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Technology implementation within enterprises and job ending among employees. A study of the role of educational attainment, organizational tenure, age and unionization

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ABSTRACT

This study examines how technology implementation within workplaces impacts job ending among employees. We advance the literature on the labor market consequences of new technologies by focusing on their impact within workplaces where they are implemented, rather than inferring from aggregate labor structural changes. We also address how the impact of technology differs depending on workers education, organizational tenure and age. Using large-scale Dutch matched employer-employee panel data directly measuring technology implementation, we find that technology implementation is associated with an overall decrease in the probability of job ending. In line with the skill biased technological change hypothesis, higher educational attainment is associated with lower probabilities of job ending. Furthermore, we find older workers (around 50+) and workers with longer organizational tenure (around 12+ years) to have a higher probability of job ending when technology is implemented. Finally, we do not find the effects of technology implementation to differ depending on the union density of the industry in which an enterprise operates.

1. Introduction

Concerns about technological advancement and the future of work greatly increased in the past decades. Such worries have been strengthened by studies examining the feasibility of replacing human jobs by soon-to-be realized technologies in robotics, machine learning and artificial intelligence. Frey and Osborne (2017) estimate that, in the coming decades, 47 % of all jobs in the U.S. are at risk of being automated. Manyika et al. (2017) argue that about 60 % of U.S. occupations have at least 30 % work tasks that will be automatable by 2055. The World Bank (2016) comes to a similar estimate: almost 60 % of jobs in the OECD are susceptible to automation in the near future. Labor economic theorizing reiterates this labor replacing potential of technological advancement (Goos, Manning, & Salomons, 2014; Acemoglu & Autor, 2011; Autor, Levy, & Murnane, 2003; Goos & Manning, 2007; Goos, Manning, & Salomons, 2009).

The current literature on technological change focuses predominantly on labor market structure and inequalities. The macro view, however, overlooks work organizations. Organizations are highly important because organizations are the sites where new technologies are implemented and where economic rewards, such as jobs, are being created and distributed (Baron & Bielby, 1980). Our paper contributes in a number of ways to the small, but emerging literature investigating the consequences of technology implementation in organizations for workers' jobs (Bauer & Bender, 2004; Beckmann, 2007; Bessen, 2016; Fernandez, 2001; King, Reichelt, & Huffman, 2017; Nedelkoska, 2013; Siegel, 1998). First, within the current literature, technological change is argued to have differential impact depending on the human capital of workers, which most papers capture with education (Acemoglu & Autor, 2011; Autor et al., 2003). Very few studies incorporate a broader concept of human capital, even though technological change has direct implications for the value of firm and technology-specific knowledge accumulated over time, as well as for the value of older workers whose adaptive capabilities may decline with age (Bartel & Sicherman, 1993; Becker, 1993; Beckmann, 2007). In fact, no paper has analyzed different forms of human capital (tenure, education, and age) jointly. In this paper we fill this gap by studying the differential impact of technology on job endings of workers by education, age, and organizational tenure.

Second, we incorporate the institutional context of organizations which is surprisingly rare in studies on the consequences of technology

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on labor outcomes. The process of technology implementation and reorganization in organizations does not occur in an institutional vacuum. In fact, several studies have shown that institutions, such as labor unions, fundamentally impact the wage determination process by increasing workers' bargaining power (Fernandez, 2001; Kalleberg, Wallace, & Althauser, 1981; Kristal, 2013). In line with this literature, we argue that the likelihood of job loss and differences by education, tenure and age depend on the industrial context of the organizations in which workers are employed. Specifically, we address to what extent industry union strength weakens the relation between technology implementation and job ending for workers with different educational attainment, tenure and age.

Finally, macro-level studies imply, rather than directly measure, technological change. The few studies that employ direct measures of technological change within enterprises, however, find mixed results which do not align with macro-level outcomes. Corroborating findings of skill-biased technological change, Siegel (1998) and Fernandez (2001) find that the implementation of technologies within firms is associated with increased employment in skill-demanding jobs. Bauer and Bender (2004) studying German firms, however, find that technology implementation is associated with increased churning rates among high skilled professionals and engineers. Furthermore, Nedelkoska (2013), studying German manufacturing firms, finds that routine-intensive occupations declined between 1975 and 2004. She finds little evidence, however, that technology implementation was the main driver of these changes. In line with this finding, Bessen (2016), studying computerization within US occupations, does not find computerization to decrease employment in routine-intensive occupations. This evidenced heterogeneity in how technology affects workers calls for research that considers factors at the organizational and institutional level (Fernandez, 2001), and research that empirically tests, rather than assumes, that employment changes are the result of technological change (Nedelkoska, 2013). Adhering to these suggestions we use a large-scale survey of (technological) innovation within Dutch enterprises which we match with register data about their employees. Our study employs a direct measure of technology at the level of enterprises which indicates whether enterprises have invested in advanced machinery, equipment (including computer hardware) or software specifically purchased to implement new or significantly improved products (goods/services) and/or processes. The linked employer-employee dataset allows us to follow over three million employees within over 30,000 enterprises over a period of fourteen years (2001–2014).

2. Theory

Educational attainment, tenure, and age are indicators of human capital on the one hand (Becker, 1993), and distinctive, meaningful, and power-enhancing social categories on the other hand (Tilly, 1998). To study the role of human capital characteristics of workers we rely on supply and demand frameworks as articulated in assignment models (Acemoglu & Autor, 2011) and complement this with relational inequality theory which addresses the role of organizational power (Avent-Holt & Tomaskovic-Devey, 2014). Within relational inequality theory it is argued that appealing to categorical distinctions, such as education or tenure, workers within organizations validate making claims to scarce resources within the enterprise, such as wages or jobs (Avent-Holt & Tomaskovic-Devey, 2010; Tilly, 1998). As we will show, the two interpretations of worker characteristics partly lead to opposing hypotheses. In the final section we elaborate on how institutional contexts shape the relation between technological change and job ending among workers.

Theories of technology-related labor market changes agree that technological developments do not universally replace human labor. In fact, certain groups of workers will be valued more as a result of technological change. Therefore, there is little rationale to theorize on an absolute effect of technological change that applies to all workers. Instead, it is more informative to examine how relative differences in the likelihood of job loss shift between groups of workers as a consequence of technological change.

2.1. Education as a human capital dimension

A core proposition within economic literature on technology is the Skill-Biased Technological Change hypothesis (SBTC) which argues that technological progress increases the relative productivity of higher skilled workers, such as programmers, scientists, analysts, consultants, and engineers (Autor, Katz, & Krueger, 1998; Berman, Bound, & Griliches, 1994; Card & DiNardo, 2002; Katz & Murphy, 1992; Krueger, 1993; Michaels, Natraj, & Van Reenen, 2014). Increased productivity leads to higher demand for skills these workers possess. Examples of skills with increasing demand due to technological change are problem-solving capabilities, analytical capabilities, intuition, creativity, inductive reasoning, and communication skills (Acemoglu & Autor, 2011; Autor et al., 2003; Fernandez, 2001; Spitz-Oener, 2006).

The level of education of workers is indicative for the accumulation of such skills (Becker, 1993). By virtue of attainment of such skills as inductive reasoning, problem-solving and analysis, the demand for higher educated workers likely increases with the implementation of technology (Spitz-Oener, 2006). Regarding chances of job ending, we expect the increase in demand for skilled labor resulting from the implementation of technology within an enterprise to result in smaller chances of job ending for higher educated workers relative to middle and lower educated workers.

The SBTC framework has been criticized for falling short in explaining the relative decrease of workers in middle skill jobs, such as clerical and production jobs, observed in recent labor market developments (Acemoglu & Autor, 2011; Autor et al., 2003; Goos & Manning, 2007; Goos et al., 2009, 2014). Assignment models argue that technology not only increases the demand for skilled workers, but also decreases the relative demand for workers in middle skilled jobs. Technology mainly replaces manual and cognitive routine tasks, such as record keeping or repetitive assembly, because these tasks are codifiable in computer language (Autor et al., 2003). As middle skilled workers are overrepresented in jobs with routine tasks, automation arguably impacts middle-skilled workers most strongly, possibly displacing their jobs.

We expect that the chances of job ending for workers with intermediate levels of education increase relative to the chances of job ending of lower educated workers. We hereby make the plausible assumption that workers with intermediate levels of education will not be reallocated to do the job tasks performed by lower educated workers, because it is more cost-efficient to keep lower-earning lower educated workers rather than reallocating more expensive middle-educated workers into low skill jobs. Second, an argument to retain and reallocate middle-educated workers to low-skilled job tasks could be that middle skilled workers are more productive performing these jobs. However, since low-skilled job tasks are simplified and less autonomous, it is debatable whether significant productivity gains can be realized (Acemoglu & Autor, 2011). Based on these arguments, we hypothesize that:

H1a. Technology implementation increases the likelihood of job ending for middle educated workers relative to lower educated workers.

2.2. Education as a source of worker power

While human capital theory sees education relating primarily to worker productivity, relational theory argues that educational credentials serve as a categorical distinction legitimating claims for organizational resources (Tholen, 2017; Weeden, 2002) (cf. Tilly, 1998). The process of any organizational change, such as adopting new technologies, involves organizational politics, conflicting interest, and power dynamics (Buchanan & Badham, 2008). Vallas (2006), studying reorganizations within manufacturing firms, noted that high-skilled engineers often referred to their educational credentials to successfully negotiate their allocation to complex analytical tasks, even when lower-educated process control engineers and technicians resisted such allocation. In a similar vein, Hanley (2014) in a historical case study of automation in General Electric, finds that managers actively constructed a new conception of productivity which valorized themselves as the firm's core productive workers, thereby legitimating increasingly unequal rewards at the expense of clerical and production workers. We expect that during the process of technological change, workers with higher education are more able to claim a (redefined) role within the organizational production process and justify their position. Based on relation theory and the skill biased technological change hypothesis we formulate the following hypothesis:

H1b. Technology implementation decreases the likelihood of job ending for higher educated workers relative to lower educated workers.

2.3. *Organizational tenure as a human capital dimension*

A large share of a workers' productivity stems from experience gained within the enterprise. As a result, tenured workers are generally more valuable for an enterprise (Crook, Todd, Combs, Woehr, & Ketchen, 2011; Gathmann & Schönberg, 2010; Jovanovic, 1979; Lazear, 2009; Topel, 1991). The impact of tenure on job endings, as a source of human capital, likely differs from that of formal education under technology implementation. Workers who have been working within the enterprise for a longer time accumulate experience with technologies linked to their job tasks. However, while generic skills, such as analytical capabilities or problem solving, are transferable across different technologies, experience is a skill specific to current and past technologies within the enterprise (Lazear, 2009; Topel, 1991). When technology does not change, accumulating experience translates to higher productivity (Dearden, Reed, & Van Reenen, 2006), which is rewarded with higher wages (Brown, 1989). When the enterprise adopts a new technology, however, skills stemming from experience with past technology may partially become obsolete and cease to support productivity. Employers are willing to pay higher wages as long as it can be justified by high productivity of an employee. When new technology is implemented, however, the "productivity premium" of tenure resulting from experience with past technology decreases, resulting in wage-costs that are out-of-balance with the productivity of tenured workers. Demotion of tenured workers and lowering their wages can negatively impact worker morale as well as organizations' reputation, and consequently is often not preferred (Josten & Schalk, 2010). Instead, organizations are more likely to recover the balance between wage costs and productivity by laying off tenured workers or incentivizing them to leave the enterprise. We expect that:

H2a. Technology implementation increases the likelihood of job ending for workers with higher organizational tenure relative to workers with lower tenure.

2.4. *Organizational tenure as source of worker power*

Relational inequality theory argues that workers' power to make claims for organizational resources increases with organizational tenure (Avent-Holt & Tomaskovic-Devey, 2012). Enterprises use internal promotions to fill higher-level positions, which usually favor tenured workers, partly because they better know and influence decision makers and they are better informed about opportunities (Althauser & Kalleberg, 1981; Pfeffer & Cohen, 1984). But tenure is also a categorical distinction, which represents valuable knowledge and experience that may justify claims for organizational resources. Due to their higher organizational power, tenured workers are likely to secure or even improve their position within the organization in the process of technology implementation. In fact, case studies by Vallas (2006) and (Hanley, 2014) show that implementation of new technologies triggers internal competition for resources, and it is likely that in such competition workers with higher seniority will fare better than workers with less seniority. These arguments lead to a prediction about the relationship between tenure and job loss that contradicts the prediction derived from human capital theory: We hypothesize that:

H2b. Technology implementation decreases the likelihood of job ending for workers with higher organizational tenure relative to workers with lower tenure.

2.5. *Age, skill accumulation over the life course and adaptability*

The capability of employees to adapt to new technologies is a salient matter when organizations implement new technologies (Bartel & Lichtenberg, 1987). Adaptive capabilities are skills that especially older workers seem to possess less than younger workers. Older workers are accustomed to certain routines and less able and willing to accommodate organizational and technological change, compared to younger workers (de Koning & Gelderblom, 2006; Meyer, 2011; Weinberg, 2004). Older workers may also find it cognitively more difficult to learn new (technological) skills (Desjardins & Warnke, 2012; Slegers, Van Boxtel, & Jolles, 2009; Westerman & Davies, 2000). Finally, the implementation of new technologies often requires workers to learn new skills, and younger workers, due to their more recent education, are more likely to have partially acquired these skills (Beckmann, 2007). Due to lower adaptability, older workers may become less attractive to employers when technology is implemented. Numerous studies found that aged workers are less likely to receive re-training (Arulampalam, Booth, & Bryan, 2004; Bartel & Sicherman, 1993; Beckmann, 2007; Carmichael & Ercolani, 2014; Guerrazzi, 2014; Taylor & Urwin, 2001), indicating the reluctance of employers to invest in workers whose expected productivity is low. However, Behaghel and Greenan (2005), studying computerization in French firms, document a decrease in productivity among older workers under circumstances of technological change that is not explained by the presence or absence of re-training. This finding seems to point to productivity losses among older workers regardless of training.

Concluding, when new technology is implemented, we expect that lower ability, training possibilities, and willingness to adapt to technological change increases the odds of both quits and layoffs. We hypothesize that:

H3. Technology implementation increases the likelihood of job ending for older workers relative to younger workers.

2.6. *Age stereotyping and discrimination*

From a relational inequality perspective, the low capability of older workers –and seniors in general– to adapt to new technologies is a powerful social stereotype that influence managerial expectations and decisions, even when actual work performance contradicts them (see Posthuma & Campion, 2009, and Shore & Goldberg, 2005 for overviews of studies on performance stereotypes and actual performance of older workers). Consequently, negative stereotypes and discriminatory practices among managers decrease older employee's claims-making power, leading to lower training participation among older workers as well as early retirement arrangements (Posthuma & Campion, 2009; Shore & Goldberg, 2005). From the older employee's perspective, experiencing discrimination and managerial favoritism towards younger workers may incentivize them to leave an enterprise. Human capital and relational inequality theories both point towards greater likelihood of job ending among older workers relative to younger ones under technological change.

2.7. Technological change and the role of institutions

Contemporary organizational theories argue that the institutional context exerts a powerful influence on the behavior of organizational actors (Scott, 2014). How technological change impacts jobs is likely to depend on the institutional context in which the enterprise operates (Avent-Holt & Tomaskovic-Devey, 2014; Orlikowski & Barley, 2001). Employer's actions are constrained by labor laws, unions, and collective agreements that can at the same time also empower workers. Fernandez (2001) studying the consequences of the retooling of a food processing plant for workers' jobs and wages, finds that the outcome of technology implementation is strongly shaped by the bargaining process between the union and the employer. In return for no-layoff and wage guarantees, the union agreed on relaxing seniority and work rule requirements and supporting retraining efforts by the enterprise.

In the current study we focus on industrial contexts in the Netherlands, differentiating between industries with stronger and weaker unions. Overall, union coverage in the Netherlands is similar to the average of OECD countries (OECD, 2018). In 2016, 17 % of wage-earning workers in the Netherlands was union member. The country ranks 20th, while the US ranks 32nd with a union density of 10 %. In the Netherlands, however, unions are more influential than their membership suggests because they bargain at the company or industry level over collective labor agreements, thereby also affecting workers who are themselves not a member of a union. Within the Netherlands, 79 % of wage earners is covered by collective bargaining agreements, ranking 9th among 36 countries included in OECD data.

There is substantial variation in union coverage between industries and sectors in the Netherlands. In manufacturing, union coverage was 31 % in 2011, whereas in business services only 11 % of workers was covered by unions (Statistics Netherlands, 2012). Procedures concerning the dismissal of workers in the Netherlands usually requires employers to find agreement with unions (Dismissal, 2011). In general, weaker unions increases the power of employers to influence labor agreements (Kristal, 2013). Organizations operating in such contexts are therefore more able to develop policies that conform to demand and supply principles. Therefore, workers in industries with stronger unions have better means to achieve favorable agreements with employers, and this improves the bargaining position of workers who otherwise would face a layoff due to technology.

Institutional contexts also influence how certain categorical distinctions are recognized within the process of relational claims-making (Avent-Holt & Tomaskovic-Devey, 2014). Workers of organizations operating in sectors that formalize labor arrangements are likely to use these institutional arrangements to legitimize their claims (Tomaskovic-Devey, Avent-Holt, Zimmer, & Harding, 2009). For example, seniority rules can limit the ability of employers to specifically target older workers for layoffs (Lindbeck, 1994), which increase the bargaining power of senior workers for wage benefits (Böckerman, Skedinger, & Uusitalo, 2018). More generally, we expect that the more labor arrangements protect the interest of a categorical group, the stronger such categories become as a resource for claims-making. In union dense industries, older and tenured workers are more protected than in industries where unions are weak (de Hek & van Vuuren, 2011; Tracy, 1986). Consequently, workers in more union dense industries are more likely to use tenure and age to legitimize claims (Bidwell, 2013). As a result, organizational policies, such as early retirement arrangements or wages, are likely to be developed conform such formalizations. When institutionalization is less strong, the degree to which workers can use categorical distinctions to legitimize claims decreases.

Regarding our hypotheses, variation in union strength implies that in industries with weaker unions we expect to find stronger evidence in favor of our hypotheses based on human capital principles: H1a, H2a. Also, since there is less protection of senior workers, we expect a stronger evidence for H3. Similarly, in industries with stronger unions we expect that claims-making by tenured workers is more successful, resulting in stronger evidence in favor of hypothesis 2b. Furthermore, we expect there is more protection of older workers, resulting in stronger evidence for H3.

3. Data

Our study makes use of the combination of a large-scale enterprise survey and social micro-register data. Data on company investment in technology is taken from the Community Innovation Survey (CIS). The CIS is a large-scale cross-national panel survey of innovation activity in enterprises, repeated every two years. In the Dutch survey used by this study, the sample is stratified by sector and establishment size, excluding enterprises smaller than ten workers (Mortensen & Bloch, 2005). Due to the longitudinal design, we are able to study changes in technology implementation within enterprises over time. We focus on the period 2001–2014, during which a total of 37,520 enterprises participated in the Dutch CIS survey. We linked these enterprises to register data on workers' jobs and demographic characteristics from the System of Social Statistics Databases (SSB) of the Dutch Central Bureau of Statistics, creating a longitudinal matched employer-employee dataset. The data is characterized by a four-level hierarchical structure in which years are nested in jobs (40,586,509 observations in 15,057,672 jobs), jobs are nested in individuals (7,015,717) and individuals nested in enterprises (37,520). A job is defined as a contractual employment relation between an individual and an enterprise. If an individual had more employment contracts with the same enterprise, we aggregated them as one record. We restrict the data to include only standard forms of employment, i.e. jobs with a permanent work contract. We excluded shareholders, trainees, social employment, fixed-term and on-call employees (4,837,025 jobs, 32.12 %). The largest group among those that are excluded, fixed-term employees, were excluded because specific rules and regulations pertain to the ending and renewal of these contracts, making job endings incomparable to those of regular, permanent employees. We exclude jobs for which no information was available on type of employment (889,216 jobs, 5,91 %). Finally, we exclude workers whose level of education was not registered (1,611,724 individuals, 22.97 %), and 207 enterprises with missing data on organizational innovation. The remaining dataset consists of 36,903 enterprises with 4, 101,472 employees holding 7,006,374 jobs. The total number of cases is 16,614,116 (jobs × years). Table 1 provides descriptive statistics before and after deletion of missing cases and selections.

4. Measurement

4.1. Dependent variable

Job ending is measured as the end of a person's contractual employment relation within an enterprise. Having information about the beginning and end of employment relations between individual and enterprise of all workers from the register data we can reliably document beginnings and endings of worker's jobs. Out of the total of 7,006,374 jobs, 4,071,822 (58.12 %) end during the period of observation. The Dutch register about employees does not provide information on the type of job ending, such as voluntary quits, layoffs, or ending contracts. We therefore use job ending as a definition capturing all different forms of ending work relationships between an employee and the employer.

4.2. Independent variables

Implementation of technology is measured using an item from the Community Innovation Survey. A higher manager from the enterprise was asked to indicate whether, over the past two to three years (depending on the survey date), the enterprise purchased advanced machinery, equipment (including computer hardware) and/or software with the goal to significantly improve products, services, and/or production processes. Out of the total of 36,903 enterprises in the data, 9688 enterprises (26.25 %) implement new technologies to significantly improve their products, services and/or production processes in the period 2001–2014.

Educational attainment is measured according to the International Standard Classification of Education (ISCED). Eight educational levels are distinguished. We recoded the levels into three broad categories following guidelines from the ISCED 2011 manual (OECD/Eurostat/UNESCO Institute for Statistics, 2015). Low education, including those who attained less than primary education, primary education, and lower secondary education (20,91 %). Medium education, including employees who attained upper secondary education and post-secondary non-tertiary education (44.45 %). And high education, including employees who attained short cycle tertiary, bachelors, a master, or doctoral equivalent education (34.64 %). Information on individuals' level of education is gathered from registers of educational institutions and self-reported data from the Dutch Labor Force Surveys (EBB) integrated into the SSB. Educational registers contain all graduates in the Netherlands, but integration of digital records with the SSB is recent, and the data do not include all workers. The register coverage for younger cohorts is very high, about three-fourth of workers under the age of 30 but drops below 50 percent for workers older than 50. Missing information is filled up from the labor force surveys, which include around 10 percent of the population above the age of 50.

Organizational tenure is measured as the duration of the employment relation within the enterprise in years. The average number of years worked within the enterprise is 5.89 years.

Age is measured in years since birth. The average age of workers over the years of observation is 33.75 years old.

Union density is measured as the number of unionized employees younger than 65 years old with paid work for at least 12 h a week, as a percentage of the total number of employees with paid work for at least 12 h per week within a sector. Data on union density are taken from Labor Force Surveys, which are available for the years 2001–2005, and 2007–2011 (Statistics Netherlands, 2012). The available surveys show very little variation in union densities within sectors over time, and we therefore take the average union density over the available years per sector to arrive at a measure for comparing union densities between sectors.

Native-(Non-)Western immigrant background is measured using information on the birthplace of a person and the birthplace of the parents. For the definition of native and (Non-)Western immigrant workers we follow the definition of Statistics Netherlands. Native is defined as those who are born in the Netherlands and whose parents are also born in the Netherlands. (Non-)Western immigrant is measured as those workers whose mother is born in a (Non-)Western country, or in case the mother is born in the Netherlands, as those workers whose father is born in a (Non-)Western country.

We control for *unemployment rate* in all models to capture labor market fluctuation, measured as the national yearly unemployment rate of the Netherlands. On average, the unemployment rate is 4.91 % over the period 2001–2014.

Furthermore, we control for *organizational innovations* to capture changes in the organization of the enterprise which can be related to job ending (Bauer & Bender, 2004; Bresnahan, Brynjolfsson, & Hitt, 2002). A higher manager from the enterprise was asked to indicate whether, over the past two to three years (depending on the survey date), the organization introduced new business procedures, new methods for the organization of professional responsibilities and decision making, or new methods to organize external relations with other companies or institutes. Among the enterprises 33.91 % engaged in organizational innovations at least once in the period 2001–2014.

Finally, we control for the gender of the respondent.

Table 1
Descriptive statistics before and after selections and deletion of missing cases.

	Before selections			
	Observations	mean	SD	Range
Job ending	40,586,509	0.23	0.42	[0–1]
Technology implementation	40,586,509	0.31	0.46	[0–1]
Level of education	28,903,717	2.12	0.74	[0–2]
Low	6,407,801	*0.22*		
Middle	12,716,463	*0.44*		
High	9,779,453	*0.34*		
Organizational tenure in years	40,586,509	7.01	7.99	[a]
Age	40,586,509	35.94	13.06	[a]
Unionism	40,080,334	18.07	8.41	[12–35.8]
Sex	40,586,509	0.38	0.49	[0–1]
Male	25,187,098	*0.62*		
Female	15,399,411	*0.38*		
Migration background	40,586,509	0.33	0.65	[1–2]
Native Dutch	31,032,668	*0.76*		
Non-Western immigrant	5,520,080	*0.14*		
Western immigrant	4,033,761	*0.10*		
Unemployment rate	40,586,509	4.79	1.30	[2.5–7.4]
Organizational innovation	40,525,797	0.44	0.50	[0–1]
Number of observations	40,586,509			
Number of jobs	15,057,672			
Number of employees	7,015,717			
Number of enterprises:	37,520			
	After selections			
	observations	mean	SD	Range
Job ending	16,614,116	0.25	0.43	[0–1]
Technology implementation	16,614,116	0.32	0.47	[0–1]
Level of education	16,614,116	2.14	0.73	[0–2]
Low	3,474,215	*0.21*		
Middle	7,384,304	*0.44*		
High	5,755,597	*0.35*		
Organizational tenure in years	16,614,116	5.89	6.75	[a]
Age	16,614,116	33.75	12.06	[a]
Unionism	16,377,888	18.45	8.56	[12–35.8]
Sex	16,614,116	0.40	0.49	[0–1]
Male	10,049,600	*0.60*		
Female	6,564,516	*0.40*		
Migration background	16,614,116	0.30	0.62	[0–2]
Native Dutch	13,020,690	*0.78*		
Non-Western immigrant	2,138,190	*0.13*		
Western immigrant	1,455,236	*0.09*		
Unemployment rate	16,614,116	4.91	1.32	[2.5–7.4]
Organizational innovation	16,614,116	0.41	0.49	[0–1]
Number of observations	16,614,116			
Number of jobs	7,006,374			
Number of employees	4,101,472			
Number of enterprises:	36,903			

[a] Due to the identifiability protocols of the Dutch Central Bureau of Statistics, minimum and maximum values cannot be included here.

5. Method

To investigate the relation between technological change and job ending we estimate linear probability models with fixed effects at the level of the enterprise and random effects at the individual level. By including fixed effects for enterprises, we control for time invariant unobserved heterogeneity at the enterprise level. Random effects at the individual level take into account that our yearly job observations are nested within individuals, as well as model individual-level unobserved heterogeneity. We opted not to include individual fixed effects for three reasons. First, we would not be able to identify the effect of education since it is virtually time-invariant. Second, due to the within-person over-time collinearity of age and tenure, the effects of these two variables would only be identifiable for a select group of workers who hold multiple jobs. Third, due to right censoring and the fixed-effects specification, cases that do not experience job ending are excluded from the analytical sample for estimation, which could overrepresent "unstable" jobs in the sample.

To the baseline models including the main effect of technology implementation we, one-by-one, add the interaction effects with education, tenure and age. Finally, a full model including all three interactions is presented. To investigate the effect sizes, we calculate predicted probabilities at meaningful values of the variables. These predicted probabilities are calculated with the other variables set at the mean. The predicted probabilities are based on an alternative model that includes fixed effects at the enterprise level but does not include a multilevel structure. In the multilevel random effects model the effects of enterprises are fixed by hand through demeaning. The alternative method; including dummies for enterprises, is computationally unfeasible with 36,000+ enterprises. The manually computed demeaned interaction variables, however, complicate standard calculations of marginal effects. We therefore calculated a slightly more parsimonious model that generates near identical results to calculate marginal effects. The results of this model are presented in Table A1 in the appendix.

We tested differences in the relation between technology implementation and job ending depending on union strength within the industry by including three-way interactions of unionism, technology implementation and consecutively; educational attainment, organizational tenure and age.

Finally, as indicated in the data section, we restrict the sample by selecting only jobs with permanent work contracts and by excluding cases for which we do not have information on educational attainment or with missing data on contract type. To assess whether these restrictions bias the results we investigate the age and technology interaction effect, which can be measured in all data subsets, in models with and without sample restrictions. The results of this robustness check are presented in Table A4 in the appendix.

6. Results

In Table 2 we present the multilevel random effects models which include organization fixed effects. Looking at the effects of technology implementation on the likelihood of job ending in the baseline model 1, we find that technology implementation is associated with a significantly lower probability of job ending in both models. Estimating the overall probability of job ending between the two conditions, we find that under technology implementation the chances of job ending are 23.24 %, which is 1,69 % lower than in times without technological innovation (24.93 %).

In model 2 the main and interaction effects of educational attainment are added to the baseline model. We find that middle and higher educated workers have a higher probability of job ending compared to lower educated workers. Due to the negative correlation of age and level of education, these effects reverse in the full model when we include age and tenure and their interaction effects with technology implementation. Looking at the interaction effects between technology implementation and middle educated workers, we find that technology implementation is associated with lower probabilities of job ending among middle educated workers. We therefore reject hypothesis 1a. For higher educated workers we find that technology implementation is associated with a decreased probability of job ending job ending, which supports hypothesis 1b. Fig. 1 shows the predicted probabilities of job ending by educational attainment and technology implementation. Overall, the figure shows that under technology implementation the probability of job ending decreases for workers of all educational groups. For higher educated workers the decrease is greatest; from a 25.12 % chance of job ending when technological innovation is absent, to a 22.95 % chance of job ending when technology is being

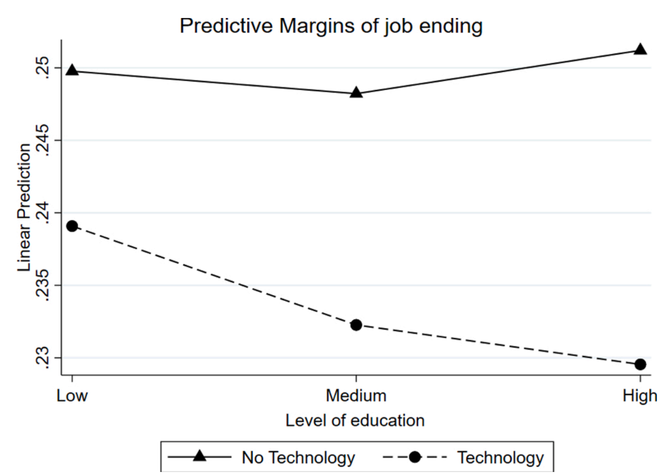

Fig. 1. Predicted probabilities of job ending by education and technology implementation.

Table 2
Multilevel random effects models of technology implementation on the likelihood of job ending, with fixed effects for enterprises.

	Model 1 Baseline model	Model 2 Education	Model 3 Org. Tenure	Model 4 Age	Model 5 Full model
Technology	−0.014*** (0.000)	−0.008*** (0.001)	−0.014*** (0.000)	−0.013*** (0.000)	−0.009*** (0.001)
(Lower education is ref.) Middle education		0.018*** (0.000)			−0.003*** (0.000)
Middle education × Technology		−0.007*** (0.001)			−0.004*** (0.001)
Higher education		0.031*** (0.000)			−0.003*** (0.000)
Higher education × Technology		−0.011*** (0.001)			−0.007*** (0.001)
Organizational tenure			−0.008*** (0.000)		−0.004*** (0.000)
Organizational tenure × Technology			0.003*** (0.000)		0.002*** (0.000)
Age				−0.005*** (0.000)	−0.004*** (0.000)
Age × Technology				0.001*** (0.000)	0.001*** (0.000)
(Male is ref.) Sex	0.007*** (0.000)	0.008*** (0.000)	0.002*** (0.000)	0.003*** (0.000)	0.001*** (0.000)
(Native Dutch is ref.) Non-Western immigrant background	0.057*** (0.000)	0.060*** (0.000)	0.046*** (0.000)	0.045*** (0.000)	0.041*** (0.000)
Western immigrant background	0.023*** (0.000)	0.023*** (0.000)	0.018*** (0.000)	0.027*** (0.000)	0.024*** (0.000)
Yearly unemployment rate	0.004*** (0.000)	0.004*** (0.000)	0.006*** (0.000)	0.006*** (0.000)	0.006*** (0.000)
Organizational innovation	0.001*** (0.000)	0.001*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
Constant	0.057*** (0.000)	0.057*** (0.000)	0.042*** (0.000)	0.040*** (0.000)	0.035*** (0.000)
Constant individual level	0.014 (0.000)	0.014 (0.000)	0.009 (0.000)	0.010 (0.000)	0.008 (0.000)
Residual variance	0.155 (0.000)	0.155 (0.000)	0.158 (0.000)	0.155 (0.000)	0.157 (0.000)
Observations	16,614,116	16,614,116	16,614,116	16,614,116	16,614,116

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

implemented (-2.17 %). Relative to lower educated workers the chance of job ending decreases with 0.53 %, for middle educated workers, and with 1.1 % for higher educated workers.

Looking at the effect of organizational tenure in model 3 we find that more senior workers have lower probabilities of job ending. In line with hypothesis 2a, we find their probability of experiencing job ending to slightly increase under technology implementation. Looking at the effect sizes we find that the interaction effect is smaller than the main effect. Thus, under conditions of no technology being implemented, organizational tenure decreases the probability of job ending. When technology is being implemented, this decrease in probability of job ending for tenured workers becomes smaller. Nevertheless, higher tenure is still associated with lower probabilities of job ending, albeit less so compared to when no technologies are implemented. Interestingly, and in line with our theoretical argumentation, this pattern only applies to workers that have fairly high levels of organizational tenure. Fig. 2 shows the predicted probabilities of job ending by job tenure and technology implementation. When we look at workers who have just started their jobs, at zero years of organizational tenure, we find that in times without technological innovation the chance of job ending is 27.48 %. When technology is being implemented, the chance of job ending for new hires is slightly lower; 24.82 %. Thus, for new hires technology implementation actually associates with lower probabilities of job ending. At around ten years of organizational tenure the predicted chances of job ending are nearly identical; 22.07 % in times without technological innovation, and 21.55 % in times of technological change. Among workers with relatively high organizational tenure we do we find technology implementation to associate with relatively higher chances of job ending. At 20 years of organizational tenure, slightly less than two standard deviations from the mean organizational tenure, the predicted chance of job ending is 1,61 % higher (18,28 %) in times of technology implementation compared to times of no technological innovation (16,67 %). All in all, we find technology implementation to associate with relative increases in the probability of job ending at higher levels of job tenure. Concluding, we find support for hypothesis 2a and no support for hypothesis 2b.

Finally, looking at the effect of age in model 4, we find a similar pattern. Higher age is associated with lower probabilities of job ending. However, this effect decreases slightly when new technologies are implemented within the organization. This finding is in line with the arguments underlying our third hypothesis, that technology increases the likelihood of job ending among older workers. However, since here too the main effect of age is greater than the interaction effect, older workers still show lower probabilities of job ending under technological change, only slightly less so compared to when the enterprise is not implementing technologies. Interestingly, the results show greater predicted probabilities of job ending from around age 50+ under technology implementation. At sixty years of age, the predicted probability of job ending under technological change is 15.10 %, which is 0.79 % higher than the predicted probability of job ending in times without technological innovation (14.34 %). All in all, the pattern supports hypothesis 3 (Fig. 3).

Table 3 reports the random effects models testing the effects of unionism. Model 6 shows that there is a statistically significant difference in the likelihood of job ending under technology implementation in unionized and non-unionized industries. The effect size, however, is practically zero, meaning that the difference is not substantial. In subsequent models, educational attainment, organizational tenure and age are added to the model. We find that all three-way interactions are statistically significant. We do not find technology implementation to increase the probabilities of job ending among middle educated more strongly in industries with lower unionization. However, in line with our expectations we do find that in more strongly unionized industries workers age and tenure associate with slightly smaller increases in the probability of job ending when technology is implemented. The effect sizes, however, are all nearly zero, indicating that the interaction effects

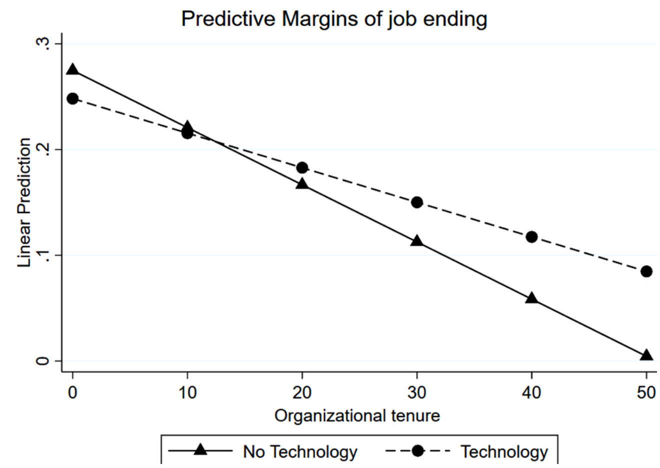

Fig. 2. Predicted probabilities of job ending by organizational tenure and technology implementation.

between worker characteristics and technology implementation are highly similar across industries with different union densities.

6.1. Additional analyses and testing for selection effects

We performed additional analyses to test whether there is a lagged effect of technological change on job ending (See Table A2 in the appendix). Lagging the effects of technology implementation for one, two and three years after implementation, we find the first two years to associate with small decreases in the probability of job ending for workers. The three-year lagged effect, however, shows a small increase in the probability of job ending. This curb in the effect of technology implementation over time indicates an over-time diminishing effect of technological change. Substantively, this shows that the apparent increase in demand of human labor found in the main analyses flattens out over time.

We also tested whether task routineness, which is a central concept in task-based models of technological change (Autor et al., 2003), similarly relates to job ending as educational attainment (See Table A3 in the appendix). Following the strategy of Goos et al., 2014, we measured routineness by attaching routineness scores to occupational measures (ISCO scores). The latter scores are taken from the Dutch Labor

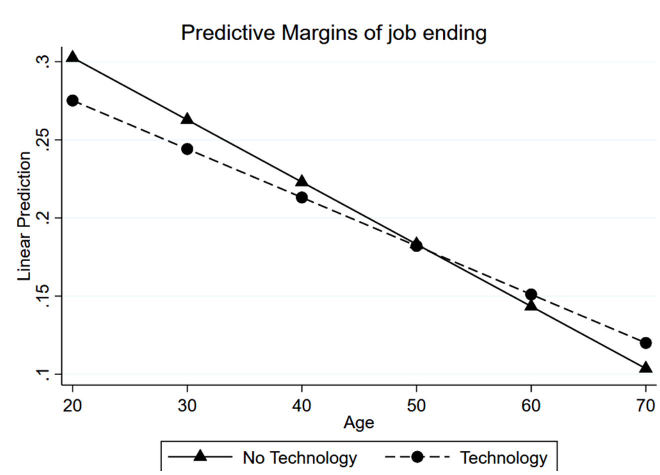

Fig. 3. Predicted probabilities of job ending by age and technology implementation.

Table 3
Multilevel random effects model of technology implementation on job ending, and the role of education, tenure, age and unionism.

	Model 6 Unionism	Model 7 Education	Model 8 Org. Tenure	Model 9 Age	Model 10 Full model
Technology	−0.015*** (0.000)	−0.006*** (0.001)	−0.012*** (0.000)	−0.011*** (0.000)	−0.004*** (0.001)
Technology × Unionism	0.000*** (0.000)	−0.000*** (0.000)	−0.000*** (0.000)	−0.000*** (0.000)	−0.000*** (0.000)
(Lower education is ref.) Middle education		0.014*** (0.001)			−0.009*** (0.001)
Middle education × Technology		−0.024*** (0.001)			−0.014*** (0.001)
Middle educated × Unionism		0.000*** (0.000)			0.000*** (0.000)
Middle educated × Technology × Unionism		0.001*** (0.000)			0.000*** (0.000)
Higher education		0.008*** (0.001)			−0.025*** (0.001)
Higher education × Technology		−0.030*** (0.001)			−0.022*** (0.001)
Higher educated × Unionism		0.001*** (0.000)			0.001*** (0.000)
Higher educated × Unionism × Technology		0.001*** (0.000)			0.001*** (0.000)
Organizational tenure			−0.011*** (0.000)		−0.006*** (0.000)
Organizational tenure × Technology			0.006*** (0.000)		0.003*** (0.000)
Organizational tenure × Unionism			0.000*** (0.000)		0.000*** (0.000)
Organizational tenure × Technology × Unionism			−0.000*** (0.000)		−0.000*** (0.000)
Age				−0.007*** (0.000)	−0.006*** (0.000)
Age × Technology				0.003*** (0.000)	0.003*** (0.000)
Age × Unionism				0.000*** (0.000)	0.000*** (0.000)
Age × Technology × Unionism				−0.000*** (0.000)	−0.000*** (0.000)
(Male is ref.) Sex	0.008*** (0.000)	0.008*** (0.000)	0.003*** (0.000)	0.004*** (0.000)	0.002*** (0.000)
(Native Dutch is ref.) Non-Western immigrant background	0.057*** (0.000)	0.059*** (0.000)	0.045*** (0.000)	0.044*** (0.000)	0.040*** (0.000)
Western immigrant background	0.023*** (0.000)	0.023*** (0.000)	0.018*** (0.000)	0.027*** (0.000)	0.024*** (0.000)
Yearly unemployment rate	0.004*** (0.000)	0.004*** (0.000)	0.006*** (0.000)	0.006*** (0.000)	0.006*** (0.000)
Organizational innovation	0.001*** (0.000)	0.001*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
Constant	0.057*** (0.000)	0.057*** (0.000)	0.042*** (0.000)	0.040*** (0.000)	0.035*** (0.000)
Constant individual level	0.015*** (0.000)	0.014*** (0.000)	0.009*** (0.000)	0.010*** (0.000)	0.008*** (0.000)
Residual variance	0.155*** (0.000)	0.155*** (0.000)	0.158*** (0.000)	0.156*** (0.000)	0.157*** (0.000)
Observations	16,347,201	16,347,201	16,347,201	16,347,201	16,347,201

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Force Surveys (EBB). We do not find a statistically significant association between the routineness of occupations and technology implementation and job ending. This result is in line with earlier research that does not find technology implementation in enterprises to relate to destruction of routine-jobs (Bessen, 2016; Nedelkoska, 2013). The absence of a relation between job routineness and technological change may explain why we do not find the probability of job ending to increase for middle educated workers, who are argued to be overrepresented in 'automation prone' routine jobs (Acemoglu & Autor, 2011).

Finally, as indicated in the data section, we made a number of sample restrictions for our analyses. We select only jobs with permanent work contracts. Furthermore, we exclude cases for which we do not have information on educational attainment, as well as jobs with missing data on contract type. To assess whether these selections and restrictions due to missing data bias the results we investigated the age and technology interaction effect in models with and without sample restrictions. The results are presented in Table A4 in the appendix. The substantive conclusions and effect sizes regarding the interaction are identical, so we are confident that the sample restrictions do not influence our results. There is, however, a noticeable increase in the main effect of job endings under technological change when we exclude non-permanent contracts from the sample. This finding can be related to the fact that non-standard jobs have a much higher natural turnover rate, decreasing the predictive power of exogenous shocks such as technological or organizational changes. Furthermore, it is possible that innovation temporarily increases the demand for flexible workers to accompany the

Table A1
Fixed effects regression model of technology implementation on job ending, and the role of education, tenure and age.

	Model 11 Technology	Model 12 Education	Model 13 Organization-al tenure	Model 14 Age	Model 15 Full model
Technology	−0.015*** (0.000)	−0.009*** (0.001)	−0.015*** (0.000)	−0.014*** (0.000)	−0.010*** (0.001)
(Lower education is ref.) Middle education		0.019*** (0.000)			−0.002*** (0.000)
Middle education × Technology		−0.007*** (0.001)			−0.003*** (0.001)
Higher education		0.035*** (0.000)			0.000 (0.000)
Higher education × Technology		−0.011*** (0.001)			−0.008*** (0.001)
Organizational tenure			−0.009*** (0.000)		−0.005*** (0.000)
Organizational tenure × Technology			0.003*** (0.000)		0.002*** (0.000)
Age				−0.005*** (0.000)	−0.004*** (0.000)
Age × Technology				0.001*** (0.000)	0.001*** (0.000)
(Male is ref.) Sex	0.009*** (0.000)	0.009*** (0.000)	0.004*** (0.000)	0.005*** (0.000)	0.003*** (0.000)
(Native Dutch is ref.) Non-Western immigrant background	0.047*** (0.000)	0.050*** (0.000)	0.036*** (0.000)	0.036*** (0.000)	0.033*** (0.000)
Western immigrant background	0.017*** (0.000)	0.018*** (0.000)	0.013*** (0.000)	0.022*** (0.000)	0.019*** (0.000)
Yearly unemployment rate	−0.001*** (0.000)	−0.001*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.003*** (0.000)
Organizational innovation	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)
Constant	0.242*** (0.001)	0.221*** (0.001)	0.222*** (0.001)	0.220*** (0.001)	0.215*** (0.001)
Observations	16,614,116	16,614,116	16,614,116	16,614,116	16,614,116

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A2
Lagged fixed effects linear probability model of technology implementation on job ending.

	Model 16 Lagged effects
Technology lagged 1 year	−0.001** (0.001)
Technology lagged 2 years	−0.002*** (0.001)
Technology lagged 3 years	0.004*** (0.001)
(Male is ref.) Sex	0.008*** (0.000)
(Native Dutch is ref.) Non-Western immigrant background	0.011*** (0.001)
Western immigrant background	0.009*** (0.001)
Yearly unemployment rate	−0.000 (0.000)
Organizational innovation	−0.003*** (0.000)
Constant	0.135*** (0.001)
Observations	4,584,819
Enterprises	14,856

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A3
Fixed effects linear probability model of technology implementation on job ending, with routineness of jobs.

	Model 17 Routineness of occupation
Technology	−0.055*** (0.007)
Routineness occupation	−0.004*** (0.001)
Routineness occupation × Technology	0.002 (0.002)
Organizational tenure	−0.003*** (0.000)
Organizational tenure × Technology	0.001** (0.000)
Age	−0.003*** (0.000)
Age × technology	0.001*** (0.000)
(Male is ref.) Sex	−0.003 (0.002)
(Native Dutch is ref.) Non-Western immigrant background	0.005 (0.004)
Western immigrant background	0.008** (0.003)
Yearly unemployment rate	0.002* (0.001)
Organizational innovation	−0.001 (0.003)
Constant	0.278*** (0.006)
Observations	174,314
Enterprises	20,642

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A4
Fixed effects linear probability model of technology implementation on job ending with selections.

	Model 18 no selection	Model 19 selection education	Model 20 selection job type	Model 21 all selections
Technology	−0.003*** (0.000)	−0.003*** (0.000)	−0.014*** (0.000)	−0.014*** (0.000)
Age	−0.004*** (0.000)	−0.005*** (0.000)	−0.005*** (0.000)	−0.005*** (0.000)
Age × Technology	0.000*** (0.000)	0.000*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
(Male is ref.) Sex	0.006*** (0.000)	0.011*** (0.000)	0.000* (0.000)	0.005*** (0.000)
(Native Dutch is ref.) Non-Western immigrant background	0.020*** (0.000)	0.018*** (0.000)	0.035*** (0.000)	0.036*** (0.000)
Western immigrant background	0.016*** (0.000)	0.013*** (0.000)	0.023*** (0.000)	0.022*** (0.000)
Yearly unemployment rate	−0.001*** (0.000)	−0.000 (0.000)	0.000** (0.000)	0.002*** (0.000)
Organizational innovation	−0.006*** (0.000)	−0.007*** (0.000)	0.003*** (0.000)	0.003*** (0.000)
Constant	0.241*** (0.000)	0.264*** (0.000)	0.203*** (0.000)	0.220*** (0.001)
Observations	43,505,187	30,845,478	24,778,508	16,614,116
Enterprises	37,303	37,220	36,990	36,903

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

process of technology implementation within enterprises. Considering these dynamics, we believe that restricting the analyses to the stable workforce reflects more robust changes in employment chances within organizations.

7. Conclusion & discussion

The current study investigates the relation between technology implementation within enterprises and job endings among employees. We address how the impact of technology implementation on job ending differs depending on human capital characteristics and categorical differences between workers. Furthermore, we investigate whether the effects of technology implementation differ depending on the union strength of the industry in which the enterprise operates. We combine Dutch register data with a large-scale survey on enterprise innovation, creating a matched employer-employee dataset including over 30.000 enterprises with over 4 million employees, covering the period 2001–2014.

The findings of the study indicate that, overall, technology implementation decreases the probability of job ending among workers with around 1,7 percent. This finding suggests that technological change does not decrease the need for employment within enterprises. Furthermore, the finding also suggests that technology implementation does not lead to a great turnover, and renewal of workforces. Instead, it suggests that enterprises (and workers) are able to adjust to the new technologies without the loss of jobs. Also, the results warn that studies predicting the decline of human labor may be overly pessimistic: employers seem to still be needing human employment following technological change. Furthermore, the findings corroborate notions that while technology alters and automates some job tasks, it is also creates new ones (Autor, 2015). Although it is possible that future technological developments in robotics and artificial intelligence may be more destructive for jobs than current technologies (Brynjolfsson & McAfee, 2014), predictions of a ‘jobless future’ may be off because predicting job generation is much harder than predicting job destruction (Frey and Osborne, 2017). The findings of the current study suggest that concerns about the disappearance of human labor due to technology may be overstated.

Our study shows that, as predicted, technology differentially impacts parts of the organizational workforce. The findings are in line with the Skill Biased Technological Change (SBTC) hypothesis proposed originally for aggregate labor market changes. We find that higher educated workers are less likely to experience job ending when technology is implemented. Furthermore, the findings are line with the argument from relational theory that educational credentials serve as a categorical distinction used to legitimate claims of (redefined) roles within the organizational production process. Based on the Routine Biased Technological Change (RBTC) hypothesis, we predicted that jobs of middle educated workers are most strongly affected by technological change. We, however, find no such pattern. Earlier studies suggest that technology may not be the primary driver of observed declines in routine jobs (Bessen, 2016; Nedelkoska, 2013), which could explain why we do not find support for this hypothesis. However, there are other explanations. One could be that jobs of middle-educated workers still consist of many non-automatable job tasks which require human labor (Bessen, 2016). Or, as we argued earlier, new technologies may enhance demand for human labor (Autor, 2015). Consequently, technology implementation may cause changes in job content rather than changes in the number of jobs. If this is the case, the results of the current study suggest that middle educated workers are generally successful in adapting their skills to perform new job tasks. We consider the question of which circumstances lead to more and less successful skill adaption by workers an interesting avenue for future research.

Our study reports that workers with high organizational tenure (around 12 years and more) and older workers (around 50+) experience higher rates of job ending under technology implementation. These results seem to support the argument that technological change brings along adaptation costs that are greater for workers with more work experience. Furthermore, these results seem to be in line with the argument that older workers have more difficulty learning new skills (Desjardins & Warnke, 2012; Slegers et al., 2009; Westerman & Davies, 2000), as well as the argument that older workers face ageist stereotypes at the workplace about their capacity to adapt to technological change (Posthuma & Campion, 2009; Shore & Goldberg, 2005). In light of the current trend of increasing retirement ages, as well as ever advancing technologies, the results of the current study suggests that policies aimed at timely preparing and training older and more experienced workers to stay competitive in a technologically innovate labor market are advisable.

Finally, we find statistically significant, but largely neglectable differences in our findings across industries. We would, however, be ill-advised to disregard unions as an important institution directing the effects of technological change. Collective bargaining in the Netherlands is highly collectivized, with the existence of industry-specific but also general employee unions, meaning that employees in industries with less degrees of union-specific bargaining benefit from across-the-board bargaining efforts. The Netherlands is not a unique case in this regard, but there are several countries, among which the often studied US-case, where collective bargaining occurs at a lower level. We encourage research using a cross-country comparative research design, including comparable labor markets and varying degrees of collectivized bargaining institutions to improve our understanding of the interplay between labor institutions and technological change.

Our focus on the individual-level, rather than aggregate, consequences of technological change opens a new avenue to study the interplay of technology with traditional dimensions of worker inequality, gender, race, and ethnicity. Currently, there is a paucity of studies on how women and minority race-ethnicity workers fare under technological change (exceptions are studies by Black & Spitz-Oener, 2010, and Warman & Worswick, 2015), but since organizational change evokes power processes, this research question is highly important to study.

Our study uses a direct measure of technology implementation, which is exceptional as the majority of the literature address technology indirectly through aggregate labor compositional shifts. Some studies nevertheless suggest that is worthwhile to differentiate between technologies, as they arguably affect work tasks differently. For example, studying German manufacturing firms, Nedelkoska (2013) finds that investment in computers replaced routine tasks with less routine ones, while full automation of machine tools and half-automated (CNC) devices replaced routine tasks with similarly routine ones. Arntz, Gregory, Lehmer, Matthes, and Zierahn (2017), find that the degree to which firm's work equipment is automated is larger in firms using mainly office and communication equipment, compared to firms using mainly production equipment. Although the measure we used in our study captures technologies that 'significantly' alter products, production processes, and services, we cannot identify the type of technology. We encourage future data collection efforts to distinguishing between the types of technology that are implemented to better understand its implications for tasks and workers.

Appendix A

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