Economics Letters
Peer-reviewed and accepted version

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Malin Gardberg, Fredrik Heyman, Pehr-Johan Norbäck and Lars Persson

Published version:
https://doi.org/10.1016/j.econlet.2020.109032

Research Institute of Industrial Economics
P.O. Box 55665
SE-102 15 Stockholm, Sweden
info@ifn.se
www.ifn.se

*Title Page

Digitization-based automation and occupational dynamics

Malin Gardberg*, Fredrik Heyman*, Pehr-Johan Norbäck,* and Lars Persson*

February 2020

Abstract: We examine the relationship between occupational automation probabilities and employment dynamics over nearly two decades. We show that employment and wage shares of occupations with a higher automation risk have declined in Sweden over the period 1996-2013. This has occurred both at the aggregate private business sector but also within firms, where the wage share changes have been larger than the employment share changes. Combining the automation risk in workers' occupations with individual worker characteristics, we find substantial heterogeneity. This includes that education dampens the automation risk of workers, as the average automation probability of low-skilled workers is almost twice as high as of university graduates. Employment shares in high-risk occupations have moreover declined across all wage levels, and most so in high-wage occupations. Our results indicate that it is not necessarily the level of risk that matter, but rather the heterogeneity between occupations.

Keywords: Automation, digitization, employment shares, wage shares
JEL classification: J31, J62, O33

*Research Institute of Industrial Economics (IFN), P.O. Box 55665, SE-10215 Stockholm, Sweden, malin.gardberg@ifn.se, fredrik.heyman@ifn.se, pehr-johan.norback@ifn.se and lars.persson@ifn.se.

Funding: We thank Marianne and Marcus Wallenberg Foundation, Jan Wallanders och Tom Hedelius stiftelse and Tore Browaldhs stiftelse for financial support. Pehr-Johan Norbäck and Lars Persson gratefully acknowledge financial support from Vinnova and Fredrik Heyman from Johan och Jakob Söderbergs Stiftelse and Torsten Söderbergs Stiftelse.

1. Introduction

Most economies now face a second wave of the digital revolution, where not only routine work but also advanced job tasks are automated. Brynjolfsson et al. (2018) highlight that no occupation and almost no job tasks will be completely unaffected by digitization and artificial intelligence, and Frey and Osborne (2017) estimate that nearly half of all jobs in the US risk being replaced by automation in the coming decades. Several studies have shown that new technology has heterogeneous effects on the demand for different types of labor. The current automation process is thus likely to have a multifaceted labor market effect.[1] Furthermore, a number of studies have found evidence of increased job polarization over the past decades, with improved employment opportunities for high-skilled, high-wage jobs and low-skilled, low-wage jobs, and less favorable developments for middle-skilled jobs.[2] Prominent explanations for this phenomenon are routine-based technological change and the offshorability and automation of jobs. The purpose of this paper is to examine how the digitization-driven automation process has affected long-term occupational dynamics. The basis of our empirical analysis is that a number of tasks and occupations will be replaced by automation. To this end we use Frey and Osborne's (2017) occupation-based automation measure, which indicates the probability that an occupation will disappear within a few decades due to computerization. Although this measure has been criticized by among others Arntz et al. (2017) for not taking into account that workers can specialize in non-automatable niches within their profession, we however show that it is not necessarily the level of risk that matters, but rather the heterogeneity between different occupations.

Our contribution is to show how automation probabilities for different occupations are related to employment share changes, but also to individual and job characteristics such as education, age and wages. Moreover, the literature on job automation has not taken into account the role played by firms, implying that the influence of firms in the observed automation processes is more or less absent in the empirical literature. To bridge this knowledge gap, we present new evidence on within-firm automation dynamics over nearly two decades.

[1] See e.g., Autor et al. (2003), Acemoglu and Autor (2011), Michaels et al. (2014), Autor (2015), Acemoglu and Restrepo (2019) and Edin et al. (2019).
[2] See e.g. Goos et al. (2009; 2014) and the references therein for evidence on job polarization. See also Heyman (2016) and Hensvik and Skans (2019) for recent evidence on within-firm job polarization.

Our analysis is based on detailed employer-employee data from Sweden spanning the period 1996-2013. We show that the share of workers in occupations with high automation probabilities has decreased over time in the whole Swedish business sector. This is also reflected in declining wage shares of high-risk occupations. We also present novel evidence on within-firm automation dynamics manifested in a gradual shift from high- to low-risk occupations also within firms, where the wage share changes have been larger than the employment share changes. Finally, we show that education dampens the automation risk of workers, and the biggest employment share drop has occurred in low-skilled high automation risk occupations. Employment shares in occupations that are the most susceptible to automation have declined in all age groups and across all wage segments, and most so for workers with high wages.

Our results show that the Swedish private sector has undergone a digitization-driven structural change, while the level of aggregate employment has remained fairly constant over the same period. As the ongoing technological progress is not specific to Sweden, our results suggest that automation does not necessarily lead to major aggregate labor market disruptions.

2. Data

We base our analysis on detailed register-based matched employer-employee data from Statistics Sweden (SCB) covering all Swedish firms and a large representative sample of workers during 1996-2013. The worker-level data contains official wage statistics based on SCB's annual salary survey and registry data.[3] In our sample, we use private business firms with at least ten employees.

Our occupation-specific automation probabilities are based on Frey's and Osborne's (2017) computerization probabilities for 702 US occupations in 2010.[4] The automation measure indicates the probability that an occupation will disappear within 10-20 years due to computerization. As the occupations were likely exposed to automation before 2010, we interpret the probabilities as reflecting an ongoing computerization-driven automation process. The probabilities are based on American SOC2010 occupational classifications. As there is no

[3] Wages are defined as full time equivalent monthly wages (in 2000 year prices).

[4] Frey and Osborne use both an objective and a subjective assessment of the occupation specific automation probability. The objective assessment is based on combinations of required knowledge, skills and abilities for each occupation, and ranks the occupations' likelihood of automation based on this. The subjective ranking categorizes (a subset of the) occupations on the basis of the different tasks they entail. The assessments are based on occupational characteristics and qualifications in the US O*NET database.

direct transition from SOC2010 to the Swedish counterpart SSYK96, we translate the US classifications to the 3-digit SSYK96 via the European ISCO08 occupational code.[5]

3. Empirical approach

We first estimate how aggregated occupational employment and wage share changes are related to the digitization-driven automation risk using the following equation:

$$\Delta Share_i = \alpha + \beta_1 Aut_i + \varepsilon_i \qquad (1)$$

where $\Delta Share_i$ is the employment or wage share change of occupation *i* in the business sector, Aut_i is the occupation-specific automation probability and ε is the error term.

To see how employment and wage shares in different automation risk groups have evolved over time within firms, we estimate firm-level regressions separately for each risk group using their respective firm employment or wage shares:

$$Share_{git} = \alpha + \delta_g Year_t + X'_{it}\beta + \theta_{gi} + \varepsilon_{git} \qquad (2)$$

where $Share_{git}$ denotes the employment or wage share of group g in firm *i* in year *t*, and *g*=H, M and L denote the respective high, medium and low automation risk groups.[6] Our main focus is on the estimated coefficient on the time trend, δ_g, which shows the annual employment or wage share change of group g. We include a vector *X* of time-varying firm characteristics that might affect the shares (value added per employee, $\frac{VA_{it}}{L_{it}}$, and capital intensity, $\frac{K_{it}}{L_{it}}$,) as well as firm fixed effects θ_{gi} to control for unobserved firm heterogeneity. Thus, all time variation in employment or wage shares originate from within-firm variation. In a slightly different specification we include time fixed effects, $\sum_{t=1996}^{2013} \delta_{gt}\, Year_t$, instead of the linear time trend in equation (2), to analyse the annual cumulated differences in the employment or wage shares as compared to the year 1996.

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[5] See the Online Appendix for details and automation estimates at different aggregation levels. In the Online Appendix we also elaborate on how the automation probabilities are related to the routine intensity and offshorability of occupations.
[6] Low: <30%, Med.: 30-70%, High: >70% automation probability.

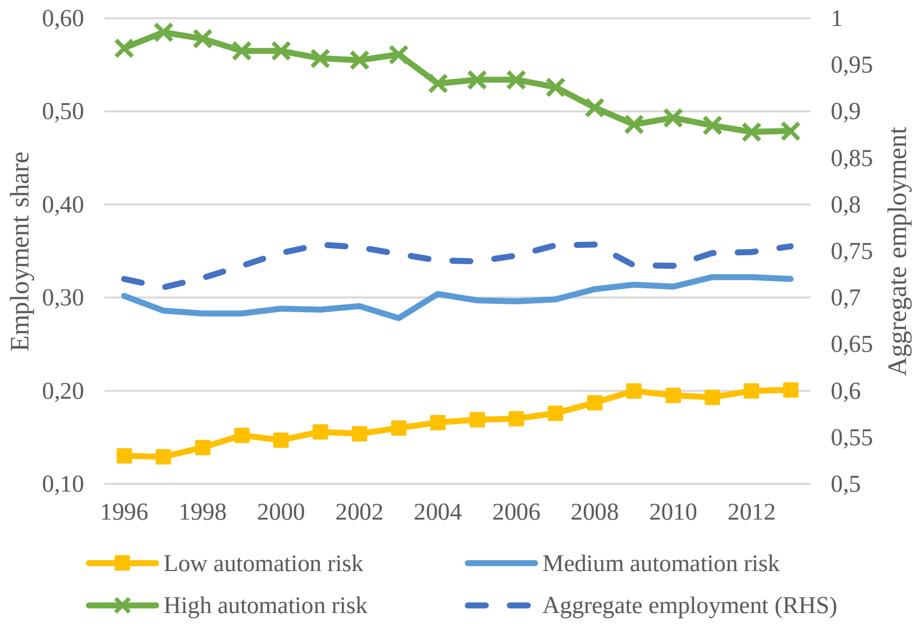
Finally, we compare how employment shares of workers with different education, wages, or ages relate to automatization. We therefore group employees by their characteristics and calculate the average automation risk for each group based on their occupations.

4. Results

4.1 Employment shares and automation

We start by looking at how the distribution of employment has changed across the automation risk groups over the years 1996-2013 in the entire Swedish private business sector. Figure 1 shows that the high-risk employment share has decreased by approximately 9 percentage points and increased by around 7 percentage points in the low-risk group over the past two decades. The dashed line illustrates that at the same time, employment-to-population has even increased slightly.[7] Thus, the shift from high- to low-risk occupations has occurred without a reduction in aggregate employment.

Figure 1. Employment shares in different risk groups



This development is also reflected in the regression results of equation (1). Columns 1-3 in Table 1 show that employment shares for occupations with higher automation probabilities have declined significantly over the sample and especially since 2005/2006.[8] The R^2's are also higher

[7] Employment-to-population is defined as the share of employed between the ages 16-64 (SCB).
[8] We use two-year averages to reduce dependence of individual years.

in the second half of the sample. High-risk occupations have also experienced a decline in wage shares (columns 4-6). Arntz et al. (2017) use job task data to study automation, and find that the occupation-level approach overstates the automation risk, as workers may specialize in non-automatable niches within their profession. We however still find that the employment shares of the high-risk occupations have declined.[9] This suggests that ranking the occupations based on their automation risk would carry over also to the case with more detailed task data.

Table 1. Aggregate employment and wage share changes (1996-2013)

	ΔEmployment share			ΔWage share		
	96/97-12/13	96/97-03/04	05/06-12/13	96/97-12/13	96/97-03/04	05/06-12/13
Autom. prob.	-0.015**	-0.005	-0.008***	-0.017***	-0.008*	-0.007***
	(0.006)	(0.004)	(0.003)	(0.006)	(0.004)	(0.002)
Constant	0.008**	0.003	0.005**	0.009**	0.004*	0.004***
	(0.004)	(0.003)	(0.002)	(0.004)	(0.002)	(0.002)
Observations	97	97	97	97	97	97
R^2	0.054	0.014	0.081	0.084	0.039	0.094

Note: The dependent variable is changes in employment shares (columns 1-3) and changes in wage shares (columns 4-6) per occupation. Robust standard errors in parentheses, ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

4.2 Firms and automation

We then look at this development within firms over time to capture within-firm automation dynamics (equation (2)). Results presented in Table 2 show a significant positive trend in the employment and wage shares of low-risk occupations. The estimated coefficients on the time trends in columns 1 and 4 suggest that employment and wage shares have increased by 0.25% and 0.3 % annually, respectively. The employment and wage shares for especially the high-risk occupations have instead declined significantly during the two decades that we study. Thus, there has been a gradual shift from high- to low-risk occupations also within firms and not only between firms. Results in Table 2 also indicate that the within-firm change in wage shares has been greater than in employment shares, as the absolute estimated trend coefficients are significantly larger for wage shares than for employment shares in the low- and high-risk groups. The same within-firm development is also illustrated in Figure 2, which plots the estimated coefficients on the year fixed effects (with 95 % confidence intervals) from equation (2). The figures depict a very gradual change for both the high- and low risk employment and wage shares, leading to a cumulated change of within-firm changes in low-risk employment

[9] Our sample only includes employed individuals. If we included unemployed workers (and base their occupations on their work experience or training), the automation effect would likely be higher, as workers with high-risk occupations are more susceptible to automation-induced unemployment.

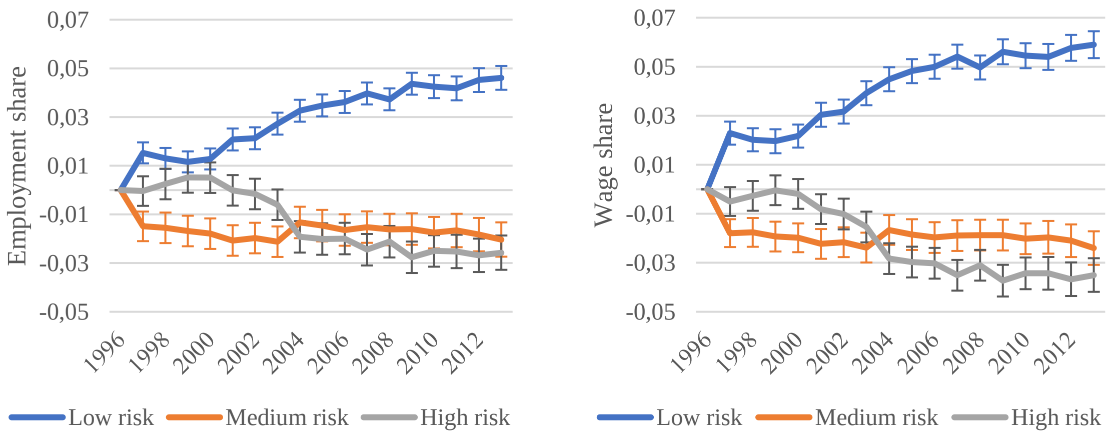
shares of around 5 % at the expense of the high-risk occupations especially. Both types of results thus indicate that firms have been part of a digitalization-driven structural change.[10]

Table 2. Within-firm automation dynamics - employment and wage shares in different risk groups (1996-2013)

	Employment share			Wage share		
Automation risk	Low	Medium	High	Low	Medium	High
Year	0.0025***	-0.0003**	-0.0022***	0.0030***	-0.0004***	-0.0026***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
VA/L	0.0012	-0.0019	0.0007	0.0010	-0.0018	0.0007
	(0.0011)	(0.0015)	(0.0015)	(0.0012)	(0.0015)	(0.0015)
K/L	-0.0018***	0.0007	0.0011	-0.0007	0.0005	0.0002
	(0.0006)	(0.0008)	(0.0008)	(0.0006)	(0.0008)	(0.0008)
Observations	69,085	69,085	69,085	69,085	69,085	69,085
R^2	0.0128	0.0001	0.0048	0.0144	0.0002	0.0066

Note: The dependent variables are firm-level employment shares or wage shares in different risk groups. Firm fixed effects are included. Standard errors are clustered at the firm level, ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Figure 2. Within-firm employment and wage share dynamics for the automation risk groups



Note: Plotted estimated coefficients on time fixed effects from equation (2) instead of a time trend. Bars denote 95 % confidence interval, with standard errors clustered at firm level.

[10] Our analysis is based on continuing firms, but the results are robust to excluding firms that exit the sample prior to 2013.

4.3 Heterogeneity: Automation and education, wages and age

We finally look at the link between automation risks and different worker characteristics. Starting with education, Table 3 indicates a strong negative correlation between education and average automation probabilities. The average occupation automation risk for workers with lower secondary education is almost twice as high as the risk faced by university graduates. This difference has decreased slightly over time, and especially university dropouts now work in occupations with a higher average automation risk than before.

Table 3. Automation risk and education

Education level		**Automation probability (%)**		
		1996	**2005**	**2013**
1	Lower secondary education, < 9 years	73.9	73.5	70.0
2	Lower secondary education, 9 years	73.8	73.1	70.9
3	High school, < 3 years	71.5	69.1	65.9
4	High school	62.6	65.1	64.5
5	University, < 3 years	46.2	51.4	52.1
6	University, ≥ 3 years	34.4	37.5	36.1
7	PhD	22.7	19.1	19.2

Panel 1 in Table 4 illustrates that the majority of workers have a medium-level education and a job with medium or high automation probability.[11] The employment share of the highly educated has generally increased (Panel 1c), while the largest employment share decline has occurred among low-skilled workers with high-risk occupations. Education thus seems to reduce the risk of "suffering" from automation. This is supported by Panel 2, which shows that most of the low-wage occupations have a high automation probability. Although there has been an increase in wage dispersion in Sweden over the sample period,[12] employment shares for high-risk occupations have, however, declined in all wage categories, and increased in all low-risk groups regardless of the wage level. Remarkably, the biggest decline has occurred for high-wage workers with high automation risk. The top right cells in Panels 1 and 2 stand in sharp contrast: a higher education appears to shelter against automation – whereas higher wages do not. Related to our results, Edin et al. (2019) analyze the impact on real earning for workers employed in declining occupations. Using Swedish data, they report a loss in cumulative earnings of about 2-5 percent, implying real effects for workers in occupations facing declining demand, possibly due to technological change and automation.

[11] Low: 1-2; Medium: 3-5; High: 6-7 (see Table 3).
[12] See e.g. official wage statistics from SCB.

If we look at the employment distribution over the age of workers (Panel 3), we note that many older employees work in high-risk occupations.[13] As these workers face retirement within 10-20 years, population ageing might thus reduce the negative labor market impact of computerization. Employment shares in the high-risk occupations have declined across all age groups, although middle-aged individuals in high-risk occupations have experienced the greatest drop.

Table 4. Employment shares by education, wage and age

		a. Employment share 1996			b. Employment share 2013			c. ΔEmployment share 1996-2013		
		Low	Med.	High	Low	Med.	High	Low	Med.	High
1. Education	High	4.8	2.2	1.4	10.9	5.6	4.0	6.1	3.4	2.6
	Med.	7.4	21.1	37.6	8.7	22.9	36.8	1.3	1.8	−0.8
	Low	0.7	6.8	17.9	0.5	3.4	7.2	−0.2	−3.4	−10.7
2. Wage	High	10.7	10.5	12.1	14.9	10.3	8.2	4.2	-0.2	-3.9
	Med.	1.8	11.1	20.4	4.1	11.4	17.9	2.3	0.3	-2.5
	Low	0.4	8.6	24.3	1.2	10.3	21.9	0.7	1.7	-2.4
3. Age	High	4.2	8.2	15.3	5.6	9.5	13.4	1.4	1.3	-1.9
	Med.	7.4	14.9	26.3	12.1	15.2	20.2	4.7	0.3	-6.1
	Low	1.4	7.1	15.3	2.4	7.2	14.3	1	0.1	-1

Automation probability

5. Conclusion

This paper examines the relationship between occupations' automation probabilities and occupational employment dynamics in Sweden over the years 1996-2013. We find that the Swedish business sector has undergone a digitization driven structural change, as we find a negative relationship between an occupation's automation probability and changes in both employment and wage shares. The wage share changes have been larger than the employment share changes. This implies that the impact of computerization on income inequality could potentially be larger than on employment inequality. We also present novel evidence on within-firm automation dynamics manifested in a gradual shift from high- to low-risk occupations also within firms.

[13] Low: 18-30 years; Medium: 30-49 years; High: 50-65 years.

Taking into account worker heterogeneity, we find that education seems to reduce the risk of being adversely affected by computerization, as highly educated workers are on average employed in occupations with much lower automation probability. Employment shares in low-skilled high-risk occupations have declined the most, while the employment shares in high-risk occupations have declined in all wage segments, and most in the high wage segment. Finally, as many older employees that face retirement in 10-20 years work in high-risk occupations, we find results indicating that population ageing might reduce the negative labor market impact of computerization

Our results can be seen as a validation of Frey and Osborne's (2017) automation measure. We show that it is not necessarily the level of risk that matter, but rather the ranking between occupations that matters, as we find substantial differences in how employment and wage shares in high- and low-automation risk occupations have evolved over time. This process has however been less disruptive than anticipated by Frey and Osborne (2017), as the level of aggregate employment has even increased over the sample period.

Acknowledgements

We thank Alexandra Allard and Hanna Thunström for excellent research assistance.

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Supplementary Files

Click here to download Supplementary Files: Online_Appendix_Gardberg_Heyman_Norback_Persson_EL_04_02_2020.pdf