-0.030***</td>
<td>0.015**</td>
</tr>
<tr>
<td>S.E.</td>
<td>0.003</td>
<td>0.007</td>
<td>0.007</td>
<td>0.007</td>
<td>0.007</td>
</tr>
<tr>
<td>Technological Change</td>
<td>-0.008</td>
<td>0.022*</td>
<td>0.014</td>
<td>0.025*</td>
<td>-0.039***</td>
</tr>
<tr>
<td>S.E.</td>
<td>0.006</td>
<td>0.013</td>
<td>0.013</td>
<td>0.013</td>
<td>0.014</td>
</tr>
<tr>
<td>Started offshoring</td>
<td>0.016</td>
<td>-0.012</td>
<td>0.044</td>
<td>-0.007</td>
<td>0.003</td>
</tr>
<tr>
<td>S.E.</td>
<td>0.011</td>
<td>0.024</td>
<td>0.025</td>
<td>0.025</td>
<td>0.026</td>
</tr>
<tr>
<td>Ceased offshoring</td>
<td>-0.012</td>
<td>0.065**</td>
<td>0.053*</td>
<td>-0.006</td>
<td>-0.047</td>
</tr>
<tr>
<td>S.E.</td>
<td>0.013</td>
<td>0.029</td>
<td>0.030</td>
<td>0.031</td>
<td>0.032</td>
</tr>
<tr>
<td>dlnSales</td>
<td>-0.007</td>
<td>-0.017</td>
<td>-0.024**</td>
<td>0.022*</td>
<td>0.001</td>
</tr>
<tr>
<td>S.E.</td>
<td>0.005</td>
<td>0.011</td>
<td>0.011</td>
<td>0.012</td>
<td>0.012</td>
</tr>
<tr>
<td>R2</td>
<td>0.017</td>
<td>0.032</td>
<td>0.030</td>
<td>0.052</td>
<td>0.032</td>
</tr>
<tr>
<td>N</td>
<td>532</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Imputations</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>25</td>
</tr>
</tbody>
</table>

*Estimate for covariate followed by S.E.; Robust standard error
Tables V and VI contain five columns as they contain the results of both a specification in three equations (high-mid-low), and a specification in four equations where managers are separated from the professionals and technicians in high. The results for the equations for middling and low are not affected by this generalization, as the equations have identical regressors and the Zellner estimator reduces to applying OLS separately for each equation. We first discuss the results of the three-equation model.

A comparison of the coefficients for tables V and VI shows that the inclusion of the control variables has only a small effect on the size and significance of the coefficients for the main variables of interest.

Focusing in on the organizational change variables in the Table VI results, a first observation is that there is a statistically significant relationship between organizational change and the relative employment shares of the high, middle and low skill groups. With respect to changes in delegation and integration of functions (DI), there is a positive relationship with the share of the middle categories composed of clerks, skilled craft workers and semi-skilled operators and a negative relationship with the share of the lower skilled group. The coefficient on the high skilled occupational group composed of technicians and professionals is positive but not statistically significant. Increases in DI, then, appear to be associated with upgrading of skills, and with changes in occupational shares along the lines of that discussed in the classic literature on skill-biased organizational change (Caroli and Van Reenen 2001). The results do imply, however, that a decline in the use of these organizational practices would be visible in increased polarization with the shares of the middle categories decreasing in relation to those of the high and low-skill groups.

The relationship between an increase in employee involvement (INV) and occupation shares are in the direction of increased polarization. The results show statistically significant positive coefficients on the high and low-skilled groups which are balanced by a statistically significant negative coefficient on the medium skilled group. The complementarity which these results point to between involvement schemes and the skills of the high skilled group, including engineers and technicians, is supported by the literature on employee involvement including the use of such practices as quality circles. One of the main objectives of quality circles is to reduce the separation between the tasks of conception and execution by supporting direct interaction and knowledge exchange between
technicians and mid-level engineers on the one hand, and workers lower down on the decision-making hierarchy on the other. What is clearly more novel in our results is the complementarity they point to between the skills of the low group, including sales and service workers and the elementary trades. In interpreting this result it is important to keep in mind the view developed in the RBTC literature that due to the importance of people skills the tasks carried out by sales and to some extent service workers, though low skilled, are largely impervious to automation through the use of such emerging technologies as robotics and AI. This technological limit linked to the importance of people skills may well explain the complementarity that our results point to between employee involvement practices and the skills of the low group. Further research, including qualitative work, would be needed to confirm this hypothesis.

Technical change is complementary to the skills of the high skill group composed of managers, professionals and technicians as hypothesized in the RBTC literature. There is a negative and statistically significant relationship with the share of the low skill occupational categories. Although the changes in the shares of the low skilled categories are typically assumed to be impervious to the effects of the recent wave of technological change it cannot be precluded that more conventional forms of mechanization are being directed towards automating the work of the elementary trades including those involved in the tasks of packing, labelling or sorting in manufacturing activities. Somewhat surprising the results show no statistically significant impact of an initiation or cessation of offshoring on the shares of the different occupational groups after adding the controls for wages (table VI).

Summarizing the result for the main covariates of interest, the results show that organizational change has a significant association with the occupational shares of the high, middle and low occupational groups. Technological change cannot in itself account for polarization as it complements the skills of high and substitutes for the skills of low. While the impact of changes in DI and INV are not in the same direction, given the differences in the size of the coefficients a unit increase in both of these types of organizational change would be visible in a polarization trend.

**Table VI**

**Model 2 results**

<table>
<thead>
<tr>
<th></th>
<th>Mangers</th>
<th>Profs/Techs</th>
<th>High</th>
<th>Middling</th>
<th>Low</th>
</tr>
</thead>
<tbody>
<tr>
<td>dDI</td>
<td>-0.003</td>
<td>0.009</td>
<td>0.007</td>
<td>0.016**</td>
<td>-0.022***</td>
</tr>
<tr>
<td>S.E.</td>
<td>0.004</td>
<td>0.007</td>
<td>0.007</td>
<td>0.007</td>
<td>0.007</td>
</tr>
<tr>
<td>dInvolvement</td>
<td>0.004</td>
<td>0.014**</td>
<td>0.017**</td>
<td>-0.034***</td>
<td>0.016**</td>
</tr>
<tr>
<td>Estimate for covariate followed by S.E.; Robust standard error</td>
<td>*: p&lt;0.1, **: p&lt;0.05, p&lt;0.01</td>
<td>R2 computed using the equivalent of the method used to compute correlation in table IV</td>
<td>The model also includes the wage controls: region, industry, age and effect of financial crisis.</td>
<td>&quot;High&quot; is the sum of &quot;Managers&quot; and Profs/Techs&quot;</td>
<td></td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td></td>
</tr>
<tr>
<td>Technological Change</td>
<td>0.003</td>
<td>0.007</td>
<td>0.007</td>
<td>0.007</td>
<td>0.007</td>
</tr>
<tr>
<td>S.E.</td>
<td>-0.008</td>
<td>0.022*</td>
<td>0.014</td>
<td>0.018</td>
<td>-0.032**</td>
</tr>
<tr>
<td>Started offshoring</td>
<td>0.006</td>
<td>0.013</td>
<td>0.014</td>
<td>0.014</td>
<td>0.014</td>
</tr>
<tr>
<td>S.E.</td>
<td>0.018</td>
<td>-0.01</td>
<td>0.007</td>
<td>-0.011</td>
<td>0.004</td>
</tr>
<tr>
<td>Ceased offshoring</td>
<td>0.011</td>
<td>0.024</td>
<td>0.026</td>
<td>0.026</td>
<td>0.026</td>
</tr>
<tr>
<td>S.E.</td>
<td>-0.008</td>
<td>0.050*</td>
<td>0.042</td>
<td>-0.010</td>
<td>-0.032</td>
</tr>
<tr>
<td>dlnSales</td>
<td>0.013</td>
<td>0.029</td>
<td>0.031</td>
<td>0.031</td>
<td>0.031</td>
</tr>
<tr>
<td>S.E.</td>
<td>-0.002</td>
<td>-0.021*</td>
<td>-0.023**</td>
<td>0.018</td>
<td>0.005</td>
</tr>
<tr>
<td>R2</td>
<td>0.005</td>
<td>0.011</td>
<td>0.012</td>
<td>0.013</td>
<td>0.012</td>
</tr>
<tr>
<td>N</td>
<td>0.065</td>
<td>0.105</td>
<td>0.096</td>
<td>0.111</td>
<td>0.129</td>
</tr>
<tr>
<td>Imputations</td>
<td>532</td>
<td>25</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table VII shows the results for the model including interaction effects. Examining possible interactions between technological and organizational change provides a means of testing the hypothesis that organizational change may have direct or independent effects on tasks and employment shares and should not be solely considered as an intermediary link between technological change and task distribution. For the most part this hypothesis is confirmed. The only statistically significant interaction between technical change and changes in DI or INV for the managerial, prof/tech, middle and low groups is the interaction with ΔINV for managers. Changes in INV have a direct positive association with managers’ share and there is a statistically significant negative
association when changes in INV are accompanied by changes in technology. A possible interpretation is that increases in INV can substitute for managers’ skills as long as they are accompanied by the introduction of ICT that facilitate the use of more decentralized forms of work organization. Plotting the marginal effect of technological change conditional on the change in INV (figure IV) reveals that such simultaneous changes complements professionals/technicians while substituting managers and low. This is consistent with the above interpretation but also indicates that low skill tasks are being substituted in the same process.

The other statistically significant interaction effects concern the variable measuring the initiation of offshoring and the organizational change variables. The initiation of offshoring, as we have seen from table VI, does not have a statistically significant direct association with the shares of the different groups. The results from table VII show, however, that the initiation of offshoring is associated with a direct positive effect on manager’s share at values of ΔINV equal to 0 and that the direct effect decreases as the value ΔINV increases above 0 due to the negative interaction effect. A possible interpretation, that is consistent with our comments in the paragraph above, is that the more intensive use of involvement practices makes it easier to reallocate managers along the restructured value chain to overseas units. Our data, however, does not allow us to fully explore this hypothesis. The statistically significant positive interaction effect between INV and starting to offshore in the equation for low suggests that the share of low benefits from the substitution effect on manager’s share. However, the statistical significance is borderline and Figure V below with 95 percent confidence intervals shows that the positive marginal effect is not statistically significant over the entire range of values for dINV, cf. figure V.

Table VII

Model 3 results

<table>
<thead>
<tr>
<th></th>
<th>Managers</th>
<th>Profs/Techs</th>
<th>Middling</th>
<th>Low</th>
</tr>
</thead>
<tbody>
<tr>
<td>dDI</td>
<td>-0.006</td>
<td>0.009</td>
<td>0.015</td>
<td>-0.018*</td>
</tr>
<tr>
<td>S.E.</td>
<td>0.005</td>
<td>0.009</td>
<td>0.009</td>
<td>0.010</td>
</tr>
<tr>
<td>dInvolvement</td>
<td>0.012***</td>
<td>0.006</td>
<td>-0.039***</td>
<td>0.020**</td>
</tr>
<tr>
<td>S.E.</td>
<td>0.005</td>
<td>0.009</td>
<td>0.009</td>
<td>0.010</td>
</tr>
<tr>
<td>Technological Change</td>
<td>-0.012**</td>
<td>0.026*</td>
<td>0.021</td>
<td>-0.036**</td>
</tr>
<tr>
<td>S.E.</td>
<td>0.006</td>
<td>0.013</td>
<td>0.014</td>
<td>0.015</td>
</tr>
<tr>
<td>Started offshoring</td>
<td>0.028**</td>
<td>0.013</td>
<td>-0.014</td>
<td>-0.010</td>
</tr>
<tr>
<td>S.E.</td>
<td>0.011</td>
<td>0.025</td>
<td>0.027</td>
<td>0.027</td>
</tr>
<tr>
<td>Ceased offshoring</td>
<td>-0.007</td>
<td>0.034</td>
<td>-0.008</td>
<td>-0.020</td>
</tr>
<tr>
<td>S.E.</td>
<td>0.015</td>
<td>0.033</td>
<td>0.035</td>
<td>0.035</td>
</tr>
<tr>
<td>dlnSales</td>
<td>-0.000</td>
<td>-0.019</td>
<td>0.016</td>
<td>0.003</td>
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</tbody>
</table>
Finally, there is a significant interaction effect between dDI and starting to offshore for the low group, which shows that the initiation of offshoring tends to substitute for the skills of low only if accompanied by an increase in DI. Increasing DI while starting to offshore also exacerbates the complementarity effect for managers. A possible explanation for this skill-biased effect is that it is easier to off-shore tasks in a way that reduces the firm’s need for the skills of the elementary trades when the firm has a decentralized and flattened organizational design.

<table>
<thead>
<tr>
<th></th>
<th>S.E.</th>
<th>0.005</th>
<th>0.012</th>
<th>0.013</th>
<th>0.012</th>
</tr>
</thead>
<tbody>
<tr>
<td>dDI x Tech. Change</td>
<td>0.002</td>
<td>0.005</td>
<td>-0.002</td>
<td>-0.006</td>
<td></td>
</tr>
<tr>
<td>S.E.</td>
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<td>0.015</td>
<td>0.015</td>
<td></td>
</tr>
<tr>
<td>dDI x Started offshoring</td>
<td>0.012</td>
<td>0.018</td>
<td>0.026</td>
<td>-0.006**</td>
<td></td>
</tr>
<tr>
<td>S.E.</td>
<td>0.011</td>
<td>0.024</td>
<td>0.025</td>
<td>0.025</td>
<td></td>
</tr>
<tr>
<td>dDI x Ceased offshoring</td>
<td>0.006</td>
<td>-0.035</td>
<td>-0.002</td>
<td>0.030</td>
<td></td>
</tr>
<tr>
<td>S.E.</td>
<td>0.014</td>
<td>0.032</td>
<td>0.034</td>
<td>0.034</td>
<td></td>
</tr>
<tr>
<td>dINV x Tech. Change</td>
<td>-0.013**</td>
<td>0.020</td>
<td>0.008</td>
<td>-0.014</td>
<td></td>
</tr>
<tr>
<td>S.E.</td>
<td>0.007</td>
<td>0.014</td>
<td>0.015</td>
<td>0.015</td>
<td></td>
</tr>
<tr>
<td>dINV x Started offshoring</td>
<td>-0.054***</td>
<td>-0.016</td>
<td>0.019</td>
<td>0.051*</td>
<td></td>
</tr>
<tr>
<td>S.E.</td>
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<td>0.026</td>
<td>0.027</td>
<td>0.027</td>
<td></td>
</tr>
<tr>
<td>dINV x Ceased offshoring</td>
<td>-0.006</td>
<td>0.037</td>
<td>0.031</td>
<td>-0.061</td>
<td></td>
</tr>
<tr>
<td>S.E.</td>
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<td>0.037</td>
<td>0.038</td>
<td>0.038</td>
<td></td>
</tr>
</tbody>
</table>

R2: 0.116 0.115 0.118 0.149
N: 532
Imputations: 25

Estimate for covariate followed by S.E.; Robust standard error
*: p<0.1, **: p<0.05, ***: p<0.01
R2 computed using the equivalent of the method used to compute correlation in table IV

The model also includes the wage controls: region, industry, age and effect of financial crisis.
Middling. Effect of tech. change conditional on \( dINV \)

Low. Effect of tech. change conditional on \( dINV \)

Figure IV
Marginal effects for technological change with 90 pct. confidence band (shaded) and 95 pct. confidence band (dashes)

The marginal effects in figure IV shows that the general upgrading, or skill bias, of technological change is exacerbated by a simultaneous increase in INV. The marginal effects on figure V shows that the tendency for offshoring to complement managers and to some degree substitute low skill workers is significantly mediated by the accompanying changes to work organization.
Managers. Effect of starting to offshore conditional on dDI

Low. Effect of starting to offshore conditional on dDI

Figure V

Marginal effects for offshoring with 90 pct. confidence band (shaded) and 95 pct. confidence band (dashes)

It is relevant that the low R squared values in tables V, VI and VII imply that our model only predicts a minor share of the observed job polarization in the data. However, as the firms are not weighted by employment the means of the dependent variables do not reflect aggregate polarization. If we add employment weights to model 3 (table VII) then the R squared values become 0.010, 0.294, 0.222 and 0.074 respectively. This means that our model does quite well at describing the shift from middling to high.8

VI. Conclusions

An important literature in labor and industrial economics has focused on the trend towards labor market polarization which has marked many of the advanced industrial economies during the 1990s and 2000s. Much of the analysis of this trend has been carried out at the level of tasks and occupations making use of labor force survey data in combination with ONET for occupational task descriptions, or in some cases specialized skills surveys adopting household sampling frames. While this work has had a big impact on how we understand changes in labor market and industrial structure, one of its limitations is that it unable to investigate firm-level decision making related to investments in new

---

8 A decomposition of the observed polarization for the Danish economy into five different effects shows that the increase in high and the decrease in middling are driven largely by within firm effects, while within firm changes play a negligible role for the increases in managers and low. Thus, our model's relative inability to explain the changes for these two job groups is not surprising. See the supplementary material for the full decomposition analysis.
technology, outsourcing and the adoption of organizational practices which can result in a polarizing trend in the firm’s occupational structure. Consequently, part of observed trend towards polarization remains a black box.

In this paper we make a first attempt to tackle this limitation by making use of a panel of Danish firms with detailed data on organizational practices as well as indicators of technical change and outsourcing activities. By combining this data with register data on employment at the occupational level we are able to model and estimate the impact of firm level decision making on organizational change as well as possible complementarities between organization change and technical change. Our results show that both technical and organizational change can have independent effects on changes in occupational shares and thus provides important support for the view that the organizational level is central to understanding possible trends towards job polarization. One of the most novel findings in this respect is that the increasing use of employee involvement practices can contribute directly to job polarization at the firm level. This may reflect, as much of the literature on skills gaps mismatches argues, the increasing importance of people skills including those of such occupational categories as sales and service staff.

Our paper is to our knowledge the first to analyze the way changes in organizational practices effect occupational shares at the firm level. We would strongly encourage other researchers with access to comparable panel data for other countries to undertake similar analyses in order to confirm the validity of our results and to assess the extent to which they apply in different national settings. This could contribute to generalizing our results and to increasing our understanding of the largely underexplored within firm factors that can contribute to job polarization.

We also recognize the limitations of our results linked to the data available. In particular our measure of technical change is quite general and cannot identify the impact of specific emerging technologies such as robotics and AI which are increasingly being identified as key drivers of the current phase of industrial and labor market change. We would hope that our work will give impetus to future data collection efforts at both the national and international levels in order provide better measures of the extent of adoption of these new and possibly disruptive technologies and as basis for studying their impacts on skills and employment.

Supplementary Material

9 There are a number of panel data sets with employer level information on organisational practices that could be used to undertake comparable analyses. Amongst them are the German IAB survey, the British WERS survey and the French REPONSE survey. For an overview of employer surveys with panel data, see MEADOW Consortium (2010) pp. 60-65.
An online appendix is available containing detailed description of accessing the data and replicating the analyses presented here. In addition, the appendix contains a decomposition analysis of job polarization in Denmark and additional details on the multiple imputation procedure, as referred to in the paper. In addition, it contains the marginal effects plots based on table VII that are not already included in figures IV and V.

References


Sanders, Mark and Bas ter Weel “Skill biased technical change: Theoretical concepts, empirical problems and a survey of the Evidence”. DRUID Working Papers, No. 00-8, 2000.

Online appendix for the paper

WORK ORGANIZATION AND JOB POLARIZATION

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I SAS code
SAS code for reproducing the results in the main paper and the results in this appendix. To be produced upon acceptance of the paper.

II Accessing the data
The data used in the analyses must be accessed remotely at Statistics Denmark. This section describes how to access the data, and which data to acquire.

III Sources of the polarization trend
We decompose the change from 2003 to 2009 into the effects of structural change, differential growth of firms, within firm changes and finally entry and exit of firms.
We use data on the entire economy, not just the data for the analysis. We use 2003-2009 corresponding to the plotted trend rather than 2006-2010 which are the years of the econometric analysis. The 2010 data require imputation which does not affect the econometric analysis significantly except for increasing the amount of available data. The logic of decompositions require population coverage and imputing in the entire population, rather than the panel of firms in the two surveys, turns out to heavily affect the results. Hence we cannot use data later than 2009 for the decomposition.

We distinguish between 25 sectors after excluding the public admin, education and health sectors. This very detailed level is possible because we use data on the entire population of firms in Denmark.

The methodology used to decompose the total change into separate effects is based on Foster et al. (1998) and the extensions applied in Holm (2014). The effects are computed by decomposing total change into five effects using the identity presented in equation 1. $\Delta Z$ is the national level change in e.g. the share of High jobs from 2003 to 2009. $Z, z_j$ and $z_{ij}$ are the shares of type high in 2003 at the national level, in industry $j$ and in firm $i$ in industry $j$ respectively. Adding a prime means the value is for 2009. $s_{ij}$ is the employment share of firm $i$ in industry $j$ and so on. The sets $C_j, N_j$ and $X_j$ are the sets of continuing, entering and exiting firms in industry $j$ defined by whether they exist in both 2003 and 2009, only 2009 or only 2003 respectively. Equation A.1 below is a reproduction of equation 9 from Holm (2014).

$$\Delta Z = \sum_j \Delta s_j (z_j - Z)$$ (Structural change)

$$+ \sum_j s_j' \sum_{i \in C_j} \Delta s_{ij} (z_{ij} - z_j)$$ (Firm growth)

$$+ \sum_j s_j' \sum_{i \in C_j} s_{ij}' \Delta z_{ij}$$ (Within firms) (A.1)

$$+ \sum_j s_j' \sum_{i \in N_j} s_{ij}' (z_{ij}' - z_j)$$ (Entry)

$$+ \left( - \sum_j s_j' \sum_{i \in X_j} s_{ij}' (z_{ij} - z_j) \right)$$ (Exit)

The changes in job composition from 2003 to 2009 is illustrated in Figure A.I. Middling jobs decline from by about 4.5 percentage points from 2003 to 2009 but it is still the largest of the four groups. The remaining three groups all increase in share of jobs and if Managers are included in High, then this combined group is larger than Middling in 2009.
The change in frequency of each job type illustrated in figure A.I can then be decomposed by applying equation A.1 to the micro data. This means applying the equation four times. The results are shown in figure A.II. The results reported in figure II are scaled by the observed change in the job type and add to unity for each type. An initial interesting finding is that the effects are very different across the four job types.

The increase in Managers is mostly driven by firm growth. That is, firms where managers make up a large share of the workforce have experienced relative growth over the period. A secondary effect is
the effect of exit meaning that firms with a relatively low share of managers in the workforce have exited thus pushing up the average share of managers in the economy.

For both types high and middling the main effect is the within firm effect. Hence the growth in high and decrease in middling is mostly caused by changes in the composition of the workforce within firms. For type high there is a secondary negative effect of structural change meaning that the economy has shifted toward industries with relatively few high jobs, thus decreasing the share of high. This negative effect is however cancelled out by other, strong positive effects.

The evolution of type low is quite different again showing a dominating effect from entry meaning that Low jobs have become more abundant because new firms have a large share of low jobs in their workforce. However there is a sizeable negative effect from exit meaning that firms with a relatively large share of low tend to exit too, thus leading to a somewhat smaller effect of net entry. For type low there is also a very large effect of structural change meaning that the increase in low jobs is to a large extent based on structural change where industries with a relatively high share of low jobs expand.

Our study focusses on mechanisms within firm that affect job polarization and it can clearly be expected that we will find more significant results for types high and middling than for managers and low.

**IV The imputation procedure**

Fully conditional specification (FCS) methods are used to impute the missing data. This means that data are assumed to be missing at random and that there exists a joint distribution for the data.

The FCS method relies on imputing the missing data through chained equations. An imputation method is specified for each variable depending on the type of variable. Regression is used for continuous variables, logistic regression is used for ordinal categorical variables and the discriminant function method is used for nominal categorical variables. The imputations are carried out before the data are transformed to first differences and hence the 532 firms become 1064 observations. The imputation is carried as a step prior to the actual analyses and hence include a number of variables that were used in the final version. These variables are indicated with an asterisk (*) in the below list.

The continuous variables are:

- The total number of employees at the firm
- The number of employees in prof/tech, mid and low occupations (managers are excluded to avoid perfect mulitcollinearity).
- The weights, cf. section III.B of the main paper
- Alternative weights computed for 2010*
- Nominal sales
- Net investment*
- Fixed capital*
- Distance to industry productivity frontier (cf. Acemoglu et al. 2007)*
- Industry productivity heterogeneity (cf. Acemoglu et al. 2007)*

The ordinal variables are:
• The six variables for work organization, as described in table II of the main paper
• The use of job rotation in the firm*
• Technological change and offshoring
• Binary variables from the GOPA survey indicating whether sales had increased or decreased over the previous three years*
• The two variables for the effect of the financial crisis used in the main paper: effect on national sales and on liquidity
• Two additional variables for the effect of the financial crisis: the effect on recruitment and access to finance*
• Age group

The nominal variables are:

• Industry
• Region

See also the SAS code in section I of this appendix.

V Additional figures for marginal effects
The results of model 2 presented in table VII in the main paper suggests 24 marginal effects that may be plotted graphically. Eight are plotted in figures IV and V of the main paper and the rest are reported in figure A.III here.
Profs/Techs. Effect of starting to offshore conditional on dDI

Middling. Effect of starting to offshore conditional on dDI

Managers. Effect of ceasing to offshore conditional on dDI

Middling. Effect of ceasing to offshore conditional on dDI

Profs/Techs. Effect of starting to offshore conditional on dINV

Middling. Effect of starting to offshore conditional on dINV

Profs/Techs. Effect of ceasing to offshore conditional on dDI

Middling. Effect of ceasing to offshore conditional on dDI

Low. Effect of ceasing to offshore conditional on dDI
Managers. Effect of ceasing to offshore conditional on dINV

Profs/Techs. Effect of ceasing to offshore conditional on dINV

Middling. Effect of ceasing to offshore conditional on dINV

Low. Effect of ceasing to offshore conditional on dINV

Figure A.III

Marginal effects with 90 pct. (shaded) and 95 pct. (dashes) confidence bands

References
