13 Technology implementation within enterprises and changes in the educational and age composition of enterprise workforces

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Introduction

Recent studies indicating that large numbers of human work tasks could be automated in the near future have sparked scientific research into the effects of technological change on work (Frey & Osbourne, 2017; Manyika et al., 2017; World Bank, 2016). Feasibility studies estimate that advances in robotics, machine learning and artificial intelligence can automate or partially automate around 47 percent of US jobs in the coming decades (Frey & Osbourne, 2017), and almost 60 percent of jobs in the Organisation for Economic Co-operation and Development (OECD) (World Bank, 2016). As technology advances, it poses a challenge to the creation of sustainable workforces: technological change can destroy a large number of job tasks (Acemoglu & Autor, 2011). More specifically, recent empirical labor market studies show that technology is associated with decreased employment in middle-skill jobs and increased employment in high- and low-skilled jobs, leading to a polarization of labor markets (Acemoglu & Autor, 2011; Autor, Levy, & Murnane, 2003; Goos & Manning, 2007; Goos, Manning, & Salomons, 2009, 2014).

What is underexposed in these studies is how organizations, in which the process of technological advancement plays out, adapt their workforces to technological changes. There are four major advantages of taking an organizational perspective on how technological change impacts jobs that macro-level studies which focus on aggregate labor flows are unable to recognize.

First, organizations are the sites where workers' jobs are created and distributed (Baron & Bielby, 1980). What remains unclear is for which workers technological changes within enterprises create job opportunities, and which workers face increasing difficulties in finding and maintaining employment within enterprises when technology is implemented. In the current chapter we contribute to the small but emerging literature on how technological change impacts work within organizations (Bauer & Bender, 2004; Beckmann, 2007; Cortes & Salvatori, 2016; Fernandez, 2001; King, Reichelt, & Huffman, 2017; Nedelkoska, 2013; Siegel, 1998).

Second, for the sustainability of workforces, the relation in organizations between technology implementation, education and age is highly important. Previous literature has shown that technology is skill biased, meaning that it provides opportunities for higher educated workers in particular, while posing challenges for middle and lower educated workers (Autor et al., 2003). In addition, technology is found to lead to a growing pace of skill depreciation and the increased importance of adaptability of workers and organizations (Beckmann, 2007; Fernandez, 2001; Siegel, 1998). In the current study we contribute to the literature by studying whether workforces change with regard to the level of education and age, and how technology implementation relates to changes in the education and age composition of workers entering and leaving enterprises.

Third, an advantage of investigating organizations is that it allows a closer inspection of how institutional contexts influence the impact of technological change (Fernandez, 2001; Kalleberg, Wallace, & Althauser, 1981; Kristal, 2013). As shown in previous studies, organizational decision making is strongly influenced by institutional context, such as unionization and collective bargaining (Fernandez, 2001; Kalleberg et al., 1981; Kristal, 2013). To clarify how the institutional contexts of enterprises shape the effects of technological change, we compare changes in the education and age composition of the workforce and worker flows as a consequence of technological change across industries varying in the degree of unionization.

Finally, macro-level studies imply, rather than directly measure, technological change. Previous research has mainly used a proxy measure of technology, namely the level of routineness of a job (Autor et al., 2003; Goos & Manning, 2007; Goos, Manning, & Salomons, 2009, 2014; Spitz-Oener, 2006). It is argued that only job tasks that follow an exact routine can be effectively codified and computerized. When a decline in routine jobs is observed, it is assumed that technology is the main driver of this change. However, testing this assumption, Nedelkoska (2013) finds little evidence that higher occupational change among routine workers and wage losses for those leaving routine jobs were the result of the implementation of code-based technologies, thus stressing the importance of employing direct measures of technology. Using a large-scale survey of (technological) innovation within Dutch enterprises, we measure technology implementation as the investment of enterprises in advanced machinery, equipment or computer hardware/software specifically purchased to implement new or significantly improved products (goods/services) and/or processes.[1] To examine the relationship between technology implementation, the flow of workers in and out of enterprises and changes in workforce composition, we match this firm-level data to Dutch register data on employees. This allows us to follow over three million employees within over 30,000 enterprises over a period of fourteen years (2000–2014).

Theory

Technology implementation and the educational composition of workers entering enterprises

A leading hypothesis within the literature on the effects of technology is the Skill-Biased Technological Change (SBTC) hypothesis, which proposes that technology increases the marginal productivity of highly skilled workers, such as engineers, scientists and consultants (Autor, Katz, & Krueger, 1998; Berman, Bound, & Griliches, 1994; Card & DiNardo, 2002; Katz & Murphy, 1992; Krueger, 1993; Michaels, Natraj, & Van Reenen, 2014). This increased marginal productivity increases the demand for highly skilled workers (Acemoglu & Autor, 2011; Autor et al., 2003; Fernandez, 2001; Spitz-Oener, 2006). Education increases problem-solving capability, analytical capacity, inductive reasoning and communication skills (Becker, 1964), which are central to high-skill work tasks (Acemoglu & Autor, 2011; Autor et al., 2003; Spitz-Oener, 2006). It can therefore be expected that as the demand for more highly skilled workers increases with technological change in enterprises, it also increases the demand for higher educated workers (Autor et al., 2003). Thus, we expect that:

> Hypothesis 1: When technology is implemented, the proportion of higher educated workers entering the enterprise increases while the proportion of lower educated workers entering the enterprise decreases.

A critique of the SBTC framework is that it falls short in explaining the relative decrease of workers in middle-skill jobs, such as clerical and production, evident in recent labor market developments (Acemoglu & Autor, 2011; Autor et al., 2003; Goos & Manning, 2007; Goos, Manning, & Salomons, 2009, 2014). This relative decline in middle-skill work is explained as resulting from the automation of work, particularly of middle-skilled tasks such as record-keeping or repetitive assembly. Technology mainly substitutes work tasks that are routine intensive, such as repetitive assembly, because these tasks are codifiable in programming language (Autor et al., 2003). Because technology reduces the demand for middle-skilled workers performing routine tasks within organizations we expect that:

> Hypothesis 2: When technology is implemented, the proportion of middle educated workers entering the enterprise decreases relative to the proportion of lower educated workers and higher educated workers entering the enterprise.

Technology implementation and the educational composition of workers exiting enterprises

With the automation of middle-skilled work tasks, the demand for middle-skilled workers already working in the enterprise also decreases. Within assignment models of technological change, the automation of work tasks is argued to lead to a reallocation of middle-skilled workers to high- or low-skill work tasks depending on the comparative advantage of workers in performing either high- or low-skilled tasks, as well as the relative demand and supply of workers' skills (Acemoglu & Autor, 2011). Based on the SBTC hypothesis, we expect that the demand for higher-skilled workers increases. However, assuming that in most cases middle-skilled workers are unable to perform high-skill work tasks, we do not expect middle-skilled workers to reallocate to perform high-skill job tasks. Furthermore, we have little cause to suspect that middle-skilled workers reallocate to perform low-skill job tasks. There are two reasons for this. First, employers cannot easily lower wages, and since middle educated workers on average have higher earnings than lower educated ones, it is more cost-efficient to keep lower educated workers and have them perform tasks that require lower skills rather than reallocating middle educated workers into low-skill jobs. Furthermore, assuming that skills are to some degree transferrable, middle-skilled workers may choose to find work in another enterprise with similar skill requirements and pay, rather than switching to a low-skill job. Second, a reason to retain and reallocate middle educated workers would be their higher productivity in low-skilled job tasks, but it is not clear whether these workers are in fact more productive in performing low-skilled job tasks than low-skilled workers (Acemoglu & Autor, 2011). In conclusion, we expect that the implementation of technology decreases both the demand for middle-skilled work tasks as well as for middle-skilled workers. We therefore expect that:

> Hypothesis 3: When technology is implemented the proportion of middle educated workers leaving the enterprise increases.

Technology implementation and the educational composition of enterprise workforces

Thus, on the one hand, we predict that under circumstances of technological change the proportion of higher educated workers entering an enterprise increases. On the other hand, we predict that the proportion of middle educated workers entering an enterprise decreases and the proportion of middle educated workers leaving it increases. Based on these predictions we expect that:

> Hypothesis 4: When technology is implemented the proportion of higher educated workers in enterprise workforces increases relative to the proportion of middle and lower educated workers.

Technology implementation and the age of workers entering enterprises

From the human capital literature, we know that within enterprises a large amount of a worker's productivity stems from experience gained within their current and previous jobs. As a result, for an enterprise, experienced workers are generally the more valuable workers (Crook, Todd, Combs, Woehr, & Ketchen, 2011; Gathmann & Schönberg, 2010; Jovanovic, 1979; Lazear, 2009; Topel, 1991). Technological change, however, alters skill requirements and increases the pace at which certain skills and knowledge become outdated. New technologies often require some form of adaption – for example, in how to organize a new production process, or how to use new technology. Consequently, experience with the old process, or knowledge about the old product (unless a prerequisite of the new product) decreases in importance with the implementation of new products or processes (Beckmann, 2007).

Skill obsolescence and human capital depreciation is likely to affect younger and older workers differently. The depreciation of existing human capital and the increase in demand for new types of skills are likely to increase the appeal of employing younger workers for two reasons. First, because younger workers have attained their education more recently, they are more likely to offer the necessary state-of-the art skills than older workers (Beckmann, 2007). Second, even if retraining can help workers to attain the necessary skills, enterprises are more likely to invest in retraining younger rather than older workers (Arulampalam, Booth, & Bryan, 2004; Bartell & Sicherman 1993; Beckmann, 2007; Carmichael & Ercolani, 2014; Guerrazzi, 2014; Taylor & Urwin, 2001). The reason for this is that retraining younger workers is more profitable because there is more time for training costs to be recouped. Furthermore, older workers have a shorter time horizon in the labor market, making them reluctant to invest in training themselves (Beckmann, 2007). We therefore expect that:

> Hypothesis 5: When technology is implemented the proportion of younger workers entering an enterprise increases.

Technology implementation and the age of workers leaving enterprises

As workers gain experience within the firm – for example, via job training about current production processes – their productivity increases (Dearden, Reed, & Van Reenen, 2006), resulting in higher wages (Brown, 1989). For employers, wages are a cost that is worth paying as long as this cost is compensated for by the high productivity of an employee. When technology implementation changes a production process, however, the productivity premium resulting from experience decreases. Thus, technology implementation negatively affects the productivity premium of having on-the-job experience, resulting in wage costs that are out of balance with the productivity of tenured workers. One way to recover the balance between costs and worker productivity is to reduce wages, but in the European context this is often unfeasible as wages are subject to wage regulation by the state, unions or through collective labor agreements. Another way to recover the balance between wage costs and productivity is to lay off or incentivize tenured workers to leave the enterprise.

Some studies argue that rather than facing actual problems with work performance, older workers suffer from negative stereotyping and discrimination, which influences managerial expectations and decision making (Posthuma & Campion, 2009). The stereotype that older workers are less adaptable than younger workers leads to lower training participation among older workers as well as early retirement arrangements (Posthuma & Campion, 2009; Shore & Goldberg, 2013). We expect that discriminatory practices and experiencing managerial favoritism, on the one hand, and actual difficulties with skill adaption and lack of retraining, on the other, will lead to increases in both workers leaving and lay-offs. We therefore expect that:

> Hypothesis 6: When technology is implemented the proportion of older workers leaving an enterprise increases.

Technology implementation and the age composition of enterprise workforces

As a result of increases in both the proportion of younger workers entering and the proportion of older workers leaving enterprises under circumstances of technological change, we expect that:

> Hypothesis 7: When technology is implemented the proportion of younger workers in enterprise workforces increases while the proportion of older workers decreases.

Technology implementation and the role of institutions

The behavior of organizational actors is strongly influenced by the institutional context of the organization (Scott, 2014). How organizations adapt their workforces is likely to depend on how they enable and constrain the actions of both employers and employees (Avent-Holt & Tomaskovic-Devey, 2014; Orlikowski & Barley, 2001). Employers are constrained by laws, unions and collective agreements that, at the same time, 'empower' employees in negotiation with the employer. Studying the adaption process to technological innovation of a food processing plant, Fernandez (2001) finds that the effects of technology implementation are strongly shaped by bargaining processes between the employer and the workers' union. In return for no-lay-off and wage guarantees, the union agreed to relax seniority and work rule requirements and to support retraining efforts by the enterprise (Fernandez, 2001). While the supply and demand framework aids us in hypothesizing how the implementation of new technologies changes employers demands for skills, the decisions that employers make to adapt to these changing skills demands are constrained by regulative institutions (Avent-Holt & Tomaskovic-Devey, 2014). More specifically, the degree to which employers can use churning as a way of adapting an enterprise's workforce to new technologies seems to be less when workers can rely on institutions to bargain for enterprise resources such as jobs, training and wages.

To study the role of institutions we compared more and less unionized industries. In 2016, out of all wage-earning workers in the Netherlands, 17 percent were union members – similar to the average for OECD countries (Organisation for Economic Co-operation and Development [OECD], 2018). In the Netherlands, however, unions are more influential than their membership suggests because they bargain at the company or industry level concerning collective labor agreements, which thereby also includes workers who are not members of a union. In the Netherlands, 79 percent of wage earners are covered by collective bargaining agreements, ranking ninth among 36 countries included in OECD data.

Looking at different industries we find substantial variation in union coverage. In manufacturing, union coverage was 31 percent (in 2011), whereas in business services only 11 percent of workers were covered by unions (Statistics Netherlands, 2012). We expect that in unionized industries, employers are less able to use worker churning to adapt their workforces to technology. We therefore expect that:

> Hypothesis 8: The effects of technology implementation on the age and educational composition of workforces, and on workers entering–leaving enterprises, are less in unionized industries.

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 in this study, the sample is stratified by sector and establishment size, excluding enterprises with less 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 2000–2014, during which a total of 36,230 enterprises participated in the Dutch CIS survey. Because enterprises do not always participate in the survey follow-ups, we generally did not observe enterprises for the full period 2000–2014. The average number of years that enterprises are observed in the data is 4.64 years. Of the total 36,230 enterprises that participated in the survey, 26,273 (72.52 percent) did not implement technologies during the period of observation, while 5,820 (16.06 percent) were observed during periods both with and without technology implementation. The remaining 4,137 enterprises (11.42 percent) implemented new technologies during all periods of observation. 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.[2] Having linked information about workers' jobs, educational attainment and age with the enterprises in the CIS, we were able to track how many workers entered and left the enterprise and what the composition of job entrants, job leavers and workforces looked like, with regard to educational attainment and age.

To study how the implementation of technologies within enterprises affects the composition of entrants, leavers and workforces with regard to educational attainment and age, we selected only the 5,820 enterprises that were observed in contexts both with and without technology being implemented. Furthermore, we exclusively analyzed enterprises in which we, over time, observed a shift from a period without technology implementation (0) to a period with technology implementation (1). Because the effects of technology implementation on the age and education composition of workforces are likely to last after the technology has been implemented, we did not include observations of time periods without technology implementation that follow time periods with technology implementation. This selection of observations excluded 2,243 enterprises (38.54 percent) in which we only observed a shift from technology being implemented (1) to technology no longer being implemented (0). Furthermore, this means that we excluded the observations that came after the observed periods of no technology implementation (0) to technology implementation (1). The remaining analytical sample consists of 3,577 enterprises and 23,156 observations. Table 13.1 provides descriptive statistics for enterprises when implementing and not implementing technologies.

Measurement

Dependent variables

Educational composition of enterprise workforces was measured as the proportion of the workforce with low, high and middle educational attainment within an enterprise, at the end of a year. Level of education was measured according to the International Standard Classification of Education (ISCED). Eight educational levels are distinguished. We recoded the levels into low, middle and high education following guidelines in the ISCED 2011 manual (Organisation for Economic Co-operation and Development/Eurostat/UNESCO Institute for Statistics, 2015): low education, including those who attained less than primary education, primary education and lower secondary education; medium education, including employees who attained upper secondary education and post-secondary non-tertiary education; and high education, including employees who attained short-cycle tertiary, bachelor's, a master's or doctoral equivalent education.

Table 13.1 Descriptive statistics of enterprises by context of technology implementation

	No technology implementation		*Technology implementation*		*All enterprises*	
	Mean	*s.d.*	*Mean*	*s.d.*	*Mean*	*s.d.*
Education of workers entering (%)						
Low	19.76	18.00	17.50	16.49	18.55	14.98
Middle	43.00	19.08	45.87	19.99	44.45	16.73
High	37.24	24.58	36.63	25.38	37.00	23.09
Education of workers leaving (%)						
Low	20.48	17.96	19.34	17.05	19.87	15.49
Middle	42.59	18.84	45.16	19.41	44.09	16.39
High	36.93	24.65	35.50	24.60	36.04	22.87
Education of workforce (%)						
Low	24.53	17.38	23.11	16.40	23.76	16.44
Middle	44.26	15.60	45.32	15.54	44.77	14.95
High	31.20	22.38	31.57	22.17	31.47	21.91
Age of workers entering (%)						
Below 30	51.61	20.24	53.17	21.33	52.64	17.88
Between 30 and 50	41.34	18.57	39.06	19.01	40.03	15.80
Above 50	7.05	8.96	7.77	9.78	7.33	7.52
Age of workers leaving (%)						
Below 30	44.68	21.55	42.05	21.67	43.24	19.60
Between 30 and 50	41.51	18.75	39.85	18.43	40.53	16.11
Above 50	13.81	13.90	18.10	15.37	16.22	12.80
Age of workforce (%)						
Below 30	25.43	16.32	21.69	15.65	23.54	15.43
Between 30 and 50	55.81	13.13	55.23	13.05	55.52	12.28
Above 50	18.75	11.37	23.08	12.44	20.94	11.41
Organizational innovation (%)	33.60	43.78	46.26	44.27	40.18	44.48
Industry union density (%)	56.00	49.65	56.00	49.65	56.00	49.64
Size enterprise	240	887	287	1,528	263	1,250

Source: Results based on calculations by Utrecht University using non-public microdata from Statistics Netherlands.

Note
N enterprises = 3,577.

Educational composition of enterprise entrants was measured as the proportion of low, middle and high educated entrants within the enterprise in a given year.

Educational composition of workers leaving an enterprise was measured as the proportion of low, middle and high educated employees who left the enterprise in a given year.

Age composition of the workforce was measured as the proportion of younger, middle-aged and older employees within an enterprise, at the end of the year. Following Beckmann's (2007) study on the age composition of workforces, we differentiated between three age categories: workers aged below 30, workers aged between 30 and 50 and workers aged above 50.

Age composition of workers entering the enterprise was measured as the proportion of workers aged below 30, between 30 and 50 and above 50, entering the enterprise in a given year.

Age composition of workers leaving the enterprise was measured as the proportion of workers aged below 30, between 30 and 50 and above 50, leaving the enterprise in a given year.

Independent variables

Implementation of technology was measured using an item from the CIS. 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 had purchased machinery, equipment and/or software with the aim of significantly improving products, services and/or production processes.

Industry unionization was captured by differentiating between industries with higher and lower union densities. Union density is defined as the number of unionized employees younger than 65 years of age with paid work for at least 12 hours a week, as a percentage of the total number of employees with paid work for at least 12 hours per week. We treated industries where union density is over 25 percent as more unionized. Industry and mining, energy and water management, manufacturing, transport and communication fall in this category: their union densities range from 26 percent (industry and mining) to 37 percent (manufacturing). Trade, retail, financial services and business services are less unionized: their union densities range from 12 percent in trade to 14 percent in financial services (Statistics Netherlands, 2012).

We controlled for *organizational innovations* to capture changes in the organization of an enterprise which can be related to worker flows in and out of enterprises (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 had introduced new business procedures, new methods for the organization of professional responsibilities and decision making or new methods for external relations with other companies or institutes.

Furthermore, we controlled for *enterprise size*, which is measured as the number of employees that worked in the enterprise at the beginning of the year.

Because the distribution of enterprise size is strongly right skewed, indicating the presence of several very large enterprises, we use the log of enterprise size in the analyses.

Method

To test the relationship between technology implementation within enterprises and changes in the composition of enterprise workforces and worker flows in and out of enterprises with regard to educational attainment and age, we took the following steps. First, we calculated the proportions of workers, with regard to educational attainment and age, entering and leaving an enterprise, on the one hand, and the workforce total, on the other, for the years 2000–2014. Second, we identified periods in which a change from no technology implementation to technology implementation could be observed – for example, the selected period 2002–2010, during which, between 2002 and 2008 the enterprise did not implement technology, while between 2008 and 2010 it did. Third, having selected periods of change we took the average of the proportions of workers, with regard to education and age, entering, working in and leaving the enterprise. These averages were subtracted from the observed proportions per year, such that observed proportions per year then represented deviations from the enterprise-period specific mean. The advantage of using these deviations from the enterprise-period mean is that when analyzing the data we only analyzed within-enterprise variation, allowing us to control for time-invariant unobserved heterogeneity.

As the dependent variables are compositions that together always add up to 1, there is covariation between the variables. We used seemingly unrelated regression (SUR) estimation to account for the correlation between error terms that arose when analyzing the proportions of entrants, leavers and workforces, with regard to education and age. Furthermore, we included dummies for years to control for over time trends in the composition of workers with regard to education and age. Finally, we added weights to the analyses. The measurement of educational attainment was taken from a combination of surveys. Consequently, the coverage of educational attainment varied per enterprise. To partially account for the error this missing data incurred, we added weights indicating the percentage of entrants, leavers and enterprise workforces with data on educational attainment. Furthermore, we added weights for the log of enterprise size to allow larger enterprises to influence the results more strongly than small enterprises, leading to more generalizable results. To test whether technology implementation continues to affect the education and age composition of enterprise entrants, leavers and workforces after periods of technology implementation we performed an additional analysis in which we included one-, two- and three-year lagged effects of technology implementation to the model (results not shown). We found the directions of the effects of technology implementation to remain the same for all models including one-, two- or three-year effects.

Results

Table 13.2 provides the results for the seemingly unrelated regression of technology implementation on the educational composition of workers. We find that the implementation of technology is associated with an increase in the proportion of middle educated workers entering enterprises, relative to higher and lower educated workers. These results are only partly in line with our first hypothesis. Corroborating Hypothesis 1, we find the relative inflow of lower educated workers to decrease. However, contradicting Hypothesis 1 we find the relative proportion of higher educated workers to decrease, rather than increase. We find that the relative proportion of middle educated workers entering enterprises increases, rather than decreases, when technology is implemented; we therefore reject Hypothesis 2. With respect to the educational composition of workers leaving enterprises, we find support for Hypothesis 3: the proportion of middle educated workers leaving enterprises increased relative to the proportions of higher and lower educated workers. The results on the effect of technology implementation on the educational composition of the enterprise do not correspond with our expectations: we do not find the proportion of higher educated workers to increase. Instead, we find that the proportion of middle educated workers increases, primarily at the expense of lower educated workers. Nevertheless, this relative increase in middle educated workers is in line with the hypothesis that technology is associated with educational upgrading of the workforce. However, we expected this upgrading to occur through an increase in the proportion of high educated workers; we therefore reject Hypothesis 4.

Table 13.3 shows the effects of technology implementation on the age composition of workers. Contrary to our expectations, we find that the proportion of workers aged 50+ entering the enterprise increases relative to the proportion of workers aged between 30 and 50. We therefore reject Hypothesis 5. Turning to the effects of technology implementation on the age composition of workers leaving enterprises, we find that, in accordance with Hypothesis 6, technology implementation is associated with an increased proportion of workers aged 50+ leaving the enterprise. Finally, changes in the age composition of enterprise workforces do not support our expectations: we find technology implementation to be associated with an increase, instead of a decrease, in the proportion of workers aged 50+.

To investigate the role of the institutional context, we included interaction effects between technology implementation and unionization within an industry. We do not find unionization to unequivocally be associated with weaker effects of technology on the education composition of enterprise workforces, entrants and leavers (see Table 13.4). Changes in the composition of high educated workers entering, leaving and working in enterprises do appear to be significantly smaller in unionized industries. However, the decrease in the proportions of lower educated workers entering, leaving and working in enterprises appear to be more pronounced in unionized industries. With respect to changes

Table 13.2 Seemingly unrelated fixed-effects regressions of technology implementation on educational composition of workers in enterprises

	Education entrants			*Education leavers*			*Education workforce*		
	% low	*% mid*	*% high*	*% low*	*% mid*	*% high*	*% low*	*% mid*	*% high*
Technology implementation	–0.013***	0.025***	–0.013***	–0.011***	0.022***	–0.010***	–0.008***	0.010***	–0.002*
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Organizational innovation	0.000	0.003	–0.003	0.001	0.003	–0.004	–0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Log enterprise size	–0.000	0.001	–0.001	–0.000	0.001	–0.001	–0.000	0.001***	–0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Constant	0.018***	–0.002	–0.017**	–0.002	–0.003	0.006	0.006***	–0.002	–0.004*
	(0.005)	(0.007)	(0.006)	(0.005)	(0.007)	(0.006)	(0.002)	(0.002)	(0.002)
Observations		21,731			21,049			22,494	

Source: Results based on calculations by Utrecht University using non-public microdata from Statistics Netherlands.

Notes
All models are weighted with the log of enterprise size*proportion of non-missing data for education and include year dummies.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (2-sided); standard errors in parentheses.

Table 13.3 Seemingly unrelated fixed-effects regressions of technology implementation on age composition of workers in enterprises

	Age entrants			*Age leavers*			*Age workforce*		
	% <30	% 30–50	% 50+	% <30	% 30–50	% 50+	% <30	% 30–50	% 50+
Technology implementation	0.002	–0.010***	0.008***	–0.020***	–0.009**	0.029***	–0.027***	–0.005***	0.032***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Organizational innovation	–0.004	0.003	0.001	–0.007*	0.007*	0.001	0.001	–0.001	0.000
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Log enterprise size	0.000	–0.000	0.000	0.000	0.000	–0.000	–0.000	–0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Constant	–0.006	0.005	0.002	0.016*	0.007	–0.024***	0.027***	–0.009***	–0.018***
	(0.007)	(0.006)	(0.004)	(0.006)	(0.006)	(0.005)	(0.002)	(0.002)	(0.002)
Observations		21,935			21,386			22,495	

Source: Results based on calculations by Utrecht University using non-public microdata from Statistics Netherlands.

Notes
All models are weighted with the log of enterprise size*proportion of non-missing data for education and include year dummies.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$(2-sided); standard errors in parentheses.

Table 13.4 Seemingly unrelated fixed-effects regressions of technology implementation on educational composition of workers in enterprises – interaction effects of industry unionization

	Education entrants			*Education leavers*			*Education workforce*		
	% low	*% mid*	*% high*	*% low*	*% mid*	*% high*	*% low*	*% mid*	*% high*
Technology implementation	–0.003	0.025***	–0.021***	–0.007*	0.024***	–0.017***	–0.003***	0.011***	–0.008***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Technology × unionized industry	–0.017***	0.001	0.016***	–0.008*	–0.005	0.013**	–0.009***	–0.003*	0.012***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)
Observations		21,935			21,386			22,495	

Source: Results based on calculations by Utrecht University using non-public microdata from Statistics Netherlands.

Notes
All models are weighted with the log of enterprise size*proportion of non-missing data for education, include year dummies and control for organizational innovation and enterprise size.
* $p<0.05$, ** $p<0.01$, *** $p<0.001$ (2-sided); standard errors in parentheses.

in age composition, we find a mixed pattern of weaker and stronger associations in unionized industries (see Table 13.5). In summary, although the effects of technology differ significantly between industries, the pattern of findings do not support our expectation of weaker associations in unionized contexts. We therefore reject Hypothesis 8.

Conclusion and discussion

In this study we investigated how the implementation of new technologies affects the education and age composition of workers entering, leaving and working in enterprises. Using a large-scale survey of (technological) innovation within Dutch enterprises, linked with register data, we created a longitudinal (2000–2014) employer–employee dataset to study the effect of technology implementation on enterprise workforces.

We did not witness an increase in the proportion of higher skilled workers, as expected, based on the skill biased technological change hypothesis. Recent empirical work, however, documents a decrease in demand for high-skilled, cognitive work tasks from the 2000s onwards (Beaudry, Green, & Sand, 2016; Mishel, Schmitt, & Shierholz, 2013). Beaudry et al. (2016) argue that during the key investment stage in technology there is high and growing demand for skilled cognitive tasks to build up new technological capital. However, they expect a reduction in demand for these tasks relative to the peak investment stage, and argue that the turn of the twenty-first century marked a turning point from peak investment to a stage of maturity. Although this argument may explain why we see decreased demand for cognitive skills, it is less clear how this dynamic may affect the demand for labor in enterprises that are implementing new technologies. One possible scenario is that when technologies enter a 'phase of maturation,' their applicability to standardized tasks increases, complementing the skills of middle educated workers (Autor, 2015; Holzer, 2015). At the same time, when technologies are in their 'revolutionary stage,' there may be a higher demand for the cognitive skills of high educated workers. If the advancement of technology indeed shows such cyclical trends, this may imply that advances in artificial intelligence (AI), machine learning and robotics will lead to a surge in technology investments, increasing the demand for high educated workers, followed by a maturation of these technologies, complementing middle educated workers.

Our findings lend mixed support for the routine biased technological change hypothesis (Acemoglu & Autor, 2011; Autor et al., 2003). While the proportion of middle educated workers leaving enterprises increased as predicted by the theory, we also find the relative number of middle educated entrants as well as the proportion of middle educated workers to increase following technology implementation. The organizational-level patterns in our study do not correspond with labor market findings of polarization in earlier research (see Acemoglu & Autor, 2011; Autor et al., 2003; Goos & Manning, 2007; Goos, Manning, & Salomons, 2009, 2014). An explanation may be that technology increases

Table 13.5 Seemingly unrelated fixed-effects regressions of technology implementation on age composition of workers in enterprises – differences by industry unionization

	Age entrants			*Age leavers*			*Age workforce*		
	% <30	% 30–50	% 50+	% <30	% 30–50	% 50+	% <30	% 30–50	% 50+
Technology implementation	0.003	–0.009***	–0.006**	–0.021***	–0.002	–0.023***	–0.031***	0.008***	0.023***
	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)
Technology × unionized industry	–0.002***	–0.002	0.004	0.001	–0.013**	0.012**	0.008***	–0.023***	0.015***
	(0.005)	(0.005)	(0.003)	(0.005)	(0.005)	(0.004)	(0.001)	(0.002)	(0.001)
Observations		21,935			21,386			22,495	

Source: Results based on calculations by Utrecht University using non-public microdata from Statistics Netherlands.

Notes
All models are weighted with the log of enterprise size*proportion of non-missing data for education, include year dummies and control for organizational innovation and enterprise size.
* $p<0.05$, ** $p<0.01$, *** $p<0.001$ (2-sided); standard errors in parentheses.

demand for workers who are qualified to work with the new technology (Autor, 2015); middle educated workforce that are less qualified are replaced by those who possess the knowledge and skills to work with and alongside new technologies (Holzer, 2015). Needless to say, such replacement processes require a steady supply of workers trained to work with the new technology. The Dutch labor context is likely to create the prerequisites: the Netherlands has a vocationally-oriented educational system characterized by close links between educational programs and the labor market (Van de Werfhorst, 2004). This system improves the match between the skill demands of employers and the skill supply of employees through, for instance, internships and company placements embedded in vocational training, as well as the higher possibility of information exchange between educational institutions and employers about skill requirements (Holzer, 2015). This explanation raises a more fundamental question: the extent to which the technology–labor composition relationship depends on the institutionalized features of skill creation (e.g., the existence of formal ties between organizations and educational institutions). We leave this interesting avenue for future studies that use a cross-country comparative design.

Our main finding regarding age compositional change is an unexpected increase in the proportion of workers aged 50+ in the workforces. This finding suggests that organizations may value older workers' experience and skills in times of technological investment more than skill-based theories might imply. For instance, organizations may consider older, experienced workers more suitable for tasks such as change management or consultancy, which are highly valued during periods of organizational change. Future research could investigate the relationship between the type of jobs created during periods of technological change and the age of their incumbents, to gain more insight into which types of older workers are attracted to enterprises in times of technological change. Nevertheless, some findings also support the notion that technology favors younger workers (see Bartell & Sicherman, 1993; Beckmann, 2007), as the proportion of older workers leaving enterprises increases, while the proportion of younger workers leaving enterprises decreases following technological change.

Our results regarding institutional variation are puzzling and, in any case, do not lend a simple interpretation of uniformly weaker effects in more unionized contexts. Remarkably, within unionized industries, technology implementation leads to lower percentages of less educated workers entering and leaving. This pattern may actually support, rather than refute, the influence of institutions: in unionized contexts, one way for employers to circumvent protection against layoff is to decrease the hiring of lower educated workers (Fernandez, 2001). Findings regarding age seem to point to institutional influences, albeit through different mechanisms. Within more unionized industries, we find the proportion of 50+ workers leaving enterprises under technological change to be significantly greater. Favorable early retirement schemes agreed by unions and employers are one possible explanation (see Raymo, Warren, Sweeney, Hauser, & Ho, 2011), but one may need to follow the destination of leavers – whether retirement, unemployment or a new job – to corroborate this.

Based on our results, the signs for workforce sustainability are generally positive, although there are also reasons to be concerned about the advance of new technologies. Lower educated workers seem to fare worse during technological change, and the extent to which unionism still provides them with protection, given the declining power of unions and increasing liberalization of labor markets, is questionable (Thelen, 2014). National policy efforts should in any case focus on the employment opportunities of these workers. Another source of concern is the labor market position of middle educated and older groups of workers after leaving jobs, a question we did not touch upon in this study. This topic definitely warrants attention, as the skills these groups bring to the labor market may prove unfitting in an environment where technologies keep advancing (Weber, 2014). On a positive note, the general pattern of our findings does not suggest that experienced, older workers and middle educated workers lose much ground in organizations. A careful consideration of organizational and labor market mechanisms is needed to identify the groups that are at risk during the process of technological change.

Notes

1 The Netherlands is a relevant case for conducting the study as it is among the top-ranking countries regarding innovation (Cornell University, INSEAD, & WIPO, 2015).

2 The results are based on calculations by Utrecht University using non-public micro-data from Statistics Netherlands. Under certain conditions, these micro-data are accessible for statistical and scientific research. Contact microdata@cbs.nl for further information.