I Z A Institute
of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 15772

Technological and Organizational Change and the Careers of Workers

Michele Battisti
Christian Dustmann
Uta Schönberg

DECEMBER 2022

I Z A Institute
of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 15772

Technological and Organizational Change and the Careers of Workers

Michele Battisti
University of Glasgow and IZA

Christian Dustmann
UCL and CReAM

Uta Schönberg
UCL, CReAM, IAB and IZA

DECEMBER 2022

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Technological and Organizational Change and the Careers of Workers*

This paper investigates the effects of technological and organizational change (T&O) on jobs and workers. We show that although T&O reduces firm demand for routine relative to abstract task-based jobs, affected workers do not face higher probability of non-employment or lower earnings growth than unaffected workers. Rather, firms that adopt T&O offer routine workers re-training opportunities to upgrade to more abstract jobs. Older workers form an important exception: T&O increases the risk that they permanently withdraw from the labor market and reduces their earnings, regardless of the tasks they performed in the firm prior to T&O.

JEL Classification: J23, J24, O33

Keywords: careers of workers, technological change

Corresponding author:
Michele Battisti
University of Glasgow
Glasgow G12 8QQ
Scotland

E-mail: Michele.Battisti@glasgow.ac.uk

* We gratefully acknowledge funding by NORFACE DIAL "Dynamics of Inequality across the Life-Course" (Project "Populism, Inequality and Institutions" (PII)) – 462-16-060. Christian Dustmann also acknowledges support from the European Research Council (ERC) Advanced Grant (MCLPS) – 833861 and the DFG – grant 1024/1-2 AOBJ:642097.

1 Introduction

Technological and organizational change (T&O) is seen as the main reason for the decline in the employment share of occupations with routine task content.[1] Much of the existing literature that analyzes the impact of T&O on demand for routine tasks finds that jobs with routine task content do indeed disappear. However, this does not imply that *workers* who worked in occupations with a predominantly routine task content before changes were implemented (hereafter, routine jobholders) exit employment, although this scenario dominates the popular public debate.[2] Even if their jobs disappear through T&O, routine jobholders may move to other jobs, possibly with more abstract skill content, either in the same firm or in other firms. Yet, whether or not such adjustment takes place cannot be studied with repeated cross-sectional data on which much of the literature relies, nor can the longer-term consequences of T&O for workers be investigated.

In this paper we address this gap using a survey panel data set of German firms which spans 18 years. We not only utilize its detailed information on T&O but also match it to registry data on entire work histories of all workers these firms ever employed. This allows us to first of all show that the decline in the employment share of routine jobs that we see in the aggregate economy is predominantly a *within-firm* phenomenon, accounting for at least 80% of the aggregate decline in the routine employment share. In contrast, increased exit and reduced entry of routine-intensive firms and lower employment growth of surviving routine-intensive firms have contributed only little to the decline.

Focusing next on the effects of T&O on routine and abstract employment shares *at the firm level*, we find that in firms that implement T&O the employment share of routine jobs

[1] See, for example, Autor, Levy, and Murnane (2003), Goos and Manning (2007), the survey by Acemoglu and Autor (2011), and the theoretical contribution of Feng and Graetz (2019).

[2] See, for example, the *Economist* (http://www.economist.com/news/specialreport/21700758will-smarter-machines-cause-mass-unemployment-automation-and-anxiety) and *MIT Technology Review* (https://www.technologyreview.com/s/515926/how-technology-is-destroying-jobs/).

declines and that of abstract jobs increases relative to firms that do not implement T&O. We further show that the negative association between T&O and the decline in the routine employment share does not only hold across industries and local labor markets but also within industries and local labor markets, across firms. Thus, while several papers have established direct evidence for the polarization hypothesis by leveaging T&O variation either across industries and countries (e.g., Michaels et al., 2014) or local labor markets (e.g., Autor and Dorn, 2013; Akerman, Gaarder, and Mogstad, 2015), our analysis highlights that the T&O-induced aggregate decline in the employment share of routine jobs occurs primarily within firms.[3]

Having established that the relation between the decline of the routine employment share and T&O is predominantly a within-firm phenomenon, we next shift our focus from *firms* to *workers* to investigate how they adjust to T&O measured at the firm level. We find that although T&O reduces the firm's employment share of routine jobs, those holding routine jobs at T&O implementation on average suffer neither employment losses nor reduced wage growth. Rather, these workers are more likely to move to more abstract jobs. We further show that these upward movements are facilitated by an increase in firm-provided training opportunities.[4]

Thus, our analysis constitutes the first direct evidence that while T&O is routine-replacing (in the following, we will refer to this as routine-biased, where the bias is to be interpreted as a potentially negative bias), it does not necessarily hurt employment of *workers*

[3] A related recent literature investigates the effects of technology that is specific to the manufacturing sector—industrial robots—on overall (rather than skill-specific) employment and wages, leveraging variation in robot exposure across industries (Graetz and Michaels, 2017, 2018) or local labour markets (see Acemoglu and Restrepo, 2019, for the US and Dauth at al., 2021, for Germany). While several papers draw on firm-level T&O data and link T&O to firms' skill or task composition (e.g., Bresnahan, Brynjolfsson, and Hitt, 2002; Caroli and van Reenen, 2001) or changes in firms' skill composition (e.g., Lindner, Muraközy, Reizer and Schreiner, 2022; Tuhkuri, 2022), these studies do not track the careers of workers affected by T&O, which is the focus of our paper.

[4] Some previous papers also establish a positive correlation between T&O and firm training activities (Lynch and Black, 1998; Bresnahan, Brynjolfsson, and Hitt, 2002; Behaghel, Caroli, and Walkowiak, 2012; Behaghel and Greenan, 2012; Behaghel, Caroli, and Roger, 2014). See Parent (1999) for a discussion of the role of employer-provided training on worker outcomes.

who held these jobs. These findings add to work by Cortes (2016), who uses PSID data to explore the effects of routine-biased technological change on the patterns of occupational transition out of routine occupations, focusing on the estimation of changes in occupation wage premia.[5] While Cortes (2016) has to rely on structural assumptions to infer the effects of T&O on task transitions and earnings as the PSID does not include direct measures of the variation in the technological change, we exploit direct information on T&O at the firm level.

Although those holding routine jobs at T&O implementation do not lose out *on average*, among those aged 55 and above most fail to upgrade to abstract jobs either within or outside the firm and are more likely to permanently move into non-employment. Moreover, not only does T&O increase such transitions for older *routine* jobholders, but for *all* older workers including those in abstract jobs and those with a university degree.[6] One reason why older workers do not respond to T&O by upgrading to abstract jobs may be lower incentives to invest in new skills due to a shorter amortization period.

We next ask whether there are particular characteristics of firms that facilitate the re-training of workers after T&O. We investigate whether firms that train a larger share of young workers within Germany's apprenticeship training system, and thus have experience with training workers in-house, are more likely to upgrade the skills of their other workers when they carry out T&O. We find strong support for this hypothesis: routine jobholders are more likely to upgrade to abstract jobs following T&O if the share of apprentices in the firm prior to T&O implementation is higher. Thus, the availability of in-house expertise in (re-)training workers seems to be a key factor allowing certain firms to restructure their workforce after T&O without shedding workers.

[5] Autor and Dorn (2009) also touch on this question, by showing that routine occupations "are getting old", and that young college workers—but not older college workers or non-college workers—reallocate to high-skill non-routine employment.

[6] This finding is in line with the evidence presented in Bartel and Sicherman (1993), Aubert, Caroli, and Roger (2006); Beckmann (2007); Rønningen (2007); Hægeland, Rønningen, and Salvanes, (2007) and Behaghel, Caroli, and Roger (2014) that T&O is age-biased and induces early retirement of older workers.

An additional reason for firms to retrain workers may be the presence of unions that support training activities. In Germany unions play an active role in advising and supporting firms and workers in all matters of apprenticeship and further training.[7] Our estimates suggest that unions do indeed mitigate T&O's effects on routine jobholders: movements from routine to abstract jobs in response to T&O occur more frequently in firms that recognize a union (and might thus bound by collectively negotiated wages, but also benefit from services—such as training support—that unions offer) than in firms that do not. These findings highlight that firms' in-house training capacity and institutions such as unions facilitate upward movements from routine to abstract task-based jobs.

2 Background, Data, and Descriptives

2.1 Background

2.1.1 Polarization and the Decline in the Routine Employment Share.

We conduct our analysis for Germany, which, similar to the U.S., the UK, and other OECD countries, witnessed an erosion of jobs in the middle of the wage distribution in the 1990s and 2000s (see Spitz-Oener, 2006; Dustmann, Ludsteck, and Schönberg, 2009; Black and Spitz-Oener 2010). Such employment polarization is commonly attributed to routine-biased technological change, which lowers firm demand for routine tasks typically located in the middle of the wage distribution, while increasing demand for the abstract tasks that dominate its upper end (Autor, Levy, and Murnane, 2003; Goos and Manning, 2007).[8] We illustrate this polarization in Figure 1a by plotting decadal changes in employment shares of

[7] See for example Bahnmüller (2009) and Seitz (1997) for an overview. Nearly all unions in Germany, including the three largest (*IG Metall*, *Verdi*, and *IG Bergbau, Chemie und Energie)*, provide further training programs at often highly subsidized rates. Dustmann and Schönberg (2009) also show that unions increase apprenticeship training in Germany.

[8] Barany and Siegel (2018) emphasize that at least part of the observed polarisation may stem from structural changes rather than responses to technological change per se.

occupations ranked according to their median wage in 1990. Figure 1a shows that employment shares of occupations in the middle of the wage distribution decreased, particularly through the 1990s. As shown in Figure 1b, the share of workers employed in routine occupations declined by 9.2 percentage points between 1992 and 2010 (from 41.6% to 32.4%), whilst the share of workers in abstract occupations increased by close to the same amount, with the share of workers in manual occupations remaining roughly constant.[9]

2.1.2 Within-Firm Changes in the Routine Employment Share.

The aggregate routine employment share in the economy may decrease either because routine-intensive firms are more likely to exit and less likely to enter the market than abstract-intensive (or manual-intensive) firms, because routine employment shares decline *within* surviving firms, or because routine-intensive surviving firms grow at a slower pace than abstract-intensive surviving firms. To quantify the importance of selective firm entry and exit, we first decompose the aggregate change in the routine employment share ΔSR as follows:

$$\Delta SR = \underbrace{\Delta SR_S}_{\text{survivors}} + \underbrace{\omega_X^0(SR_S^0 - SR_X^0)}_{\text{exits}} + \underbrace{\omega_E^1(SR_E^1 - SR_S^1)}_{\text{entries}}, \qquad (1)$$

where superscripts 1 and 0 denote current period and base period respectively; subscript X denotes exit, subscript S denotes surviving and subscript E denotes entry. Therefore, ΔSR_S denotes the decline in the routine employment share among surviving firms; ω_X^0 denotes the base period employment share of firms that exit between the base and current period; and ω_E^1 denotes the current period employment share of firms that entered between the base and current period.[10] We report the results from this decomposition in Panel A of Table 1,

[9] See Section 2.2.3 for the classification of occupations into manual, routine and abstract.

[10] That is, $\omega_X^0 = \frac{E_X^0}{E_S^0 + E_X^0}$ and $\omega_E^1 = \frac{E_E^1}{E_S^1 + E_E^1}$, where E_X^0 and E_S^0 denote employment at baseline in surviving and exiting firms and E_E^1 and E_S^1 denote employment in the current period in surviving and entering firms.

separately for the overall period 1992 to 2010 and three six-year sub-periods.[11] The results indicate that selective firm entry and exit play only a minor role in accounting for the decline in the routine employment share in the economy, regardless of which time period we consider. Rather, the bulk (more than 90%) of the decline in the aggregate routine employment share occurs among surviving firms.

In a second step, we decompose the decline in the routine employment share among surviving firms into three components, within-firm changes, differential employment growth between routine-intensive and abstract-intensive surviving firms and an interaction term:

$$\Delta SR_S = \underbrace{\sum_{j \in S} \Delta SR_j \omega_j^0}_{\text{within firm changes}} + \underbrace{\sum_{j \in S} \Delta\omega_j SR_j^0}_{\text{differential firm growth}} + \underbrace{\sum_{j \in S} \Delta SR_j \Delta\omega_j^0}_{\text{interaction term}} \qquad (2)$$

where $j \in S$ denotes the set of surviving firms; ΔSR_j denotes the change in the routine employment share in firm j; ω_j^0 denotes relative firm size of firm *j* at baseline[12]; $\Delta\omega_j$ denotes the change in relative firm size of firm j; and SR_j^0 denotes the routine employment share in firm *j* at baseline.

The first component of this decomposition captures within-firm changes in routine employment shares. To make results representative for workers, within-firm changes are weighted by firm size at baseline to compute the economy-wide average. The second component captures differential employment growth of surviving firms with different routine employment shares at baseline, while the third component captures co-movements of within-firm changes in routine employment shares and employment growth in the firm.

We present results from this decomposition in Panel B of Table 1. The results indicate that the decline in the aggregate routine employment share is predominantly a within-firm phenomenon: Within-firm changes account for at least 85% of the decline in the routine employment share among surviving firms and thus at least 80% of the overall decline in the

[11] See Section 2.2.2 for a description of the data and sample used in this analysis.

[12] That is, $\omega_j^0 = \frac{E_j^0}{E^0}$, where E_j^0 and E^0 denote the number of employees in the firm and in the economy.

routine employment share, irrespective of the time-period considered. Moreover, routine-intensive surviving firms grow at a slower pace than less routine-intensive surviving firms (the second component in Equation (2)), accounting for up to 45% of the decline in the routine employment share among surviving firms. Consequentially, the third component in Equation (2), the interaction term, is strongly positive, indicating that firms that experience stronger declines in their routine employment shares grow on average less than firms that experience weaker declines. This negative correlation between within-firm declines in routine employment shares and employment growth of the firm is mainly due to larger firms at baseline experiencing sharper declines in their routine employment shares (as illustrated in Appendix Figure A.1) while also growing at a slower rate than smaller firms at baseline.

Motivated by the finding that the decline in the aggregate routine employment share primarily occurs within firms, our analysis below first explores the link between T&O and the decline in middle wage routine jobs at the level of the firm. We then investigate how T&O in the firm affects workers' careers.

2.2 Data and Descriptives

Our empirical analysis combines three main data sources: the IAB Establishment Panel (IABEP), registry data for all firms and workers covered by social security, and the Qualification and Career Survey. The IABEP, administered from 1993 to 2012, is an annual representative survey of up to 16,000 firms in Germany that provides detailed information on organizational change, innovation, and training activities. We match these data with registry records of the work histories of all workers ever employed at a surveyed firm and are thus able to trace out workers' careers even after they have left the company. To assess occupational task content we rely on the Qualification and Career Survey.

2.2.1 The IAB Establishment Panel

The IABEP survey was first administered in 1993 to 4,265 West German firms and extended to East German firms in 1996. By 2010, the number of surveyed firms had increased to over 16,000. From this database, we select all West German firms that participated in the IABEP in any of the years for which information on organizational change is available. Furthermore, we require that these firms employed at least 10 workers, and we exclude firms in agriculture as our T&O measures are not well-suited for that sector. In addition to data on such variables as IT investments, product innovation and training activities, the survey contains a series of questions on different types of organizational changes occurring in the company over the previous three years. Questions were asked first in 1995 and then at three-year intervals (i.e. in 1998, 2001, 2004, 2007, and 2010). We focus on four questions asked consistently in all these waves to which the firm answers either yes or no: whether it has shifted responsibilities and delegated decisions; whether it has introduced teamwork or working groups with their own responsibilities; whether it has introduced profit centers (that is, units or departments that carry out their own cost and result calculations); and whether it has internally restructured or merged departments or areas of activities. Our measure of T&O then adds up the number of any individual changes over a given three-year period.

We view this variable as a broad and comprehensive measure of technological and organizational change that has important advantages over other measures of T&O, such as IT investments or robotization. It captures not only important alterations in how the firm operates but also changes in technology that accompany organizational change, such as new computer systems required for the introduction of a profit center, or organizational changes that accompany IT investments, such as restructuring of workplaces due to IT investment

(Bresnahan, Brynjolfsson, and Hitt, 2002).[13] It also incorporates changes in management practices that have been found to be an important driver of total factor productivity for firms and countries (Bloom, Sadun and Van Reenen, 2016). Overall, our measure of T&O embodies productivity-enhancing restructuring in firms more effectively than alternative measures of T&O such as robotization or ICT equipment, which only capture particular changes in technology. It is also commonly argued that aspects of the "fourth industrial revolution", such as artificial intelligence, machine-to-machine communication, strong customization of products, profoundly change the organization of firms, in a way captured by our measures of T&O (see for example Fountaine at al., 2019 and Makarius et al., 2020 within the business literature).

Our measure of T&O is also widely used and common across all sectors in the economy. Pooling over all three-year periods between 1992 and 2010 and weighting by baseline employment (i.e. employment at the beginning of the three-year period) to make results representative across workers, Figure 2a shows that over half of all workers are employed by firms that implemented at least one measure of T&O in the previous 3 years, while about 12% of workers are employed in firms that adopted at least three changes (see also Panel A of Table 2). According to Figure 2b, departmental mergers were the most common type of T&O; more than 40% of workers are employed in firms that implemented at least one merger over the previous three-year period. For comparison, 28%, 18% and 17% of workers work in firms that shifted responsibilities across departments, that introduced teamwork, or a profit center, respectively. Dauth et al., (2021) using IFR and IAB data find that the stock of robots per thousand workers in Germany was 7.6 in 2014. According to a recent survey of German firms with more than 100 employees in 2019, only 9 percent of

[13] See also Gaggl and Wright (2017) who show that in a sample of UK firms ICT tax credits did not only induce firms to undertake increased ICT investments, but also to adopt organizational changes at a higher rate. In the appendix, we show that our T&O measure is correlated with ICT investments as well as product improvement or innovation (Table A.1).

firms with 100-199 employees used artificial intelligence in the context of the recently adopted measures associated with the “fourth industrial revolution” (Bitkom, 2020). According to our measure, T&O is present across all sectors in the economy, as Panel A of Table 2 shows. This stands in contrast to robot adoption which exclusively occurs in the manufacturing sector, which in Germany employed 29.5% of the workforce in 1992 and 21.4% in 2010 (according to ALFS data of the OECD).

In Panel B of Table 2, we compare characteristics at baseline (i.e., at the beginning of the three-year measurement period) of firms that reorganize and firms that do not. Firms that carried out at least three organizational changes over a three-year period are larger than firms that implemented between one and two changes only, which in turn are larger than firms that did not adopt any change. Restructuring firms also pay higher wages, have a higher firm fixed effect and employ workers with a higher worker fixed effect at baseline than non-restructuring firms. They also employ a larger share of workers in abstract jobs.[14] All these differences, however, are quite small and largely disappear when comparing firms that implemented one to two versus three to four organizational changes.

2.2.2 Registry Data

Our second data source is the registry of social security records in Germany over the 1975 to 2010 period, which, in addition to unique worker and establishment identifiers, contains detailed information on factors such as workers’ wages, age, occupation, industry, and place of work. From this database, we select all individuals employed at least once in an IABEP firm (as of June 30 in a given year) together with all their (non-)employment spells before joining and after leaving the firm, thereby tracing out their pre- and post-T&O careers. As is typical in registry data, wages are censored at the social security limit. Following Dustmann,

[14] We employ the full registry data to compute a firm and worker fixed effect for each firm and worker in our sample estimated over rolling 7-year windows prior to T&O adoption, building on Abowd, Kramarz, and Margolis (1999) and Card, Heining, and Kline (2013).

Ludsteck, and Schönberg (2009), Card, Heining, and Kline (2013), and others, we impute the censored wages by assuming that wages are drawn from a normal distribution with a variance that depends on age, gender, and education (please see our Appendix section A.1 on censored wages for details). As detailed below, we use the occupation variable in the registry data, combined with detailed information on task usage from the Qualification and Career Survey to classify workers into those that hold manual, routine, or abstract jobs.

We differentiate between three roughly equally sized main age groups: individuals aged below 30, between 30 and 49, and above 50. In the firm level regressions, we restrict the sample to regular employees not in training and aged between 16 and 65; in the worker level regressions, we additionally exclude workers aged over 62 at the beginning of the observation period (who are thus over 65 at the time of observation).

We use the full registry data (as of June 30 and restricted to individuals between 16 and 65) to decompose the aggregate decline in the routine employment share into its various components, including selective firm entry and exit and within-firm declines, as explained in Section 2.1.2 and presented in Table 1. We further use full-time employment spells from the same full registry data to estimate wage regressions that include both a firm fixed effect and a worker fixed effect (as in Abowd, Kramarz, and Margolis, 1999, and Card, Heining, and Kline, 2013), in addition to controls for age, age squared, and year fixed effects. We estimate these regressions in 7-year rolling windows, starting with 1985–1992. Then, for each worker and firm in our sample, we merge in the pre-estimated worker and establishment fixed effects that refer to a 7-year period *before* T&O implementation.

2.2.3 The Qualification and Career Survey

To categorize the occupations in the registry data, we use detailed information from the 1991/1992 wave of the German BIBB/IAB Qualification and Career Survey (BIBB) on 19 activities performed at work, which we classify into routine, abstract, and manual tasks (see

Appendix Table A.2). Following Antonczyk, Fitzenberger, and Leuschner (2009), we proxy the time spent on each task type by each survey individual *i* as the number of tasks performed of type *j* divided by the total number of tasks performed:

$$\text{Task}_{ij} = \frac{\text{Number of tasks of type j performed by individual i}}{\text{Total number of tasks performed by i}}$$

Thus, if an individual carries out 6 tasks in total, 3 of which are routine tasks, the routine index is 0.5. We then aggregate the individual task indices at the 3-digit occupational level, use the maximum mean task index to classify the occupation as routine, manual, or abstract, and finally merge this information with the registry data, again at the 3-digit occupational level.

Table 3 (Panel A) shows that routine, abstract, and manual occupations across all years represent 37.1%, 45.2%, and 17.7% of employment in our sample, respectively. Abstract occupations enjoy a 33% wage premium over routine occupations, while wages in routine and manual occupations are roughly similar.

Table 3 (Panel B) further shows that over a three-year period, 4.76% of routine job holders in our sample upgrade to an abstract occupation and 2.46% do so within the firm. Common transitions from a routine to an abstract occupation include for example transitions from a warehouse worker to a technician or data processing specialist; or from a warehouse administrator to a consultant or data processing specialist.

Workers who move from a routine to an abstract occupation also experience higher wage growth than workers who stay in their abstract occupations, especially if movements occur within the firm, in line with the idea that such upgrades are associated with promotions. It should be noted however that the differences in wage growth between routine stayers and upgraders are small in comparison to the differences in wage levels between routine and abstract occupations.

3 Empirical Specification and Identification Strategy

We first explain how we estimate the extent to which a firm's T&O affects its employment shares of task and age-based worker groups (e.g., workers in routine vs. abstract jobs; younger vs. older workers). We then describe how we trace out the effect of T&O on the careers of workers whose jobs it affects.

3.1 Estimation at the Firm Level

Firm Level Regressions. Consider the following relationship between the employment share for workers of type *g* (e.g., workers in routine jobs or older workers) in firm *j* at time *t*, i.e. $S_{jt}^{g} = \frac{E_{jt}^{g}}{E_{jt}}$, and technological and organizational capital (TO_{jt}):

$$S_{jt}^{g} = \gamma^{g} TO_{jt} + \tau_{t}^{g} + f_{j}^{g} + e_{jt}^{g},$$

where τ_{t}^{g} denotes worker type-specific year fixed effects and f_{j}^{g} designates firm fixed effects that are allowed to vary across worker types. We estimate this regression in first differences, relating three-year *changes* in the employment shares of type *g* workers to *changes* in technological or organizational capital (ΔTO_{jt}):[15]

$$\Delta S_{jt}^{g} = \gamma^{g} \Delta TO_{jt} + \Delta\tau_{t}^{g} + \Delta e_{jt}^{g}. \tag{3}$$

We measure ΔTO_{jt} as the number of technological and organizational changes implemented by a firm over a three-year period, between *t-3* and *t*, corresponding to our measure of T&O as explained above.

By first differencing, we eliminate worker type-specific time-constant firm fixed effects f_{j}^{g} and any other (worker type-specific) time-constant variables such as industry and

[15] Results using wage bill shares as the dependent variable, as for example in Michaels, Natraj, and Van Reenen (2014), Caroli and van Reenen (2001), and Behaghel, Caroli, and Roger (2014) are very similar to those reported below. Caroli and van Reenen (2001) discuss how wage bill share equations emerge naturally from a setup in which the firm's cost function is assumed to be a restricted translog and firms minimize costs under given factor prices and fixed capital stock so that the only variable inputs are different types of labor (i.e., workers with different types of skills).

region fixed effects that may affect both the firm's demand for T&O, and for routine, abstract, or older jobholders. By focusing on changes in firms' group-specific employment *shares* as the dependent variable, we also differentiate out any firm-level shocks that proportionally affect labor demand for the different worker groups on the one hand, and T&O on the other hand (i.e., if a firm-specific shock increases the firm's labor demand for each worker group by 10%, then the respective employment shares in the firm will remain unchanged). We acknowledge that Equation (3) does not allow for firm-specific shocks that differentially affect worker groups and that may be correlated with T&O.

Hence, in Equation (3), a positive coefficient $\gamma^g > 0$ is indicative of complementarity, whereas a negative coefficient $\gamma^g < 0$ is indicative of substitutability between technological and organizational capital and the employment share of group g workers *at the level of the firm*.

We additionally adopt an even tighter specification that controls for worker type-industry-specific fixed effects (at the one-digit level, I_j^g) and worker type-location-specific fixed effects (50 commuting zones, R_j^g), as well as firm size (in logs) at baseline (FS_{jt-3}) in the first differenced Equation (3) (which corresponds to interactions of those same variables with time in a level equation). This specification thereby compares workforce composition shifts *in equally sized firms* that do and do not implement T&O *within* the same local labor market and industry, and results in the following first-difference equation:

$$\Delta \mathrm{S}_{jt}^g = \gamma^g \Delta TO_{jt} + \Delta\tau_t^g + I_j^g + R_j^g + \beta^g \mathrm{FS}_{\mathrm{jt-3}} + \Delta u_{jt}^g. \quad (4)$$

Equation (4) allows for the possibility that larger firms, certain industries or certain local labor markets experience shocks (e.g., an industry-level trade shock or a local labor supply shock) that differentially affect firms' labor demand for certain worker groups, and at the same time induce the firm to implement T&O. When estimating (3) and (4), we weight firm level observations by employment at baseline and cluster our standard errors at the firm level.

3.2 Estimation at the Worker Level

To investigate T&O's effects on the careers of workers, we estimate specifications of the following type:

$$\mathrm{y}_{ij't}^{g'} = \gamma^{g'} \Delta TO_{j't} + I_{j'}^{g'} + R_{j'}^{g'} + \tau_t^{g'} + \delta_1^{g'} \mathrm{FS}_{\mathrm{j't-3}} + \boldsymbol{x}'_{it-3}\delta_2^{g'} + \delta_3^{g'} O_{ij't-3}^{g'} + \delta_4^{g'} \hat{f}_{j'} + \delta_5^{g'} \hat{\theta}_{it-3} + e_{ij't}^{g'} \tag{5}$$

Here *j'* denotes the firm at which worker *i* was employed in *t*-3 (the baseline firm) and *g'* designates the group to which worker *i* belonged at baseline (e.g., employed in a routine job), so that $\mathrm{y}_{ij't}^{g'}$ measures the career outcome at time t (e.g., employment or upgrading) of worker i who was employed in firm j' and belonged to group g' in the baseline period $t-3$. Analogous to our firm level regressions, $\Delta TO_{j't}$ denotes the number of organizational changes implemented over a three-year period (*t-3* to *t*) by the firm at which individual *i* was employed at baseline (in *t-3*).

Our registry data allow us to control for an unusually wide variety of worker and firm characteristics that may be correlated with T&O adoption and career outcomes alike. As in the tighter firm level regression (4), we control for worker type-specific industry and commuting zone fixed effects $I_{j'}^{g'}$ and $R_j^{g'}$ of the baseline firm, in addition to worker type-specific year fixed effects, $\tau_t^{g'}$. These control variables address concerns that T&O may occur more frequently in certain industries and local labor markets where transitions into non-employment may be less and occupational upgrading more common. Our control variables further include the size of the firm at baseline ($\mathrm{FS}_{\mathrm{j't-3}}$) as well as several individual baseline characteristics $(\boldsymbol{x}'_{it-3})$ that may be correlated with career outcomes (gender, foreign citizenship, and age). We allow the effects of these firm and individual characteristics to vary by worker group *g'*.[16] To rule out the possibility that the occupational structure may differ in

[16] In practice, we estimate worker level regressions separately by worker group.

restructuring and non-restructuring firms, and that workers within the same broad (e.g., routine) occupational group work in different narrow occupations, some of which may facilitate occupational upgrading more than others, we include very detailed (three-digit) fixed effects for the occupation the worker was employed in at baseline ($O^{g'}_{ij't-3}$).

To account for the possibility that restructuring firms are high-wage firms that offer differential career prospects to their employees irrespective of organizational change, we additionally control for (baseline) firm wage fixed effects ($\hat{f}_{j'}$), pre-estimated jointly with worker fixed effects on the full registry wage data or the *t-9* to *t-3* period (see Section 2.2.2). Likewise, to allow for the possibility that restructuring firms employ high-wage workers unlikely to transit into non-employment and prone to upgrade to higher paying jobs, we further condition on worker wage fixed effects ($\hat{\theta}_{it-3}$), also pre-estimated jointly with the firm fixed effects on the full registry data for the *t-9* to *t-3* period.

Our empirical analysis focuses primarily on routine job holders and older workers, the two groups of workers that are likely hit hardest by T&O. To paint a detailed picture of how T&O affects worker careers, we consider the following main outcome variables ($y^{g'}_{ij't}$): whether the individual is working; the earnings ratio (i.e. daily wage in year *t*, set to zero if the worker is not working, divided by daily wage in *t-3*); whether the individual has left the firm; whether the individual is working in a manual, routine or abstract occupation; or whether the individual has upgraded to an abstract occupation within the same or a different firm. In our baseline specifications, we measure these outcomes up to three years after the implementation of T&O. In some cases, we also adopt a more long-term perspective and analyze the impact on workers' career outcomes over a six-year period. We cluster standard errors at the baseline firm level.

As a robustness check, we further estimate worker level regressions that condition on firm fixed effects that refer to the firm the worker was employed in at baseline ($\zeta_{j'}$), while controlling for the same set of variables as in regression Equation (4). When focusing on the effects of T&O on career outcomes for workers who performed different tasks at baseline, the estimated regression is:

$$\mathrm{y}_{ij't}^{g'} = \gamma^R \Delta TO_{j't} + \gamma^A \Delta TO_{j't} \cdot A_{it-3} + \gamma^M \Delta TO_{j't} \cdot M_{it-3} + \tau_t^{g'} + \delta_1\ \mathrm{FS}_{\mathrm{j't-3}} + x'_{it-3}\delta_2 \ + \delta_3\ O_{ij't-3}^{g'} + \delta_4\ \hat{f}_{j'} + \delta_5^{g'} \hat{\theta}_{it-3} + \zeta_{j'} + \tilde{e}_{ij't}^{g'} \qquad (6)$$

where A_{it-3} and M_{it-3} are indicator variables that are equal to 1 if individual *i* performed abstract or manual tasks at baseline, respectively. In this regression, we leverage variation in T&O within firms over time (i.e. firms may not implement any T&O in some three-year periods but may do so in others) to estimate the impact of T&O on career outcomes on routine job holders (γ^R in the Equation (6)). The coefficients γ^A and γ^M then pick up the impact of T&O on career outcomes of abstract and manual workers *relative to routine workers in the same firm*. By conditioning on baseline firm fixed effects $\zeta_{j'}$, this regression allows for an arbitrary correlation between time-constant firm-specific factors that affect T&O and career outcomes alike.

4 Results

4.1 Effects of T&O on Jobs

4.1.1 T&O and Firm Workforce Composition

Firm Level Regressions. In Table 4, we present results based on Equations (3) and (4) to determine whether and to what extent firm T&O affects workforce composition in terms of tasks and age. In Columns (1), we control only for year fixed effects (as in Equation (3)); in Columns (2), we add controls for firm size at baseline, commuting zones, and industry (as in Equation (4)). As Panel A shows, T&O is associated with a reduction in the employment share of routine jobs, with each organizational change over the previous three years reducing this share by between 0.227 and 0.363 percentage points. Given the average 1.2 percentage point overall reduction in the routine employment share over a three-year period (last row of Panel A), this response is substantial. The estimated reduction in Column (2) implies that each additional organizational change can account for about 19% of the overall decline in routine employment over that period. Given that firms may adopt up to four organizational changes over a three-year period, multiple changes have an even larger impact on routine employment shares. Panel A also shows that the reduction in the routine employment share is accompanied by an increase in the abstract employment share of roughly the same magnitude, while the manual employment share remains largely unchanged.

Panel B of Table 4 reveals the age bias of T&O by showing the relation between T&O and changes in the employment shares of younger (aged below 30), medium-aged (aged between 30 and 49), and older workers (aged 50 and above). That is, although T&O is not associated with any change in the employment share of younger workers, it is associated with an increase in the employment share of medium-aged workers and with a decrease in the employment share of older workers. We confirm similar associations when we use alternative measures of T&O, such as ICT investments and whether the firm introduced a new or improved an existing product (see Appendix Table A.3).[17]

In Panel C of Table 4, we regress changes in the task-specific employment shares on both *contemporaneous* and *future* T&O with the sample restricted to firms who participated in the IABEP over two consecutive three-year periods. The estimated effects of contemporaneous T&O for this restricted sample are similar to those for the full sample (Panel A). Future T&O, in contrast, has little impact on firm workforce composition, which

[17] To investigate whether our findings are driven by one specific element of our measure of T&O, we eliminate one of the four elements at a time (Appendix Table A.4). Estimates are similar to our baseline results in Panels A and B of Table 4, suggesting that all four organizational changes (merging of departments, shifting of responsibilities, introduction of teamwork and introduction of cost centers) contribute to the decline in the employment share of routine jobs and older workers.

highlights that firms adjust their employment task structure during the three-year period when T&O is implemented, and not in the three-year period *before* T&O takes place.

Comparison with Industry Level Regressions. To compare our estimates from firm-level regressions with estimates from industry level regressions such as estimated in Michaels at al. (2014), we next aggregate information on T&O from our firm-level data at the 2-digit industry level (which roughly corresponds to the industry aggregation used in Michaels et al., 2014), and regress changes in the employment shares of various task groups in the industry (obtained from the full registry data) on T&O in that industry, controlling for year fixed effects (Table 5). Estimates are considerably larger than those in Columns (2) in Table 4. One explanation for the stronger association at the industry than the firm level is that the industry level estimates do not only capture the effects of T&O on within-firm changes in routine employment shares, but also the effects of T&O on selective entry and exit and differential employment growth of routine intensive firms.

We investigate these alternative adjustment margins to T&O in Panel B of Table 5, by breaking down the overall change in the routine employment share in the industry into its various components as indicated in Equations (1) and (2) and using these as dependent variables in the industry level regressions. Even though selective entry and exit of routine-intensive firms play only a minor role in accounting for the aggregate decline in the routine employment share (see Table 1), it accounts for about one fourth (0.215/0.91) of the association between T&O and the overall decline in routine employment at the industry level (Panel B1 of Table 5). Yet, in line with the aggregate evidence in Table 1, the association between T&O and the decline in the routine employment share at the industry level is primarily a within-firm phenomenon; in contrast, the industry-level associations between T&O and differential employment growth is small in magnitude (see Panel B2 of Table 5).[18]

4.1.2 T&O, Firm Growth, and Reshuffling

One might expect T&O to not only have a substitution effect, leading to a reduction in the number of routine jobs, but also a scale effect, leading to an increase in overall firm size. However, firms' total employment of routine jobholders may well increase even though their routine employment share declines. Alternatively, a reduction in the latter, accompanied by an increase in the abstract employment share, could also be driven by routine jobholders switching to abstract occupations within the firm ("internal reshuffling"). In Table 6, we provide initial evidence on the relation between T&O and firm growth, hiring, internal reshuffling, and worker separations, based on the estimation of firm level regressions of specification (4).

As the table shows, conditional on year, commuting zone, industry fixed effects, and baseline firm size, each additional organizational change is associated with a slight (statistically insignificant) increase in firm wages and employment. The increase in employment is driven by both a decrease in the separation rate (the number of workers leaving the firm over the three-year period divided by employment at baseline) and a (statistically significant) increase in the external hiring rate (the number of workers joining the firm over the three-year period divided by employment at baseline). Estimates in the last column provide clear evidence that T&O is associated with more internal task reshuffling (measured as the number of continuing employees who changed task over the three-year period divided by baseline employment). Even though the estimated coefficient is only half

[18] It should be noted that the association between T&O and the decline in the routine employment share continues to be larger at the industry than at the firm level even when we consider within-firm changes in routine employment only as the dependent variable. This is because the two types of regressions leverage different variation in T&O (across industries versus across firms within industries in Equation (4)).

the size as the estimated coefficient for the external hiring rate, this is a large effect if evaluated against the reshuffling rate at baseline (1.20%).

4.2 Effects of T&O on Jobholders

Our analysis so far revealed that T&O reduces firms' relative demand for routine-based *jobs*. We now explore how *workers* who held routine-based jobs before T&O implementation are affected by T&O. Do they exit into non-employment, downgrade to manual occupations, or upgrade to abstract occupations? If the latter holds true, does this upgrading take place within the same firm and how do these transition rates differ by workers' age?

4.2.1 Transitions for Routine Jobholders

For workers who hold a routine job at baseline (Table 7, Panel A), estimates based on Equation (5) show that T&O decreases the probability to be employed in a routine occupation three years later (Column (3)), in line with our findings that T&O reduces the firm's routine employment share (Table 4, Panel A). While this effect is somewhat imprecisely estimated for three-year transitions (p-value of 0.118), it increases in magnitude and turns statistically significant for six-year transitions. Yet, for three-year transitions, T&O appears to neither affect the probability that these workers will transit into non-employment[19] (Column (1)) nor increase the probability that they will downgrade to a manual occupation (Column (2)). Rather, T&O primarily increases the probability of a routine jobholder being assigned to an abstract occupation (Column (4)). This effect is not only highly statistically significant but also large in magnitude if evaluated against the overall probability of switching tasks from routine to abstract within the same firm over a three-year period (2.93%). In fact, for three-year transitions, a remarkable 69% (0.150/0.218) of routine jobholders affected by T&O respond to T&O by upgrading to an abstract occupation. In line with the evidence in Table 6,

[19] This may include self-employment, irregular employment and migration outside of Germany, since those are not recorded in our Registry data.

75% (0.113/0.150) of the switches to abstract occupations take place within firms. Moreover, T&O is not associated with a lower earnings ratio of workers holding routine jobs at baseline (Column (7)). Turning to six-year transitions, upward movements to abstract occupations continue to be important, but now predominantly occur between firms. At the same time, downward movements toward manual occupations following T&O become more frequent. While the effect of T&O on the earnings ratio is negative in the six-year regressions, the effect is not statistically significant and small in magnitude and, as we show in Panels B and C below, entirely driven by routine job holders older than 49.

Overall, the estimates provide little support for the view that T&O harms the careers of routine jobholders, in large part because it increases the probability of them undertaking different tasks within the same firm, and across firms in the longer run.

4.2.2 Transitions of Routine Jobholders by Age

To explore (three-year) transitions of routine jobholders in more detail, we repeat the analysis in Panel B of Table 7, but now split our sample into three roughly equal-sized age groups: younger workers (aged below 30), medium aged workers (between 30 and 49), and older workers (50 and above).[20] The findings show that T&O increases upward movements from routine to abstract occupations for all age groups, but particularly for workers younger than 50. Whereas for workers under 30 upgrades occur to a similar extent both within and between firms, for workers aged 50 and above, almost all upgrades into abstract occupations take place within the firm. Contrasting estimates in Columns (1) and (3) further reveals that transitions into non-employment are a quantitatively important (but imprecisely estimated) adjustment channel for older workers: 89% (0.628/0.701) of older routine jobholders affected by T&O respond to T&O by moving into non-employment.

[20] Results from six-year transitions broken down by age groups can be found in Appendix Table A.5. They corroborate the findings from the three-year regressions.

To better understand which age groups among older workers are particularly affected by T&O, we further distinguish between those aged 50–54, 55–59, and >59 (Table 7, Panel C). Our estimates indicate that upgrading to abstract occupations within the same firm is an important adjustment channel only for routine jobholders aged between 50 and 54, but not for workers older than 54. In contrast, routine jobholders older than 54 respond to T&O primarily by leaving employment. According to our longitudinal data that allow us to follow these workers over the next decade, most such movements are permanent and likely to represent transitions into early retirement.

4.2.3 Firm Training Activities

Our results so far imply that firms can play an important role in actively curtailing T&O's harmful effects by offering upgrading opportunities to routine jobholders. This interpretation is further supported by the results in Table 8, which highlights that T&O is associated with a rise in firms' internal and external training activities (based on regressions of firms' employment share in training on T&O, as well as year, commuting zone, and industry fixed effects as well as (log) baseline firm size). Not all workers benefit equally, however. Training activities increase for medium- and high-skilled workers (i.e., workers with an apprenticeship or university degree) more than for low-skilled workers (i.e., workers without postsecondary education).

4.2.4 Labour Market Transitions of Older Workers

The findings in Table 7 show that T&O results in routine jobholders aged 55 and over transitioning predominantly into non-employment and thus seem to be benefiting little from a larger number of firm training opportunities. These observations suggest that for firms and workers to undertake investment in new skill acquisition, the period over which this investment amortizes must be sufficiently long, which makes it not worthwhile for routine jobholders aged 55 and over who are near retirement age. Older workers might also find it more difficult to learn the new skills required after T&O implementation.

For a better understanding of how older workers are affected by T&O more generally, we next explore whether T&O also increases non-employment rates for older abstract jobholders or whether a university education shields older workers from such adverse effects. According to Table 9, T&O increases the probability that workers over 55 separate from the firm and move to non-employment regardless of whether they were previously employed in a manual, routine, or abstract occupation. These effects are as strong for high-skilled workers as for low- or medium-skilled workers. Hence, neither employment in a (previously) abstract occupation nor a university education appear to cushion T&O's adverse career effects on older workers. Rather, our results support the notion that investing in new skill acquisition may be less worthwhile for older workers close to retirement, as the pay-off period to any investment is short.

4.2.5 Robustness Checks

Our estimates in Table 7 and Table 9 condition on a wide array of baseline worker and firm characteristics typically not available in other data sources, such as (pre-estimated) firm and worker wage fixed effects ($\hat{f}_j$, and $\hat{\theta}_{it-3}$ in Equation (3)); the worker's occupation, age and gender; the firm's industry affiliation and location as well as its size. Controlling for these variables should eliminate all obvious sources of bias.

Nevertheless, to provide additional support for the hypothesis that the association between T&O and routine jobholders' upward movement from routine to abstract occupations and T&O and older workers' movements into non-employment reflect a causal relation, we perform an event study as a robustness check. We summarize these findings in Figure 3. The figure contrasts firms that do not introduce T&O between *t*-3 and *t* but implement at least two changes between t and *t*+3 (treated firms) with firms that carry out no changes over the entire *t*-3 to *t*+3 period (control firms). Figure 3a plots the number of organizational changes implemented by treatment and control firms in each three-year period, between *t*-6 and *t*+6. By construction, neither treatment nor control firms implement any T&O between *t*-3 and *t* (the pre-treatment period). In the treatment period (between *t* and *t*+3), treatment firms implement 2.6 changes on average, compared to no changes in control firms. Treatment firms also introduce more organizational changes than control firms in the *t*+3 to *t*+6 post-treatment period (1.3 vs 0.4 on average).

Figure 3b shows that upgrading from routine to abstract occupations in treatment relative to control firms predominantly occurs in the *t* to *t*+3 treatment period, during which treatment firms adopt at least two organizational changes while control firms do not adopt any. Likewise, differences between treatment and control firms in the transition rates of older workers into non-employment are largest in the treatment period *t* vs *t+3* when differences in T&O activities between the two types of firms are largest. Moreover, for both upgrading and transitions into non-employment, differences in transition rates between treated and control firms are very similar in period *t-6* to *t-3* and period *t-3* to *t*, suggesting that the two types of firms exhibit similar trends in transition rates leading up to the uptake of T&O. Overall, these findings support the hypothesis that transitions into abstract occupations (of routine job holders) and non-employment (of older workers) are indeed caused by T&O.

In Figure 3, we leverage variation in T&O within firms over time to gauge the effects of T&O on upgrading of routine job holders and employment for older workers. In Table 10 we take this idea further and report estimates of T&O effects on workers' career outcomes more generally, exploiting once again variation in T&O within firms over time to identify effects, by controlling for firm fixed effects in the regressions as in Equation (6). For routine job holders (row (i) in Panel A), estimates indicate that T&O has no significant effect on employment and earnings but reduces the probability of remaining employed in the same task and increases the probability of being employed in a different task, in line with our previous findings. Our findings further highlight that routine job holders are less likely to be employed in the same task and also more likely to be employed in a different task relative to their colleagues in abstract and manual occupations in the same firm. The findings of Table 10 Panel B further illustrate that T&O pushes older workers out of their previous task and into non-employment and reduces their earnings relative to their younger colleagues in the same firm as well.

4.3 Task Upgrading, Education and Labour Market Institutions

Overall, our findings suggest that, supported by firms' training opportunities, routine jobholders younger than 55 affected by T&O respond by moving from routine to abstract occupations, rather than to non-employment or manual and/or lower paid jobs. An important question is whether this upgrading is facilitated by particular institutional and firm characteristics.

Facilities inside the firm that support retraining of workers may be a first factor that promotes upgrading following T&O. For example, firms that routinely train young workers may find it easier and less costly to provide the necessary support for more experienced workers to upgrade to an occupation with more abstract skill content. Germany has a well-established youth training scheme (apprenticeship system) that educates nearly 65% of school leavers and equips them with both practical skills through hands-on training inside a firm and academic skills through classroom-based learning in vocational schools (see Dustmann, 2004 for details). To qualify as a training firm, firms need to fulfill certain conditions, such as employing qualified training personnel (see Dustmann and Schönberg, 2012, for details). We might therefore expect that firms that train a larger share of young workers through the apprenticeship scheme are also more likely to retrain adult workers when they carry out T&O.

To investigate this hypothesis, we exploit variation in the employment share of apprentices in the firm at baseline (i.e., the number of apprentices divided by all employees in year *t-3*). We regress workers' career outcomes at time *t* on T&O implemented by the baseline firm between *t-3* and *t*, the share of apprentices at baseline (at *t-3*), and an interaction of both variables, in addition to our usual control variables. The estimates in Panel A of Table 11 show that a higher share of apprentices in the firm at baseline does indeed significantly increase the probability that a routine jobholder succeeds in moving up to an abstract occupation following T&O (Column (2)). The estimates imply that T&O has no impact on upgrading from routine to abstract jobs in firms that did not train any apprentices at baseline (25% of firms), but increases upward movements to abstract jobs by 0.13 percentage points in firms with an apprenticeship share at the median (2.89%, i.e. 4.369*0.029-0.003) and by 0.51 percentage points in firms with an apprenticeship share at the 90th percentile (11.1%, i.e. 4.369*0.111-0.003). Estimates in Columns (3) and (4) further highlight that firms' involvement in apprenticeship training predominantly affects upgrades within firms rather than between firms. Overall, these findings suggest that firms experienced in the training of young workers are more likely to retrain adult workers when T&O renders their existing skills obsolete.

The presence of formal worker representation in the firm may be a second factor that facilitates upgrading of workers following T&O, in particular if unions actively support the skill acquisition of workers throughout their career. Unions in Germany play an active role in advising and supporting firms and workers in all matters of apprenticeship and further training,[21] but have no direct control over layoffs and hiring. In our sample, 52% of firms are members of an employer association and 84.5% of workers are covered by union agreements through their firms' membership. To test whether unions promote upgrading following T&O,

[21] See for example https://www.igmetall.de/besser-mit-bildung-tarifvertraege-sichern-weiterbildung-12923.htm; https://www.igbce.de/themen/bildung/weiterbildung/analyse-instrumente/14072; https://www.igbau.de/Bildung_Berufsbildung.html.

we estimate similar regressions as in Panel A, but now interact the firm's membership in an employer association ("union recognition") with T&O. The findings in Panel B of Table 11 suggest that unions may indeed play an important role in facilitating within-firm (but not between-firm) upward movements from routine to abstract occupations following T&O: such upgrading takes place only in firms that recognize a union.

5 Discussion and Conclusions

Based on 18 years of detailed T&O data combined with entire work histories for those workers who were ever employed in surveyed firms, we first show that, in line with the routine-bias (or routine-replacing) technological change hypothesis, firms that implement T&O reduce their employment share of workers in routine jobs. Yet, workers holding routine jobs at T&O implementation do not suffer employment losses or reduced earnings growth on average. Rather, they succeed in moving up to more abstract jobs, often facilitated by firms' training opportunities.

Despite this lack of harm *on average*, we also demonstrate a decline in employment prospects of routine jobholders over 55 years of age, who withdraw permanently from the labor market. Interestingly, T&O leads to withdrawal not only for older workers in routine jobs but also for older workers in abstract jobs, including those with a university degree.

Although older workers seem to suffer from T&O, our findings first and foremost highlight that changing skill requirements caused by technological innovations need not result in a large welfare loss even for those workers whose jobs disappear and whose current skills become partially obsolete. Rather, firms may accomplish the necessary skill upgrading by training workers who lack the required skills, as opposed to replacing them with workers who already possess those skills.[22]

[22] Retraining and upskilling incur costs, which are difficult to quantify and will affect the overall welfare effects.

Our findings for Germany contrast with the common view driven mostly by US-based research that new technologies and accompanying organizational restructuring led to non-employment or a deterioration in job quality for a large fraction of the workforce. For example, Cortes, Jaimovich, and Siu (2017) conclude, based on CPS data, that those groups that are most affected by a decline in employment in routine jobs are increasingly likely to be non-employed. In a New York Times article, Autor and Dorn (2013) argue that computerization has led to job degradation for a large group of workers. In a similar vein, Acemoglu and Restrepo (2019) report substantial job losses caused by industrial robot usage across commuting zones. One reason for why we draw different conclusions could be differences in methodology and data—existing studies for the US do not directly investigate the impact of T&O (measured at the firm level) on *workers* by following them across commuting zones and industries, as we do. However, different conclusions may also be due to fundamental differences between the German and the US labor markets. Being characterized by consensus-based industrial relations, with most workers trained within firm-based apprenticeship schemes, the German labor market may simply respond differently to technological change. Anecdotal evidence supports this view. For example, Volkswagen's production site in the German town of Zwickau has, in agreement with its trade union, committed to intensively upskill its workforce when implementing a large-scale automation program, the switch from the production of petrol cars to (more capital-intensive) electric cars.[23] Labor market institutions may therefore affect the way technological change impacts workers and their welfare. We find some evidence in line with this hypothesis: the upgrading of routine workers to abstract tasks in response to organizational restructuring takes place

[23] See for example the article in the leading German national newspaper *Die Zeit* on July 8 2019 (https://www.zeit.de/wirtschaft/2019-07/automatisierung-volkswagen-vw-arbeitsplaetze-roboter-elektromobilitaet-werk-zwickau). In a similar vein, Bosch, Europe's largest car parts supplier, will spend a total of about €2bn on retraining to limit further job losses; see for example the article in the *Financial Times* on February 9 2022 (Bosch to spend €2bn on reskilling workers as car industry shifts to electric | Financial Times).

predominantly in firms that recognize a union and is increasing in the training “know-how” of the firm, measured as the share of apprentices in the firm. The wide-spread apprenticeship system and unions’ involvement in training activities may therefore promote upward movements from routine to abstract jobs following T&O, and thus help lessen T&O’s possibly harmful career effects.

Our findings not only highlight that there are possibilities to cushion T&O’s adverse effects on the workforce through in-firm training, likely without compromising competitiveness. They also have significant implications beyond the labor market. For example, if economic factors do indeed play an important role in explaining the recent rise of populism,[24] then institutions that can shield vulnerable workers from the possibly negative consequences of technological progress (and globalization) may also have far-reaching political consequences.

[24] Recent evidence suggests that increased import competition from China (Autor et al., 2016) or globalisation more generally (Rodrik, 2018) may affect political preferences and the support for populist movements. A recent op-ed in the Financial Times (https://www.ft.com/content/5557f806-5a75-11e7-9bc8-8055f264aa8b/) offers a more general discussion on the role of economic factors leading to the rise of populism over recent years.

References

Abowd, John M, Francis Kramarz, and David N Margolis. 1999. “High Wage Workers and High Wage Firms.” *Econometrica* 67 (2): 251–333.

Acemoglu, Daron, and David Autor. 2011. “Skills, Tasks and Technologies: Implications for Employment and Earnings.” In *Handbook of Labor Economics*, 4B:1043–1171.

Acemoglu, Daron, and Pascual Restrepo. 2019. “Robots and Jobs: Evidence from US Labor Markets.” *Journal of Political Economy (forthcoming).*Akerman, Anders, Ingvil Gaarder, and Magne Mogstad. 2015. “The Skill Complementarity of Broadband Internet.” *Quarterly Journal of Economics* 130 (4): 1781–1824.

Antonczyk, Dirk, Bernd Fitzenberger, and Ute Leuschner. 2009. “Can a Task-Based Approach Explain the Recent Changes in the German Wage Structure?” *Jahrbuecher Fuer Nationaloekonomie Und Statistik* 229 (2-3): 214–38.

Aubert, Patrick, Eve Caroli, and Muriel Roger. 2006. “New Technologies, Organisation and Age: Firm-Level Evidence.” *Economic Journal* 116 (509): F73–93.

Autor, David, and David Dorn. 2009. “This Job is ‘Getting Old’: Measuring Changes in Job Opportunities Using Occupational Age Structure.” *American Economic Review* 99 (2): 45–51.

Autor, David H, and David Dorn. 2013. “The Growth of Low-Skill Service Jobs and the Polarisation of the US Labor Market.” *American Economic Review* 103 (5): 1553–97.

———. 2013. “How Technology Wrecks the Middle Class.” *New York Times Opinion Pages*. https://opinionator.blogs.nytimes.com/2013/08/24/how-technology-wrecks-the-middle-class/.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. “The Skill Content Of Recent Technological Change: An Empirical Exploration.” *Quarterly Journal of Economics* 118 (4): 1279–1333.

Bahnmüller, Rainhard. 2009. “Tarifverträge Als Instrument Der Beruflichen (Weiter) Bildung in Deutschland.” *Forschungsinstitut Für Arbeit, Technik Und Kultur Der Universität Tübingen.*

Bárány Zsófia L. and Christian Siegel, 2018. "Job Polarisation and Structural Change," *American Economic Journal: Macroeconomics* 10(1): 57-89. January.Bartel, Ann P, and Nachum Sicherman. 1993. “Technological Change and Retirement Decisions of Older Workers.” *Journal of Labor Economics* 11 (1): 162–83.

Bitkom Research. 2020. *Industrie 4.0 - so digital sind Deutschlands Fabriken*, Report by Bitkom President Achim Berg, retreaved from here https://www.bitkom.org/sites/default/files/2020-05/200519_bitkomprasentation_industrie40_2020_final.pdf on 7 February 2022

Bauer, Thomas, and Stefan Bender. 2004. “Technological change, organisational change, and job turnover.” *Labour Economics* 11 (3): 265-291.

Beckmann, Michael. 2007. “Age-Biased Technological and Organisational Change: Firm-Level Evidence and Management Implications.” *WWZ Discussion Paper No. 05/07*. Faculty of Business and Economics - University of Basel.

Behaghel, Luc, Eve Caroli, and Muriel Roger. 2014. “Age-Biased Technical and Organisational Change, Training and Employment Prospects of Older Workers.” *Economica* 81 (322): 368–89.

Behaghel, Luc, Eve Caroli, and Emmanuelle Walkowiak. 2012. “Information and Communication Technologies and Skill Upgrading: The Role of Internal vs External Labour Markets.” *Oxford Economic Papers* 64 (3): 490–517.

Behaghel, Luc, and Nathalie Greenan. 2012. “Training and Age-Biased Technical Change.” *Annals of Economics and Statistics / Annales d’Economie et de Statistique*, no. 99/100: 317–42.

Black, Sandra E., and Alexandra Spitz-Oener. 2010. “Explaining Women’s Success: Technological Change and the Skill Content of Women's Work.” *Review of Economics and Statistics* 92 (1): 187–94.

Bloom, Nicholas, Raffaella Sadun and John Van Reenen. 2016. Management as a Technology? *NBER Working Papers 22327*. National Bureau of Economic Research.

Bresnahan, Timothy F., Erik Brynjolfsson, and Lorin M. Hitt. 2002. “Information Technology, Workplace Organisation, and The Demand for Skilled Labor: Firm-Level Evidence.” *Quarterly Journal of Economics* 117 (1): 339–76.

Card, David, Jörg Heining, and Patrick Kline. 2013. “Workplace Heterogeneity and the Rise of West

German Wage Inequality.” *Quarterly Journal of Economics* 128: 967–1015.

Caroli, Eve, and John Van Reenen. 2001. “Skill-Biased Organisational Change? Evidence from a Panel of British and French Establishments.” *Quarterly Journal of Economics* 116 (4): 1449–92.

Cortes, Guido Matias. 2016. “Where Have the Middle-Wage Workers Gone? A Study of Polarisation Using Panel Data.” *Journal of Labor Economics* 34 (1): 63–105.

Cortes, Guido Matias, Nir Jaimovich, and Henry E Siu. 2017. “Disappearing Routine Jobs: Who, How, and Why?” *Journal of Monetary Economics* 91: 69–87.

Dauth Wolfgang, Sebastian Findeisen, Jens Suedekum, Nicole Woessner. 2021 The Adjustment of Labor Markets to Robots, *Journal of the European Economic Association* 19 (6): 3104–3153

Dustmann, Christian, Johannes Ludsteck, and Uta Schönberg. 2009. “Revisiting the German Wage Structure.” *Quarterly Journal of Economics* 124 (2): 843–81.

Dustmann, Christian, and Uta Schönberg. 2009. “Training and Union Wages.” *Review of Economics and Statistics*, 91 (2): 363–376.

Dustmann, Christian, and Uta Schönberg. 2012. “What Makes Firm-Based Vocational Training Schemes Successful? The Role of Commitment.” *American Economic Journal: Applied Economics* 4 (2): 36–61.

Feng, Andy, and Georg Graetz. 2019. “Training Requirements, Automation, and Job Polarisation,.” *Economic Journal (forthcoming)*.

Fountaine Tim, Brian McCarthy, and Tamim Saleh. 2019. Building the AI-Powered Organization - Technology isn’t the biggest challenge. Culture is. Harvard Business Review, July-August 2019. https://hbr.org/2019/07/building-the-ai-powered-organization

Gaggl, Paul, and Greg C. Wright. 2017. “A Short-Run View of What Computers Do: Evidence from a UK Tax Incentive.” *American Economic Journal: Applied Economics* 9 (3): 262–94.

Goos, Maarten, and Alan Manning. 2007. “Lousy and Lovely Jobs: The Rising Polarisation of Work in Britain.” *Review of Economics and Statistics* 89 (1): 118–33.

Graetz, Georg, and Guy Michaels. 2017. “Is Modern Technology Responsible for Jobless Recoveries?” *American Economic Review* 107 (5): 168–73.

———. 2018. “Robots at Work.” *Review of Economics and Statistics* 100 (5): 753-768.

Hægeland, Torbjørn, Dag Rønningen, and Kjell G. Salvanes. 2007. “Adapt or Withdraw? Evidence on Technological Changes and Early Retirement Using Matched Worker-Firm Data.” *Discussion Paper No. 509*. Statistics Norway, Research Department.

Lynch, Lisa M., and Sandra E. Black. 1998. “Beyond the Incidence of Employer-Provided Training.” *Industrial and Labor Relations Review* 52 (1): 64–81.

Makarius Erin E., Debmaly Mukherjee, Joseph D.Fox and Alexa K.Fox. 2020. “Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization”, Journal of Business Research, Volume 120, November 2020, Pages 262-273. https://www.sciencedirect.com/science/article/pii/S0148296320305002

Michaels, Guy, Ashwini Natraj, and John Van Reenen. 2014. “Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years.” *Review of Economics and Statistics* 96 (1): 60–77.

Parent, Daniel. 1999. “Wages and Mobility: The Impact of Employer-Provided Training.” *Journal of Labor Economics* 17(2): 298-317

Rodrik, Dani. 2018. “Populism and the Economics of Globalisation.” *Journal of International Business Policy 1(2) 12-33..*

Rønningen, Dag. 2007. “Are Technological Change and Organisational Change Biased against Older Workers? Firm-Level Evidence.” *Discussion Paper No. 512, Statistics Norway*. Statistics Norway, Research Department.

Seitz, Beate. 1997. “Tarifierung von Weiterbildung: Eine Problemanalyse in Der Deutschen Metallindustrie.” *eBook, Springer Verlag, Wiesbaden.*

Spitz-Oener, Alexandra. 2006. “Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure.” *Journal of Labor Economics* 24 (2): 235–70.

Table 1: The Decline in the Aggregate Routine Employment Share: Margins of Adjustment

Panel A: Changes among Surviving Firms and Selective Firm Entry and Exit

	Overall Change	Change among Surviving Firms	Selective Firm Entry and Exit
1992-2010	-0.0919	-0.0856	-0.0064
1992-1998	-0.0412	-0.0350	-0.0062
1998-2004	-0.0290	-0.0271	-0.0019
2004-2010	-0.0217	-0.0214	-0.0003

Panel B: Within-Firm Changes (Weighted) and Differential Wage Growth among Surviving Firms

	Change among Surviving Firms	Within-Firm Changes (Weighted)	Differential Employment Growth	Interaction Term
1992-2010	-0.0856	-0.0730	-0.0387	0.0304
1992-1998	-0.0350	-0.0329	-0.019	0.0169
1998-2004	-0.0271	-0.0284	-0.0109	0.0121
2004-2010	-0.0214	-0.0187	-0.0131	0.0105

Notes: The table presents the results from an exercise that decomposes the decline of the routine employment share in the economy into various components. Panel A quantifies, based on Equation (1), the importance of selective entry and exit of routine- vs abstract- or manual-intensive firms. Panel B further decomposes, based on Equation (2), the decline in the routine employment share among surviving firms into within-firm changes, differential employment growth of surviving routine-intensive firms, and an interaction term capturing co-movements between employment growth and the change in the routine employment share in the firm.

Sources: Registry data for years 1993–2010. We calculate task shares based on a categorization constructed using the 1991/1992 wave of the German BIBB/IAB Qualification and Career Survey.

Table 2: T&O: Descriptives (Worker Weighted)

Panel A: Organizational changes and alternative measures of technological change

	Number of changes over past 3 years		
	0	1 or 2	3 or 4
(i) percentage of workers employed in firms with ….. changes	44.32%	43.29%	12.39%
(ii) by sector (five largest broad sectors)			
Manufacturing of Producer Goods	32.58%	52.36%	15.05%
Manufacturing of Investment Goods	31.65%	47.98%	20.38%
Wholesale and Retail Trade	50.05%	39.94%	10.01%
Health and Social Work	47.83%	40.93%	11.23%
Real Estate, Renting and Business Services	47.86%	40.23%	11.91%

Panel B: Number of organizational changes and firm characteristics (at baseline)

	Number of changes over past 3 years		
	0	1 or 2	3 or 4
(i) firm size	44.16	89.92	134.27
p-value		0.00	0.00
(ii) firm daily wage (in logs)	4.40	4.49	4.49
p-value		0.00	0.00
(iii) fixed firm effect (relative to nonrestructuring firms)		2.68%	2.45%
p-value		0.00	0.00
(iv) fixed worker effect (relative to nonrestructuring firms)		2.93%	1.33%
p-value		0.00	0.02
(v) baseline task usage, in percentages			
abstract	39.95%	46.06%	43.89%
p-value		0.00	0.00
routine	39.59%	38.08%	40.24%
p-value		0.14	0.55
manual	20.46%	15.86%	15.87%
p-value		0.00	0.00
(vi) baseline age structure, in percentages			
<30	19.83%	19.64%	21.04%
p-value		0.49	0.00
31-50	57.36%	58.04%	57.38%
p-value		0.01	0.96
>50	22.81%	22.32%	21.58%
p-value		0.04	0.00

Notes: Panel A reports the share of workers employed in firms that do not implement any, between one and two, or more than two measures of organizational change (T&O) over the past three years in the overall economy and separately for the five largest broad sectors. Broad industries are constructed aggregating 2-digit industries of our registry data and based upon NACE Rev 1 classifications. The four organizational changes considered are whether firms transfer responsibilities to subordinates, introduce teamwork or self-responsible working groups, introduce profit centers, and/or pool or restructure internal departments. Panel B reports correlations between the number of organizational changes (T&O) over the past three years and firm and worker characteristics at baseline. Fixed firm effects and fixed worker effects are pre-estimated from registry data using the previous seven calendar years for each point in time. All statistics are weighted by employment to make them representative of workers and use firm panel weights to correct for oversampling of larger firms and certain industries in the IAB Establishment Panel. p-values are derived from pseudo-regressions in which standard errors are clustered at the firm level.

Sources: Registry data and the IAB Establishment Panel, 1993–2010. We calculate task shares based on a categorization constructed using the 1991/1992 wave of the German BIBB/IAB Qualification and Career Survey.

Table 3: Differences between Manual, Routine, and Abstract Tasks

	routine	manual	abstract
Panel A: Task shares and wages			
employment shares	37.11%	17.70%	45.19%
mean wage (log difference compared to routine)		2.63%	33.41%
Panel B: Movements from routine to abstract occupations (over a three-year period)			
	Incidence		
overall	4.76%		
within firms	2.46%		
		Wage Growth	
	routine stayers	upgraders	abstract stayers
overall	2.30%	3.66%	3.50%
within firms	2.47%	4.48%	3.38%

Notes: Panel A shows employment shares and wages by task. Panel B presents some summary statistics on the likelihood of worker transitions—overall and within firms—from routine to abstract occupations, as well as wage growth of 'routine stayers' (workers who stay in a routine occupations over a 3-year periods), 'upgraders' (workers who move from a routine to an abstract occupation over a 3-year period) and 'abstract stayers' (workers who are employed in an abstract occupation over a 3-year period).

Sources: Registry data linked to the IAB Establishment Panel, 1993–2010. We calculate task shares based on a categorization constructed using the 1991/1992 wave of the German BIBB/IAB Qualification and Career Survey.

Table 4: T&O and the Firm's Task, Education, and Age Structure: Firm Level Regressions

Panel A: Tasks

	Manual Occupations		Routine Occupations		Abstract Occupations	
	(1)	(2)	(1)	(2)	(1)	(2)
number of changes	0.015	0.029	-0.363***	-0.227**	0.347**	0.198
	(0.054)	(0.060)	(0.122)	(0.111)	(0.151)	(0.145)
year fixed effects	yes	yes	yes	yes	yes	yes
firm size, commuting area, industry	no	yes	no	yes	no	yes
mean change in employment share	-0.31%		-1.22%		1.53%	

Panel B: Age

	Age <30		Age 30-49		Age 50-65	
	(1)	(2)	(1)	(2)	(1)	(2)
number of changes	-0.033	-0.043	0.370***	0.308**	-0.337**	-0.265*
	(0.065)	(0.073)	(0.115)	(0.135)	(0.131)	(0.148)
year fixed effects	yes	yes	yes	yes	yes	yes
firm size, commuting area, industry	no	yes	no	yes	no	yes
mean change in employment share	-3.25%		1.55%		1.71%	
number of observations (firm-year)	26,908	24,939	26,908	24,939	26,908	24,939

Panel C: Placebo Tasks Regressions

	Manual Occupations		Routine Occupations		Abstract Occupations	
	(1)	(2)	(1)	(2)	(1)	(2)
contemporenuous number of changes	-0.026	-0.029	-0.352***	-0.227**	0.378***	0.257**
	(0.043)	(0.046)	(0.082)	(0.089)	(0.090)	(0.103)
future number of changes	0.071*	0.089*	-0.042	0.027	-0.029	-0.116
	(0.041)	(0.047)	(0.102)	(0.105)	(0.110)	(0.117)
year fixed effects	yes	yes	yes	yes	yes	yes
firm size, commuting area, industry	no	yes	no	yes	no	yes
number of observations (firm-year)	12,450	11,893	12,450	11,893	12,450	11,893

Notes: The table reports estimates for the effects of T&O on the occupational groups (manual, routine, abstract; Panel A) and age (Panel B) structure of the firm. Panel C investigates the same occupational groups as in Panel A but includes in the regressions the number of future organizational changes (implemented between t and t+3) in addition to the number of contemporaneous organizational changes (carried out between t-3 and t). The dependent variable in each panel and column is the change in the firm level employment share (from 0 to 100) of the specific group (e.g., routine workers) between t-3 and t. The main variable of interest, "number of changes", measures the number of organizational changes between t-3 and t and ranges between zero and four. In Columns (1), we control for year fixed effects only, as in Equation (3) in the text; in Columns (2), we add controls, as in Equation (4), for firm size (measured as log employment at baseline), commuting zones (a regional control derived by dividing West Germany into 50 regions based on commuting patterns), and industry (one digit controls). The unit of observation is the firm/year, and all regressions are weighted by baseline employment. Standard errors are clustered at the firm level; the significance levels are *10%, **5%, ***1%. In the last rows of each panel, the table shows the mean three-year changes in employment shares of the specific group.

Sources: Registry data linked to the IAB Establishment Panel, 1993–2010. We calculate task shares based on a categorization constructed using the 1991/1992 wave of the German BIBB/IAB Qualification and Career Survey.

Table 5: T&O and Task and Age Structure: Industry Level Regressions

Panel A: Tasks

	Manual Occupations	Routine Occupations	Abstract Occupations
number of changes	0.180	-0.910***	0.721**
	(0.133)	(0.285)	(0.344)

Panel B: How does Routine Employment Adjust?

Panel B1: Changes among Surviving Firms and Selective Entry and Exit

	Overall Change	Change among Surviving Firms	Selective Entry and Exit
number of changes	-0.910***	-0.695**	-0.215*
	(0.285)	(0.269)	(0.114)

Panel B2: Within-Firm Changes (Weighted) and Differential Wage Growth among Surviving Firms

	Change among Surviving Firms	Within-Firm Changes (Weighted)	Differential Employment Growth	Interaction Term
number of changes	-0.695**	-0.615***	-0.050	-0.029
	(0.269)	(0.210)	(0.157)	(0.193)
number of industries	56	56	56	56
number of time periods	5	5	5	5

Notes: Panel A reports estimates for the effects of T&O on the change on the task structure in two-digit industries. The dependent variables are the change in the industry level employment shares (between 0 and 100) of manual, routine and abstract workers between t-3 and t. The main variable of interest, "number of changes", measures the number of organizational changes between t-3 and t in the industry and ranges between zero and four. Panel B decomposes the overall effect of T&O on the change in the routine employment share in the industry into various components. Panel B1 quantifies the importance of selective entry and exit of routine-intensive firms, following Equation (1). Panel B2 quantifies the importance of within-firm changes, differential employment growth of surviving routine-intensive firms and an interaction term capturing co-movements between employment growth and changes in the routine employment share in the firm, following Equation (2). We control for year fixed effects in all regressions. The unit of observation is the two-digit industry-year, and all regressions are weighted by (baseline) employment in the industry. Standard errors are clustered at the industry level; the significance levels are *10%, **5%, ***1%.

Sources: Panel A: Registry data linked to the IAB Establishment Panel, 1993–2010. Panel B: Registry Data to compute changes in th routine employment shares, as well as its components, in the industry. IAB Establishment Panel to compute changes in T&O in the industry.

Table 6: T&O, Wage and Employment Growth, Churning, and Internal Reshuffling

	Wage growth	Employment growth	External separations	External hiring	Internal reshuffling
number of changes	0.074	0.473	-0.199	0.274**	0.131**
	(0.123)	(0.328)	(0.316)	(0.117)	(0.053)
number of observations (firm-year)	25,821	25,866	25,866	25,866	25,866
mean of dep. var.	7.64%	-8.28%	11.60%	19.89%	1.20%

Notes: The table reports estimates for the effects of T&O on firm wage growth (log difference in firm-level mean wages between t-3 and t), employment growth (employment in t minus employment in t-3, divided by employment in t-3), external hiring (number of workers who joined the firm between t-3 and t, divided by employment in t-3), external separations (number of workers who left the firm between t-3 and t, divided by employment at t-3) and internal reshuffling (number of individuals who changed task within the firm between t-3 and t, divided by baseline employment). The main variable of interest, "number of changes," measures the number of organizational changes between t-3 and t and ranges between zero and four. All regressions control for firm size (log employment at baseline), commuting zones (a regional control derived by dividing West Germany into 50 regions based on commuting patterns), and industry (one-digit controls). The unit of observation is the firm/year, and all regressions are weighted by (baseline) employment. Standard errors are clustered at the firm level; the significance levels are *10%, **5%, ***1%. The last row of the table shows the mean of each dependent variable in our sample. To compute these, we again weight by (baseline) employment and additionally use firm panel weights to correct for oversampling of larger firms and certain industries.

Sources: Registry data linked to the IAB Establishment Panel, 1993–2010. We calculate tasks for the internal reshuffling regression based on a categorization constructed using the 1991/1992 wave of the German BIBB/IAB Qualification and Career Survey.

Table 7: T&O and Career Outcomes for Routine Jobholders

	(1) Working	(2) Manual Occupation	(3) Routine Occupation	(4) Abstract Occupation	(5) Abstract same firm	(6) Abstract diff. firm	(7) Earnings Ratio
Panel A: All Routine Jobholders							
after 3 years							
number of changes	-0.032	0.037	-0.218	0.150***	0.113***	0.037*	-0.067
	(0.123)	(0.061)	(0.139)	(0.040)	(0.035)	(0.021)	(0.130)
mean of dep. var.	83.64	2.20	78.50	2.93	1.69	1.24	81.16
after 6 years							
number of changes	-0.151	0.164**	-0.490**	0.175**	0.032	0.143***	-0.182
	(0.166)	(0.080)	(0.195)	(0.079)	(0.081)	(0.050)	(0.182)
mean of dep. var.	73.77	3.31	65.69	4.76	2.46	2.30	71.48
Panel B: By age (3-year periods)							
<30							
number of changes	0.085	0.093	-0.160	0.153**	0.084*	0.069*	0.063
	(0.088)	(0.088)	(0.144)	(0.060)	(0.050)	(0.037)	(0.102)
mean of dep. var.	86.16	3.92	77.20	5.01	2.56	2.45	79.4
30-49							
number of changes	0.103	0.030	-0.082	0.156***	0.126***	0.030	0.072
	(0.090)	(0.067)	(0.123)	(0.047)	(0.041)	(0.022)	(0.101)
mean of dep. var.	91.71	2.19	86.51	3.01	1.81	1.20	88.61
>49							
number of changes	-0.628	-0.019	-0.701*	0.092***	0.078***	0.014	-0.703*
	(0.388)	(0.029)	(0.382)	(0.030)	(0.026)	(0.016)	(0.397)
mean of dep. var.	59.06	0.74	57.37	0.95	0.63	0.32	63.49
Panel C: Detailed age groups for workers older than 49 at baseline (3-year periods)							
50-54							
number of changes	-0.209	-0.029	-0.322	0.142***	0.116***	0.026	-0.288
	(0.520)	(0.038)	(0.518)	(0.042)	(0.035)	(0.024)	(0.536)
mean of dep. var.	73.99	1.03	71.68	1.27	0.85	0.42	78.49
55-59							
number of changes	-1.331***	0.002	-1.355***	0.022	0.027	-0.005	-1.394***
	(0.378)	(0.023)	(0.364)	(0.022)	(0.020)	(0.010)	(0.382)
mean of dep. var.	41.56	0.37	40.63	0.54	0.35	0.19	50.8
>59							
number of changes	-0.528**	-0.040***	-0.505**	0.018	0.022	-0.004	-0.554**
	(0.225)	(0.016)	(0.219)	(0.022)	(0.018)	(0.012)	(0.228)
mean of dep. var.	19.99	0.120	19.62	0.249	0.16	0.09	21.35

Notes: This table reports estimates for the effects of T&O on the career outcomes over a 3-year period of older workers who were employed at a firm in the IAB firm panel and between 55 and 62 at baseline. Panel A displays results pooled for older workers. Panels B and C break down the analysis by occupational category at baseline (manual, routine, abstract) and education (low, medium, high) respectively. The main variable of interest, "number of changes," measures the number of organizational changes in the baseline firm between t-3 and t and ranges between zero and four. We consider the following outcome variables: whether the individual is employed (at any firm in Germany) at time t (Column (1)); earnings ratio (daily wage in t, set to zero for those not working, divided by the daily wage in t-3, multiplied by 100; Column (2)); whether the worker is employed at the same firm as at baseline at time t (Column (3)); and whether the individual is employed in manual, routine or abstract occupations at time t (Columns (4)-(6)). The various employment variables take the values of either 0 or 100 so that the reported coefficients refer to the impact of one additional organizational change on the percentage point change of the particular event (Columns (1) and (3)-(6)). All regressions control for age, foreign status, year fixed effects, firm size (measured as log employment at baseline), commuting zones (a regional control derived by dividing West Germany into 50 regions based on commuting patterns), three-digit occupation fixed effects at baseline, industry (one-digit), as well as pre-estimated fixed firm effects and fixed worker effects calculated using the seven years prior to the baseline year. The unit of observation is the worker/year. Standard errors are clustered at the firm level; significance levels: *10%, **5%, ***1%.

Sources: Registry data and IAB Establishment Panel, 1993–2010. We calculate tasks based on a categorization constructed using the 1991/1992 wave of the German BIBB/IAB Qualification and Career Survey.

Table 8: T&O and Training

	(1) All	(2) low-skilled	(3) medium-skilled	(4) high-skilled
mean employment share in training	17.61%	7.54%	18.41%	22.84%
number of organizational changes	1.278***	0.842*	2.513***	2.960***
	(0.321)	(0.454)	(0.388)	(0.475)
number of observations (firm-year)	17,199	12,788	15,212	12,786

Notes: The table reports estimates for the effects of T&O on firms' training activities. The main variable of interest, "number of organizational changes", measures the number of organizational changes over three years between t-3 and t, and ranges between zero and four. The dependent variables are the shares of workers (all workers in Column (1) and low-, medium-, and high-skilled workers in Columns (2)-(4)) who received further training between t-3 and t. These shares vary from 0 to 100; hence, the coefficients reported in the table refer to the effect of one additional organizational change on the percentage point change in the respective training share. All regressions control for year fixed effects, firm size (log employment at baseline), commuting zones (a regional control derived by dividing West Germany into 50 regions based on commuting patterns), and industry (one-digit controls). The unit of observation is the firm/year, and all regressions are weighted by (baseline) employment. Standard errors are clustered at the firm level; the significance levels are *10%, **5%, ***1%.

Sources: Registry data linked to the IAB Establishment Panel, 1993–2010. We calculate tasks based on a categorization constructed using the 1991/1992 wave of the German BIBB/IAB Qualification and Career Survey.

Table 9: T&O and Career Outcomes for Workers Aged 55 and Over

	(1) Working	(2) Earnings Ratio	(3) Same firm	(4) Manual Occupation	(5) Routine Occupation	(6) Abstract Occupation
<u>Panel A: All</u>						
number of changes	-1.252***	-1.307***	-0.857***	-0.147**	-0.554***	-0.551***
	(0.302)	(0.310)	(0.289)	(0.074)	(0.126)	(0.147)
<u>Panel B: By occupational group at baseline</u>						
Manual						
number of changes	-0.985**	-1.029***	-0.772*	-1.008**	-0.020	0.044**
	(0.431)	(0.440)	(0.432)	(0.417)	(0.047)	(0.022)
Routine						
number of changes	-1.265***	-1.327***	-1.066***	-0.004	-1.281***	0.021
	(0.331)	(0.336)	(0.349)	(0.020)	(0.319)	(0.021)
Abstract						
number of changes	-1.251***	-1.312***	-0.661**	-0.008	-0.003	-1.240***
	(0.314)	(0.325)	(0.291)	(0.006)	(0.010)	(0.314)
<u>Panel C: By education at baseline</u>						
Low						
number of changes	-1.236***	-1.337***	-0.851**	-0.091	-0.853***	-0.292**
	(0.339)	(0.344)	(0.347)	(0.081)	(0.245)	(0.133)
Medium						
number of changes	-1.282***	-1.336***	-0.958***	-0.196**	-0.586***	-0.500***
	(0.317)	(0.323)	(0.309)	(0.089)	(0.140)	(0.138)
High						
number of changes	-1.205***	-1.192***	-0.494	-0.006	-0.000	-1.199***
	(0.389)	(0.393)	(0.400)	(0.017)	(0.033)	(0.376)

Notes: This table reports estimates for the effects of T&O on the career outcomes over a 3-year period of older workers who were employed at a firm in the IAB firm panel and between 55 and 62 at baseline. Panel A displays results pooled for older workers. Panels B and C break down the analysis by occupational category at baseline (manual, routine, abstract) and education (low, medium, high) respectively. The main variable of interest, "number of changes," measures the number of organizational changes in the baseline firm between t-3 and t and ranges between zero and four. We consider the following outcome variables: whether the individual is employed (at any firm in Germany) at time t (Column (1)); earnings ratio (daily wage in t, set to zero for those not working, divided by the daily wage in t-3, multiplied by 100; Column (2)); whether the worker is employed at the same firm as at baseline at time t (Column (3)); and whether the individual is employed in manual, routine or abstract occupations at time t (Columns (4)-(6)). The various employment variables take the values of either 0 or 100 so that the reported coefficients refer to the impact of one additional organizational change on the percentage point change of the particular event (Columns (1) and (3)-(6)). All regressions control for age, foreign status, year fixed effects, firm size (measured as log employment at baseline), commuting zones (a regional control derived by dividing West Germany into 50 regions based on commuting patterns), three-digit occupation fixed effects at baseline, industry (one-digit), as well as pre-estimated fixed firm effects and fixed worker effects calculated using the seven years prior to the baseline year. The unit of observation is the worker/year. Standard errors are clustered at the firm level; significance levels: *10%, **5%, ***1%.

Sources: Registry data and IAB Establishment Panel, 1993–2010. We calculate tasks for the internal reshuffling regression based on a categorization constructed using the 1991/1992 wave of the German BIBB/IAB Qualification and Career Survey.

Table 10: T&O and Career Outcomes: Regressions with Firm Fixed Effects

	(1) Working	(2) Same Task	(3) Other Task	(4) Earnings Ratio
Panel A: routine vs abstract and manual workers				
(i) number of changes (routine)	-0.129	-0.469***	0.341***	-0.204
	(0.163)	(0.165)	(0.117)	(0.164)
(ii) number of changes X manual	0.073	0.178	-0.105	0.098
	(0.074)	(0.163)	(0.151)	(0.084)
(iii) number of changes X abstract	-0.0724	0.418***	-0.491***	-0.059
	(0.088)	(0.147)	(0.144)	(0.099)
Panel B: older vs medium-aged and younger workers				
(i) number of changes (workers older than 49)	-2.135***	-2.108***	-0.025	-2.256***
	(0.269)	(0.251)	(0.102)	(0.280)
(ii) number of changes X young (<31)	2.935***	2.565***	0.369***	2.970***
	0.358	(0.311)	(0.141)	(0.369)
(iii) number of changes X mid age) (31-49)	2.422***	2.297***	0.126*	2.517***
	0.306	(0.276)	(0.069)	(0.320)

Notes: The table reports estimates for the effects of T&O on career outcomes of workers employed at a firm in the IAB Establishment Panel at baseline, leveraging variation in T&O within firms over time. The main variable of interest, "number of changes" (0-4) measures the number of organizational changes in the baseline firm between t-3 and t. Panel A considers workers in three occupation groups (routine, manual, abstract) and coefficients in rows (ii) and (iii) show estimated effects fof T&O on career outcomes of manual and abstract workers relative to routine workers in the same firm. Panel B considers workers in three age groups (older than 49, between 31 and 49 and younger than 31) and coefficients in rows (ii) and (iii) show estimated effects of T&O on career outcomes of younger and medium-aged workers relative to older workers in the same firm. Outcome variables: whether the individual is employed at any firm in Germany ("working"); whether the individual is employed in the same task at t (Column (2), whether the worker is employed in a different task (Column (3); and the earnings ratio (daily wage in t, set to zero for those not working, divided by daily wage in t-3, multiplied by 100; Column (4)). The various employment variables take the values of either 0 or 100. Regressions include firm fixed effects that refer to the firm where the worker was employed at baseline (i.e., at time t-3). All regressions also control for age, foreign status, year fixed effects (interacted with baseline occupation group or age group), firm size (log employment at baseline), commuting zones, three-digit occupation fixed effects at baseline, industry (one digit controls), and pre-estimated fixed firm effects and fixed worker effects calculated using the seven years prior to the baseline year. The unit of observation is the worker/year. Standard errors are clustered at the firm level. Significance levels: *10%, **5%, ***1%.

Sources: Registry data and IAB Establishment Panel, 1993–2010. We calculate tasks based on a categorization constructed using the 1991/1992 wave of the German BIBB/IAB Qualification and Career Survey.

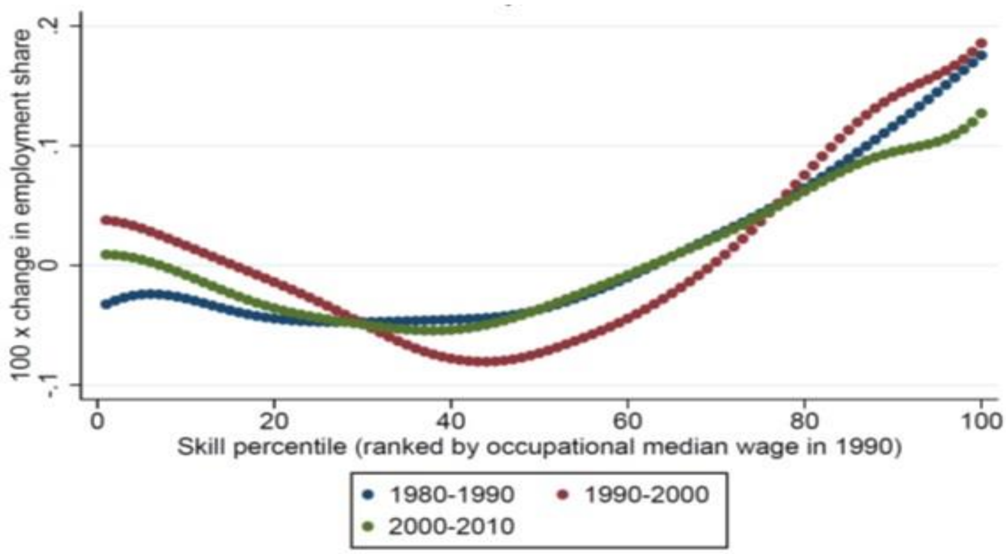
Table 11: T&O, Career Outcomes of Routine Jobholders, and Labor Market Institutions

	all routine jobholders			
	(1) working	(2) abstract	(3) abstract, same firm	(4) abstract, other firm
Panel A: by apprenticeship training				
number of changes (T&O)	-0.003	-0.003	-0.004	0.000
	(0.169)	(0.077)	(0.074)	(0.033)
T&O X share apprentices	-1.064	4.369**	3.317*	1.052
	(2.360)	(1.855)	(1.895)	(0.823)
mean share apprentices	0.044			
Panel B: by firm's union status				
number of changes (T&O)	0.480	-0.202**	-0.142**	-0.060
	(0.349)	(0.100)	(0.063)	(0.067)
T&O X union recognition	-0.519	0.372***	0.273***	0.099
	(0.358)	(0.106)	(0.070)	(0.070)
mean union recognition rate	0.845			

Notes: The table investigates how the apprenticeship share at baseline (Panel A) and union recognition (firm's membership in an employer association) at baseline (Panel B) affect T&O's effects on career outcomes of workers who were employed in one of the firms in the IAB firm panel and held routine jobs at baseline. The main variable of interest, "number of changes", which measures the number of organizational changes in the baseline firm between t-3 and t, ranges between zero and four. This variable is interacted with the share of apprentices in the firm at baseline (Panel A) and whether the firm recognized a union at baseline (Panel B). We consider the following four outcome variables: whether the individual is employed (at any firm in Germany) at time t (Column (1)); whether the individual is employed in an abstract occupation at time t in any firm (Columns (2)); whether the individual is employed in an abstract occupation at time t at the baseline firm (Column (3) or at an outside firm (Columns (4)) at time t. All regressions control, in addition t the apprenticeship share at baseline in Panel A and union recognition in Panel B for age and age squared at baseline, foreign status, year fixed effects, firm size (log employment at baseline), commuting zones (a regional control derived by dividing West Germany into 50 regions based on commuting patterns), occupation (three digit controls), industry (one digit controls), pre-estimated fixed firm effects and fixed worker effects calculated using the seven years prior to the baseline year (cf. Card, Heining, and Kline, 2013). The unit of observation is the worker/year. Standard errors are clustered at the firm level; the significance levels are *10%, **5%, ***1%.

Sources: Registry data and IAB Establishment Panel, 1993–2010. We calculate tasks for the internal reshuffling regression based on a categorization constructed using the 1991/1992 wave of the German BIBB/IAB Qualification and Career Survey.

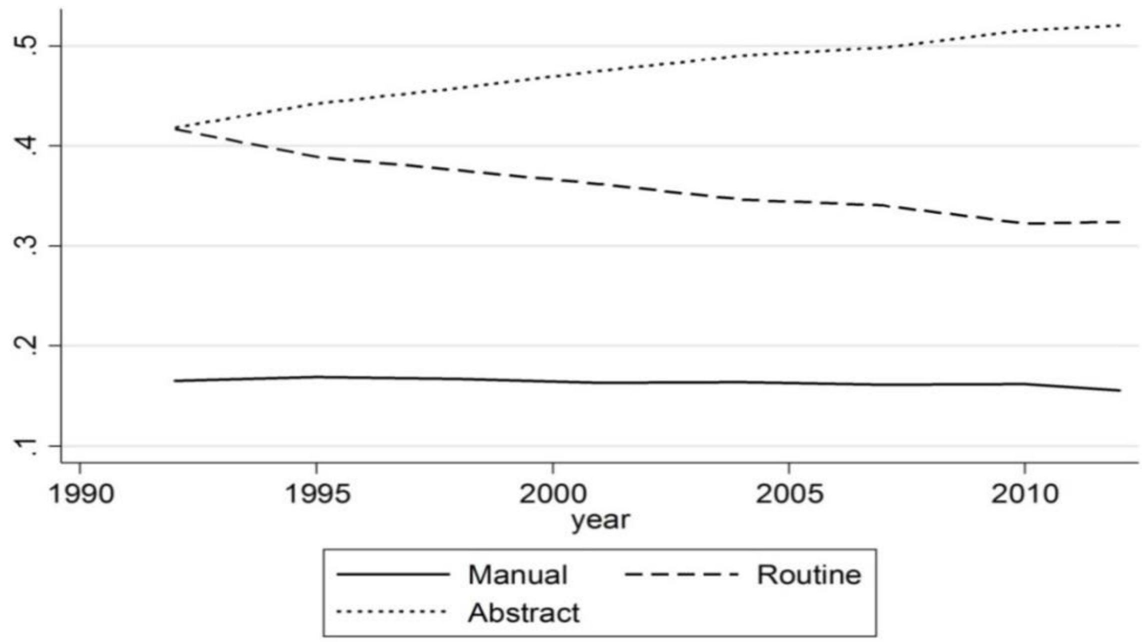
Figure 1a: Changes in Employment Shares by Occupational Skill Percentile



Notes: The figure plots log changes in employment shares by 1990 occupational skill percentile rank using a locally weighted smoothing regression (bandwidth 0.8 with 100 observations), where skill percentiles are measured as the employment-weighted percentile rank of an occupation's median log wage in 1990 (cf. Acemoglu and Autor, 2011). The sample is composed of male workers aged 18-65 in full time employment and representative of the corresponding worker population in West Germany.

Source: 2% random sample of the Registry Data (SIAB7510), 1980–2010.

Figure 1b: Task Shares Over Time



Notes: This figure plots the share of workers in manual-, routine-, and abstract dominated occupations between 1993 and 2012. The unit of observation is the firm/year, and observations are weighted by (baseline) employment and the firm panel weights, to make sure that they are representative of the worker population in West Germany.

Source: Registry data and IAB Establishment Panel, 1993–2012.

Figure 2a: Frequency of T&O

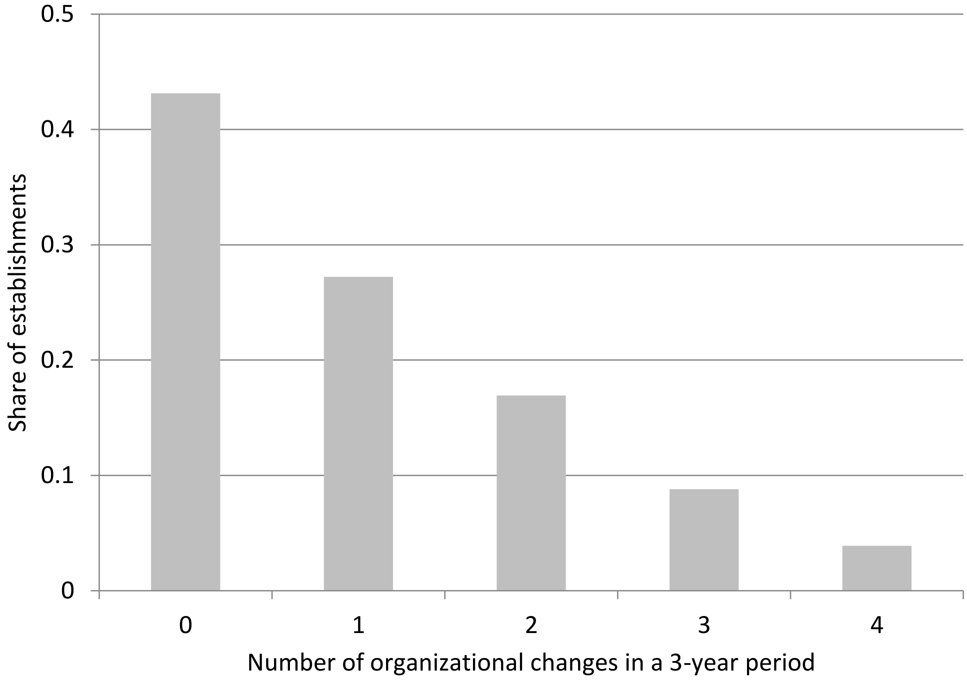
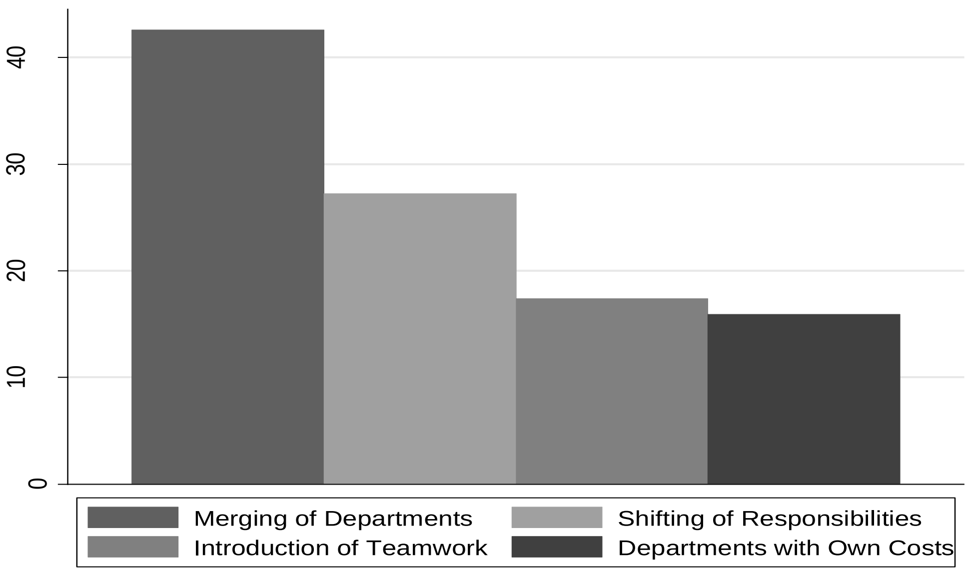


Figure 2b: Types of T&O



Notes: The figures provide some descriptive evidence about the frequency and type of T&O. Panel A displays the share of firms that implement no, 1, 2, 3, or 4 organizational changes over a 3-year period. Panel B shows the share of firms that over a 3-year period merge or restructure departments internally; transfer responsibilities to subordinates; introduce teamwork or self-responsible working groups; or introduce profit centers (i.e., units or departments that carry out their own cost and result calculations). The unit of observation is the firm/year, and observations are weighted by (baseline) employment and the firm panel weights, to make sure that they are representative of the worker population in West Germany.

Source: IAB Establishment Panel, 1995-2010.

Figure 3a: Average number of organizational changes, treatment vs. control groups

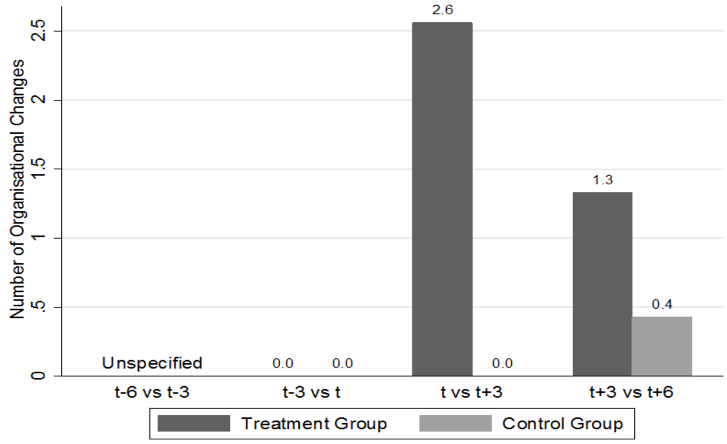


Figure 3b: Routine to abstract transitions, treatment vs. control groups

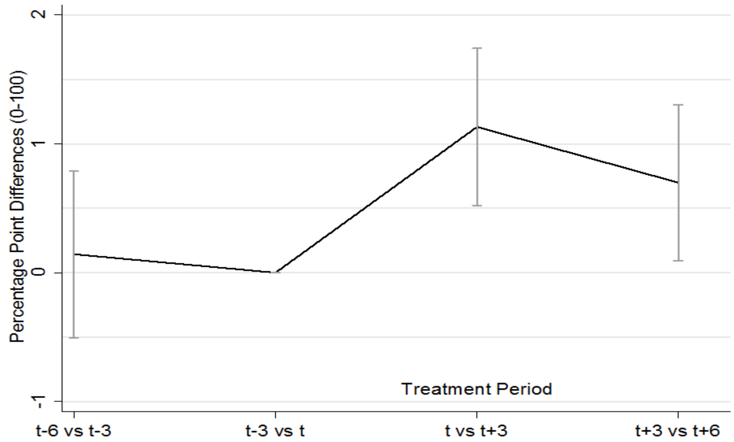
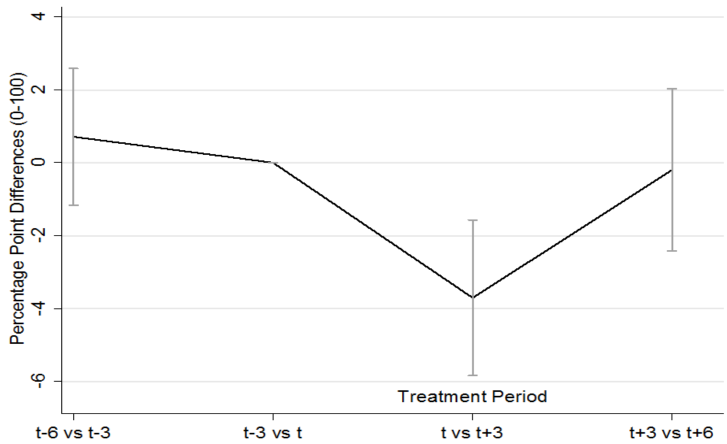


Figure 3c: Shares remaining employed, workers aged 55 and older, treatment vs control groups



Notes: The figures display the results of an event-study analysis focused on two outcome variables: upgrades from routine to abstract occupations (Panel B) and transitions from employment to non-employment of workers age 55 and over at baseline (Panel C). "Treatment" firms do not implement any T&O between t-3 and t but carry out at least two organizational changes between t and t+3 (the "treatment period"). "Control" firms introduce T&O neither between t-3 and t nor between t and t+3. No restrictions on the number of organizational changes implemented by either treatment or control firms between t-6 and t-3 or between t+3 and t+6 are imposed. Figure 3a contrasts the number of organizational changes that treatment and control firms carry out in each period. Figure 3b plot differences in the firm-level shares of workers upgrading from routine to abstract tasks (either within or across firms) between treatment and control firms. Figure 3c plots equivalent differences in shares of older workers who are still employed at the end of the period. Differences between treatment and control firms are normalized to 0 in the t-3 vs t pre-treatment period. Firm-level shares vary from 0 to 100. The sample consists of 520 treatment and 2,626 control firms, which we follow over time. The unit of observation is the firm/year. Observations are weighted by (baseline) employment. The vertical bars in Figure 3b and 3c indicate 95% confidence intervals.

Sources: Registry data and the IAB Establishment Panel, 1993–2010. We calculate task shares based on a categorization constructed using the 1991/1992 wave of the German BIBB/IAB Qualification and Career Survey.

Appendices

A.1 Imputing Censored Wages

To impute top-coded wages, we first define age-education cells based on five age groups (with 10-year intervals) and three education groups (no postsecondary education, vocational degree, and college or university degree). Within each of these cells, following Dustmann, Ludsteck, and Schönberg (2009) and Card, Heining, and Kline (2013), we estimate Tobit wage equations separately by year while controlling for age, firm size (a quadratic and a dummy for firm size greater than 10), the focal worker's mean wage and mean censoring indicator (each computed over time but excluding observations from the current time period), and firm mean wage, mean censoring indicator, mean years of worker schooling, and mean university degree indicator (each computed at the current time period by excluding the focal worker observations). For workers observed in one time period only, the mean wage and mean censoring indicators are set to sample means and a dummy variable is included. A wage observation censored at value c is then imputed by the value $X\hat{\beta} + \hat{\sigma}\Phi^{-1}[k + u(1-k)]$, where Φ is the standard normal CDF, u is drawn from a uniform distribution, $k = \Phi\left[\left(c - X\hat{\beta}\right)/\hat{\sigma}\right]$, and $\hat{\beta}$ and $\hat{\sigma}$ are estimates for the coefficients and standard deviation of the error term from the Tobit regression.

A.2 Correlation between T&O and measures of ICT and product innovation

In Appendix Table A.1, we provide evidence that our measures of T&O and ICT investments are complements. Every year firms in the IABEP are asked whether or not they have carried out *any* investment in ICT over the past year (the question thus does not distinguish between minor investments such as the purchase of a USB stick and major investments such as the overhaul of a computer system). Despite the imprecise measurement of ICT investments, we find a strong positive correlation between the number of ICT investments and the number of organizational changes that a firm has adopted over a three-year period (row (ii)). For some selected years (2001 to 2007), firms in the IABEP were additionally questioned about the exact amount of their ICT investments. Firms that heavily reorganize invest more than twice as much in IT per employee than firms that do not reorganize at all (row (iii)).

Bresnahan et al. (2002) do not only argue that ICT investments and reorganization are complementary, but also that both are complementary to product innovation, as the ultimate goal of both ICT investments and reorganization is to help firms offer better services and products. We would therefore expect firms that heavily reorganize to be more engaged in product innovation than firms that do not. Indeed, we find this to be the case: Firms that have implemented at least three organizational changes over the past three years are 18 percentage points more likely to have improved an existing product or introduced a new product (row (iv)).

Table A.1: Organizational Change, IT investments and Product Innovation

	Number of changes over past 3 years		
	0	1 or 2	3 or 4
(i) percentage of firms	44.32%	43.29%	12.39%
(ii) # investments in IT (sum of yearly dummies)	1.31	1.73	1.79
p-value		0.00	0.00
(iii) investment in IT per employee (=1 in firms with no change)		1.63	2.38
p-value		0.00	0.00
(iv) dummy for product innovations (3 year period)	0.11	0.20	0.29
p-value		0.00	0.00

Notes: The table reports the number of IT investments over the past three years (each year, the variable is equal to 1 if the firm undertook any type of IT investment and 0 otherwise, row (i)), the value of IT investments per employee over the past three years (calculated from total investment in Euros, share of IT investment in total investment, and employment levels and normalized to one for firms that implement no organizational change, row (ii)), and whether or not the firm introduced a new or improved an existing product over the past three years (row (iii)) separately for three groups of firms: firms that did not implement any T&O over the past three years; firms that implemented one or two measures; and firms that implemented at least three measures.

Sources: Registry data linked to the IAB Establishment Panel, 1993–2010. We calculate task shares based on a categorization constructed using the 1991/1992 wave of the German BIBB/IAB Qualification and Career Survey; see Section 2.2.3 for details.

Table A.2: Classification of Activities into Tasks using BIBB

Manual tasks	Repairing machines Driving vehicles Hosting , serving (e.g. wait tables), accommodating customers Securing, watching over, keeping guard Nursing, personal care of others
Routine tasks	Attending, feeding, equipping machinery Fabricating, manufacturing materials, preparing (e.g., food) Building, constructing and installing appliances Filing, sorting, labeling Billing, computing and bookkeeping[*] Writing and correspondence[**] Buying, selling, managing payments, assisting customers[***]
Abstract tasks	Planning, designing, sketching Executing or interpreting laws, rules, or regulations Analysis and research Computing and programming Educating, training, teaching, consulting Publicizing, presenting, disseminating Hiring, management and control, organizing or coordinating Billing, computing and bookkeeping[*] Writing and correspondence[**] Buying, selling, managing payments, assisting customers[***]

Notes: This table categorizes the activities in the 1991/1992 wave of the German BIBB/IAB Qualification and Career Survey into routine, manual, and abstract tasks. Three task sets—billing, calculating, and bookkeeping; writing and correspondence; and buying or selling—are considered routine if the work process is predefined to the last detail and the tasks are highly repetitive or regularly accomplished using a calculator or accounting machine; a photocopier, filing cards, computer lists, microfilm reader; or a cash register or counter, respectively. Otherwise, these activities are classified as abstract.

Source: 1991/1992 wave of the German BIBB/IAB Qualification and Career Survey.

Table A.3: T&O and the Firm's Task and Age Structure: Alternative Measures of T&O

Panel A: Tasks

	Manual		Routine		Abstract	
	(1)	(2)	(1)	(2)	(1)	(2)
Panel A1: ICT investments						
ICT total investment per employee (log)	-0.017	-0.008	-0.179***	-0.182***	0.196***	0.190***
	(0.024)	(0.029)	(0.049)	(0.051)	(0.052)	(0.055)
number of observations (firm by year)	13,434	12,601	13,434	12,601	13,434	12,601
Panel A2: Product innovation						
equal to 1 if new or improved an existing product	-0.068	-0.034	-1.301***	-0.942***	1.370***	0.976**
	(0.144)	(0.147)	(0.431)	(0.364)	(0.512)	(0.441)
number of observations (firm by year)	23,474	21,576	23,474	21,576	23,474	21,576
year fixed effects	yes	yes	yes	yes	yes	yes
firm size, commuting area, industry	no	yes	no	yes	no	yes
mean change in employment share	-0.308%		-1.222%		1.530%	

Panel B: Age

	Age <30		Age 30-49		Age 50-65	
	(1)	(2)	(1)	(2)	(1)	(2)
Panel B1: ICT investments						
ICT total investment per employee (log)	-0.022	-0.009	0.154***	0.084	-0.132***	-0.075*
	(0.036)	(0.037)	(0.057)	(0.059)	(0.040)	(0.041)
number of observations (firm by year)	13,434	12,601	13,434	12,601	13,434	12,601
Panel B2: Product innovation						
equal to 1 if new or improved an existing product	-0.071	0.035	0.193	0.053	-0.122	-0.088
	(0.194)	(0.210)	(0.445)	(0.513)	(0.547)	(0.621)
number of observations (firm by year)	23,474	21,576	23,474	21,576	23,474	21,576
year fixed effects	yes	yes	yes	yes	yes	yes
firm size, commuting area, industry	no	yes	no	yes	no	yes
mean change in employment share	-3.25%		1.55%		1.71%	

Notes: This table reports estimates for the effects of two alternative measures of T&O, ICT investments per employee (in logs) and product innovation over the past three years, on the occupational group (manual, routine, abstract, Panel A) and age structure of the firm (Panel B). ICT investments can be calculated from the IAB Establishment Panel for the period 2001 and 2007 using responses on total investment in Euros, share of ICT investment in total investment, and employment levels. Information on whether or not the firm introduced a new product or improved an existing product is available in the IAB Establishment Panel for the 1998, 2001, 2004 and 2007 to 2010. The dependent variable in each panel and column is the change in the employment share (from 0 to 100) of the specific occupation group (Panels A1 and A2) and age group (Panels B1 and B2) in the firm between t-3 and t. In Columns (1), we control for year fixed effects only, as in Equation (3) in the text; in Columns (2) we add controls for firm size (measured as log employment at baseline), commuting zones (a regional control derived by dividing West Germany into 50 regions based on commuting patterns), and industry (one digit controls). The unit of observation is the firm/year, and all regressions are weighted by baseline employment. Standard errors are clustered at the firm level; the significance levels are *10%, **5%, ***1%. In the last rows of each panel, the table shows the mean 3-year changes in employment shares of the specific group over our 1992-2010 time period. To compute these, we weight by (baseline) employment and additionally use firm panel weights to correct for oversampling of larger firms and certain industries.

Sources: Registry data linked to the IAB Establishment Panel, 1993–2010. We calculate task shares based on a categorization constructed using the 1991/1992 wave of the German BIBB/IAB Qualification and Career Survey.

Table A.4: T&O, Task and Age Structure excluding One Measure of T&O at a Time

Panel A: Tasks

	Manual		Routine		Abstract	
	(1)	(2)	(1)	(2)	(1)	(2)
Excl. merging of departments	0.008	0.025	-0.403**	-0.237*	0.395**	0.212
	(0.069)	(0.078)	(0.157)	(0.139)	(0.195)	(0.182)
Excl. shifting of responsibilities	0.014	0.031	-0.439***	-0.264*	0.425**	0.233
	(0.064)	(0.070)	(0.148)	(0.139)	(0.184)	(0.180)
Excl. introduction of team work	-0.004	0.005	-0.507***	-0.363**	0.511***	0.358*
	(0.061)	(0.066)	(0.163)	(0.146)	(0.197)	(0.184)
Excl. introduction of cost centres	0.053	0.073	-0.364***	-0.192	0.312**	0.119
	(0.069)	(0.075)	(0.130)	(0.125)	(0.155)	(0.157)

Panel B: Age

	Age <30		Age 30-49		Age 50-65	
	(1)	(2)	(1)	(2)	(1)	(2)
Excl. merging of departments	-0.003	-0.011	0.429**	0.363*	-0.425**	0.352*
	(0.088)	(0.096)	(0.170)	(0.194)	(0.193)	(0.214)
Excl. shifting of responsibilities	-0.015	-0.028	0.363***	0.272**	-0.347**	-0.244*
	(0.085)	(0.092)	(0.136)	(0.136)	(0.162)	(0.143)
Excl. introduction of team work	-0.044	-0.062	0.495***	0.423**	-0.451**	-0.362
	(0.075)	(0.086)	(0.162)	(0.202)	(0.185)	(0.232)
Excl. introduction of cost centres	-0.086	-0.093	0.451***	0.365***	0.364***	0.272**
	(0.074)	(0.081)	(0.119)	(0.127)	(0.134)	(0.132)

Notes: The table reports estimates for the effects of T&O on the occupational groups (manual, routine, abstract; Panel A) and age (Panel B) structure of the firm. Regressions are comparable to those of Panels A and B of Table 3, with the difference that in this table we exclude one of the four measures used to construct T&O at a time. The dependent variable in each panel and column is the change in the firm level employment share of the specific group (e.g., routine workers) between t-3 and t. All coefficients refer to our main variable of interest, i.e. the number of organizational changes between t-3 and t, ranges between zero and three (one of the four measures is excluded in each regression). Employment shares vary from 0 to 100; hence, the coefficients reported in the table refer to the effect of one additional organizational change on the percentage point change in the respective employment share. In Columns (1) we control only for year fixed effects; in Columns (2) we add in controls for firm size (log employment at baseline), commuting zones (a regional control derived by dividing West Germany into 50 regions based on commuting patterns), and industry (one-digit controls). The unit of observation is the firm/year, and all regressions are weighted by (baseline) employment. Standard errors are clustered at the firm level; the significance levels are *10%, **5%, ***1%.

Sources: Registry data linked to the IAB Establishment Panel, 1993–2010. We calculate task shares based on a categorization constructed using the 1991/1992 wave of the German BIBB/IAB Qualification and Career Survey.

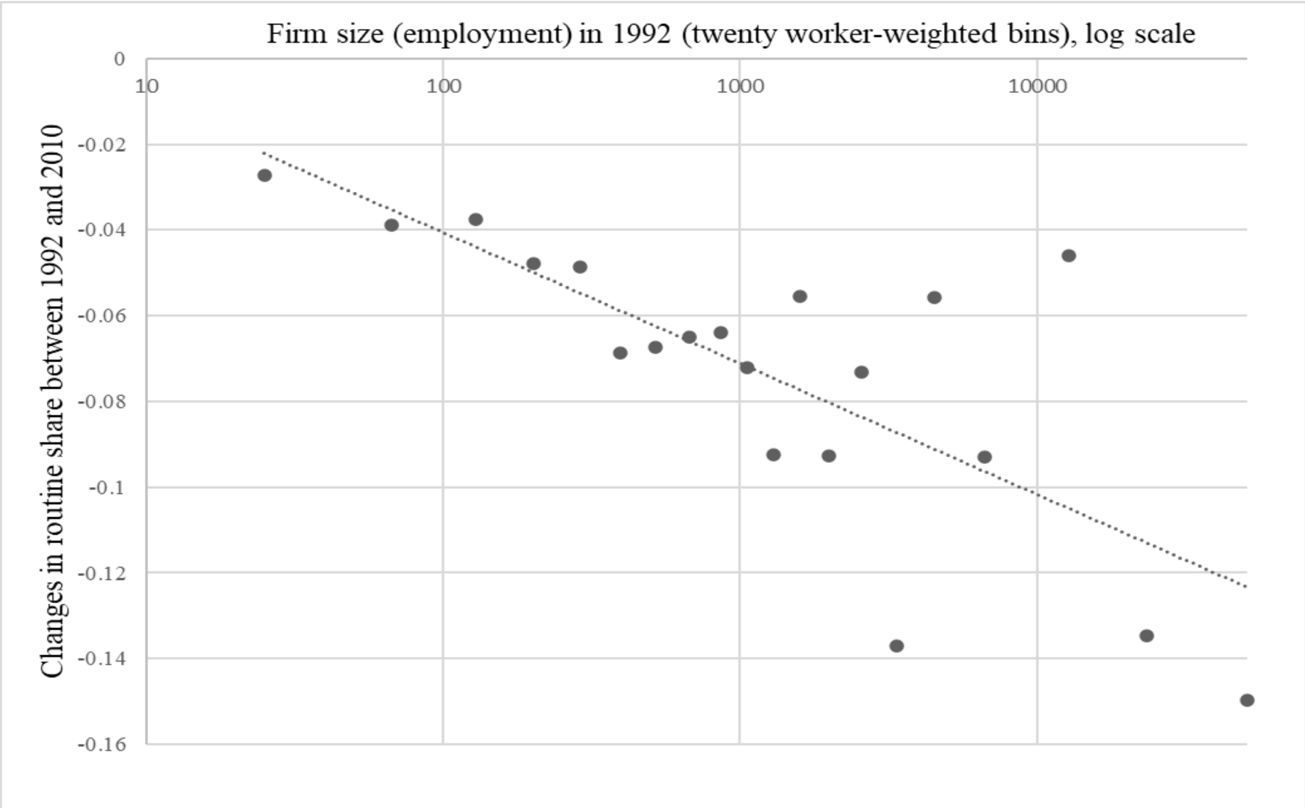
Table A.5: T&O and Career Outcomes for Routine Jobholders: 6-year Changes

	(1) Working	(2) Manual Occupation	(3) Routine Occupation	(4) Abstract Occupation	(5) Abstract same firm	(6) Abstract diff. firm	(7) Earnings Growth
Panel A: All Routine Jobholders							
number of changes	-0.151	0.164**	-0.490**	0.175**	0.032	0.143***	-0.182
	(0.166)	(0.080)	(0.195)	(0.079)	(0.081)	(0.050)	(0.182)
mean of dep. var.	73.77	3.31	65.69	4.76	2.46	2.30	74.11
Panel B: By age at baseline							
<30							
number of changes	0.064	0.267**	-0.464**	0.257*	-0.021	0.278***	0.071
	(0.113)	(0.105)	(0.200)	(0.142)	(0.145)	(0.098)	(0.127)
mean of dep. var.	82.25	5.74	67.98	8.51	3.92	4.59	81.87
30-49							
number of changes	0.001	0.167*	-0.345*	0.180*	0.047	0.133**	-0.020
	(0.143)	(0.096)	(0.192)	(0.092)	(0.091)	(0.054)	(0.158)
mean of dep. var.	86.15	3.41	77.88	4.84	2.66	2.18	86.47
>49							
number of changes	-0.732*	0.023	-0.786*	0.032	0.043*	-0.011	-0.711*
	(0.428)	(0.018)	(0.416)	(0.027)	(0.025)	(0.013)	(0.426)
mean of dep. var.	30.17	6.42	28.72	8.07	4.70	3.37	30.05
Panel C: Detailed age groups for workers older than 49 at baseline (after 3 years)							
50-54							
number of changes	-0.902	0.026	-0.987*	0.060	0.072**	-0.013	-0.864
	(0.580)	(0.025)	(0.564)	(0.038)	(0.034)	(0.019)	(0.583)
mean of dep. var.	41.1	9.03	39.06	11.31	6.57	4.74	40.81
55-59							
number of changes	-0.436**	0.015	-0.442***	-0.008	-0.002	-0.005	-0.473***
	(0.173)	(0.014)	0.169)	(0.016)	(0.014)	0.010)	0.180
mean of dep. var.	12.96	2.30	12.44	2.95	1.75	1.21	13.02

Notes: The table reports estimates for the effects of T&O on career outcomes of workers employed at a firm in the IAB Establishment Panel in a routine job at baseline. Panel A displays results pooled for all routine jobholders; Panels B and C distinguish between different age groups (under 30, between 30 and 49, 50-59 and above at baseline in Panel B and between 50 and 54 and between 55 and 59 at baseline in Panel C). The main variable of interest, "number of changes" (0-4) measures the number of organizational changes in the baseline firm between t-3 and t+3. Outcome variables: whether the individual is employed at any firm in Germany at t+3 ("working"); whether the individual is employed in a manual, routine or abstract occupation at t+3; whether the worker is employed in an abstract occupation within the same or a different firm at t+3; and earnings ratios (the daily wage at t+3, set to zero for those not working, divided by the daily wage in t-3, multiplied by 100). The various employment variables take the values of either 0 or 100. All regressions control for age and age squared at baseline, foreign status, year fixed effects, firm size (log employment at baseline), commuting zones, three-digit occupation fixed effects at baseline, industry (one digit controls) as well as pre-estimated fixed firm effects and fixed worker effects calculated using the seven years prior to the baseline year. The unit of observation is the worker/year. Standard errors are clustered at the firm level. Significance levels: *10%, **5%, ***1%.

Sources: Registry data and IAB Establishment Panel, 1993–2010. We calculate tasks based on a categorization constructed using the 1991/1992 wave of the German BIBB/IAB Qualification and Career Survey.

Figure A.1: Within-Firm Declines in Routine Employment Shares by Baseline Firm Size



Notes: The figure plots within-firm changes in routine employment shares between 1992 and 2010 against firm size at baseline (in logs), where firms are divided into 20 groups such that the same number of workers is employed in each firm group. We restrict the sample to establishments with at least 10 employees at baseline. The dotted line depicts the predicted within-firm change in routine employment shares from a log-linear regression (R-squared = 0.56).

Source: Registry data linked to the IAB Establishment Panel, 1993–2010.