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Digitization-Based Automation and Occupational Dynamics

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- Employment and wage shares have declined in occupations with high automation risk.
- New evidence on within-firm automation dynamics is presented.
- Wage shares of high-risk occupations have declined faster than employment shares.
- Education reduces the risk of suffering from automation.
- Employment shares in high-risk occupations have declined across all wage levels.

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 in 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.

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

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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]

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. 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.

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 (as measured by Frey and Osborne (2017)) 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.

[1] See e.g., Autor et al. (2003), Acemoglu and Autor (2011), Michaels et al. (2014), Autor (2015) and Acemoglu and Restrepo (2019).

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. 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.[2] 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 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.[3]

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:

[2] 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.

[3] See the Appendix for details and automation estimates at different aggregation levels. In the Appendix we also elaborate on how the automation probabilities are related to the routine intensity and offshorability of occupations.

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

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.[4] 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.

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.

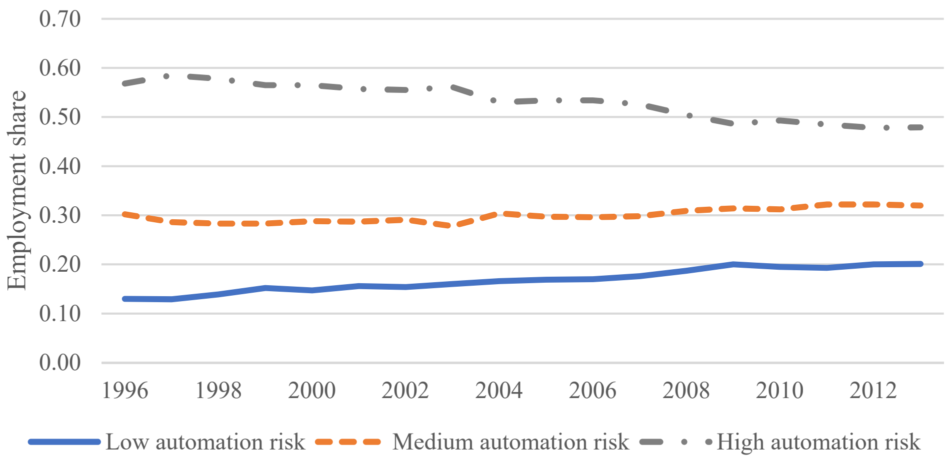
4. Results

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.

[4] Low: <30%, Med.: 30-70%, High: >70% automation probability.

Figure 1. Employment shares in different risk groups



This development is also reflected in the regression results of equation (1). Columns 1-3 in show that employment shares for occupations with higher automation probabilities have declined significantly over the sample and especially since 2005/2006.[5] The R^2's are also higher 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.[6] 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.	-0.014**	-0.005	-0.008***	-0.016***	-0.007*	-0.007***
	(0.006)	(0.004)	(0.003)	(0.006)	(0.004)	(0.002)
Constant	0.008**	0.003	0.004**	0.009**	0.004*	0.004***
	(0.004)	(0.003)	(0.002)	(0.004)	(0.002)	(0.001)
Observations	99	99	101	99	99	101
R^2	0.053	0.014	0.076	0.081	0.039	0.089

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.

[5] We use two-year averages to reduce dependence of individual years.

[6] 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.

4.2 Firms and automation

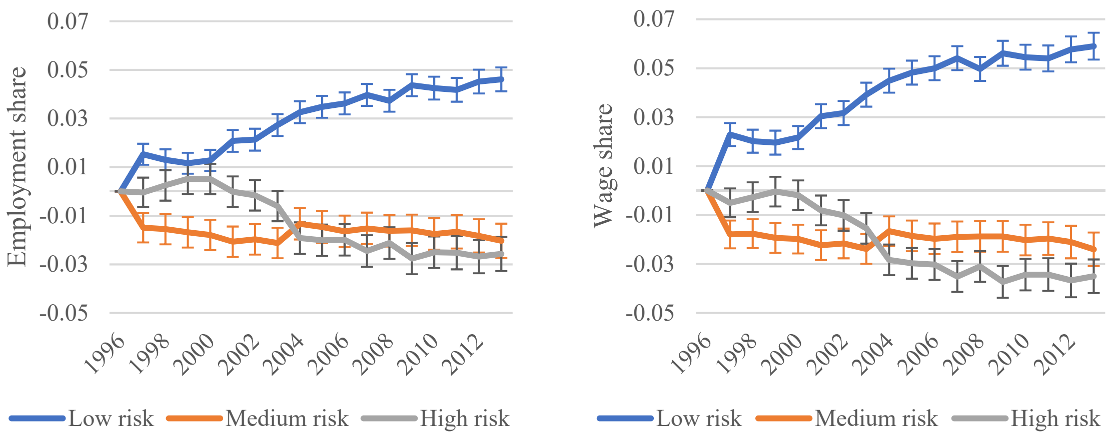
We then look at this development within firms over time to capture within-firm automation dynamics (equation (2)). Results presented in Table 2 show a significant positive trend in the employment and wage shares of low-risk occupations. The estimated coefficients on the time trends in columns 1 and 4 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 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.

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.

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.[7] 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

[7] Low: 1-2; Medium: 3-5; High: 6-7 (see Table 3)

of "suffering" from automation. This is supported by Panel 2, which shows that most of the low-wage occupations have a high automation probability. 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.

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.[8] 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 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

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

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.

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.

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Appendix

A.1. Automation measure

Digitization can be measured in a variety of ways. In this study, we use an automation measure developed by Frey and Osborne (2017), which indicates the probability that a job will be replaced by computers or robots. We start by describing Frey and Osborne's measure of computerization probability[9], and then show estimated automation probabilities by individual occupations. We moreover relate the automation probability measure to two additional factors that could influence job insecurity, which is the risk of offshoring and the routine intensity of occupations.

The occupation-specific automation probability, i.e. the risk that an occupation will be replaced by computers or robots, is based on a study by Frey and Osborne (2017). Frey and Osborne estimate the computerization probabilities for 702 US occupations in 2010, where the estimated risk should be interpreted as the risk that an occupation will be automated within 10 to 20 years.

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 categorize (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 O*NET database, developed by the US Department of Labor.[10] Finally, in order to obtain a probability measure for each occupation, they use a Gaussian process classifier to identify factors that increase or reduce the ability to computerize a profession. Based on this analysis, the authors provide an occupation specific automation probability (see Frey and Osborne (2017) for details).

Frey and Osborne (2017) calculate the automation probabilities for US SOC2010 occupational classifications. This classification is not used in Sweden nor in the EU, and there is no direct translation from the SOC2010 classifications to the Swedish counterpart SSYK96. We

[9] Frey and Osborne (2017) define computerization as "job automation by means of computer-controlled equipment."

[10] The database covers almost 1,000 occupations, and for each occupation there are 300 variables. The variables describe the daily work, skills and interests of the typical employee. The descriptive variables are organized into six different main areas: Characteristics of the Performer, Performer Requirements, Experience Requirements, Occupational Specific Information, Labor Characteristics and Occupational Requirements.

therefore translate the US classifications to the European occupational code, ISCO08, which in turn can be translated to SSYK96.[11] There are, however, a few problems with this translation. The US code is more detailed than both the EU and Swedish occupational classifications, i.e. some European codes include several US occupations (and vice versa in some cases). We account for this by using occupational employment weights from the United States (Bureau of Labor Statistics, BLS) and from SCB, when there is no 1:1 relationship between US and European occupations. Furthermore, we use the new Swedish occupational classification SSYK2012 for translating ISCO08 to SSYK96. While SSYK2012 is almost identical to ISCO08 differences exist; in these cases, we use different methods to convert the occupational codes.

In Tables A.1 and A.2, we present the translated automation probabilities for Swedish occupations at both the 2-digit and 3-digit level. We calculate employment weights using data from Statistics Sweden and US BLS for the year 2012. We also estimate the occupation specific automation probabilities for other years (2010, 2011 and 2013) and find that our results are robust to such changes. We moreover calculate alternative versions of the automation probabilities, where we use the mean and median automation probabilities when our Swedish occupations do not fully correspond to the ones in the US. Again, the results are roughly unchanged by these alternative methods.[12]

Table A.1 shows that for occupations at the 3-digit level, occupations like accountants, machine operators, library assistants and cash employees face the highest risk of automation. In contrast, occupations like senior officials and politicians, special education teachers, other educators with special skills, priests and land-surveyors, forest masters, etc. face the lowest risk of being automated.

[11] See http://www.bls.gov/soc/soccrosswalks.htm for a translation key between ISCO08 and SOC2010.

[12] The translation of the estimated probabilities to Swedish conditions is partly based on an assumption of similar technology in the US and Sweden. In order to take this into account and differences over time, as described above, we have assessed relationships in several different ways, resulting in estimates that are very similar regardless of the method used. An additional aspect of the translation is differences in relative wages in the United States and Sweden. It is not clear how these can systematically influence the estimates.

A.2. Routine intensity and offshoring

There are additional factors that could influence job insecurity, which may or may not be related to digitization. We therefore look at and discuss two additional measures used in the literature that studies occupational dynamics: (i) the risk of offshoring and (ii) the routine intensity of occupations.

The offshorability measure, a measure of the extent to which occupations can be located abroad, is identical to the measure crated by Blinder and Krueger (2013). This measure is also available at the 2-digit SSYK96 level. A higher value indicates a higher offshoring risk. Machine operator and assembly work are most suitable for offshoring while transport and machine operations have the lowest risk.

The measure for routine task intensity (RTI) is constructed identically to the measure used by Autor (2013) and Autor and Dorn (2013). This RTI index is constructed using detailed occupational information and the tasks pertaining to each occupation and is available at the 2-digit level for the Swedish job classification SSYK96. A higher value indicates that the occupation involves more routine intense tasks. The most routine intense occupations contain various office work, while management jobs in small companies have the lowest RTI score.

In order to see how the Offshorability and RTI measures are related to the Automation probability, we plot these in Figure A.1. From the figures can be seen that the Offshorability and automation probability measures are not very highly correlated, while there seems to be a positive correlation between the RTI and automation probability measure.

Figure A.3 Offshorability and RTI measures vs. Automation risk

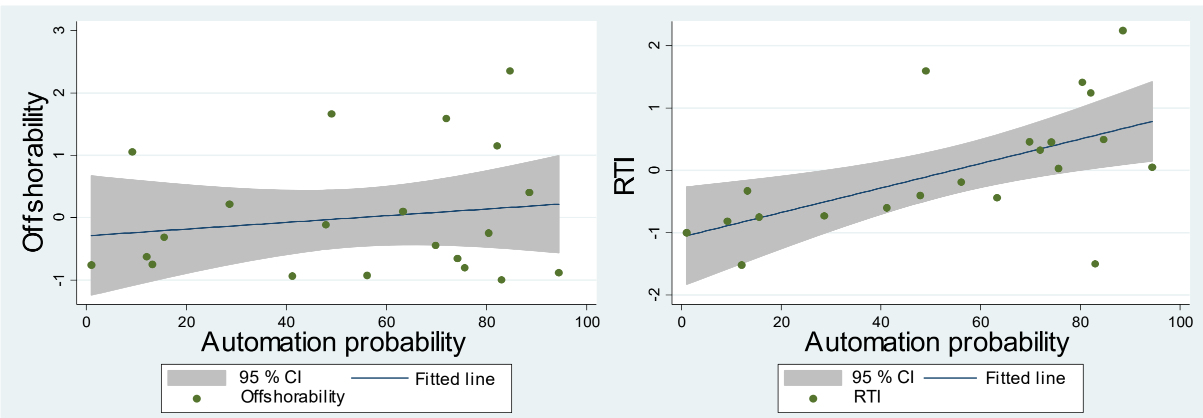

Table A.1: 3-digit occupation (sorted by probabilities)

Occupational code	Description	Aut. share (%)
521	fashion and other models	98.0
412	numerical clerks, such as accounting assistants	97.0
824	wood-products machine operators	97.0
414	library and filing clerks	96.6
421	cashiers, tellers and related clerks	95.3
921	agricultural, fishery and related labourers	95.0
829	other machine operators and assemblers	94.8
522	shop and stall salespersons and demonstrators	94.4
911	street vendors and market salespersons	94.0
915	garbage collectors and related labourers	93.0
411	office secretaries and data entry operators	92.2
419	other office clerks	91.6
828	assemblers	91.5
833	agricultural and other mobile-plant operators	90.2
823	rubber- and plastic-products machine operators	89.8
831	locomotive-engine drivers and related worker	89.6
343	administrative associate professionals, such as administrative secretaries and bookkeepers	89.3
913	helpers in restaurants, such as kitchen and restaurant assistants	88.6
512	housekeeping and restaurant services workers, such as cooks and waiters/waitresses	88.4
722	blacksmiths, tool-makers and related trades workers	87.1
741	food processing and related trades workers	87.1
811	mineral-processing-plant operators	86.8
742	wood treaters, cabinet-makers and related trades workers	86.0
815	chemical-processing-plant operators	85.0
931	mining and construction labourers	84.8
813	glass, ceramics and related plant operators	83.3
721	metal moulders, welders, sheet-metal workers, structural-metal preparers and related trades workers	82.4
342	business services agents and trade brokers	81.7
834	ships' deck crews and related workers	81.2
825	printing-, binding- and paper-products machine operators	81.1
832	motor-vehicle drivers	80.1
614	forestry and related workers	79.8
413	stores and transport clerks	78.8
415	mail carriers and sorting clerks	78.6
821	metal- and mineral-products machine operators	78.4
933	transport labourers and freight handlers	77.9
827	food and related products machine operators	76.8
714	painters, building structure cleaners and related trades workers	75.5
914	doorkeepers, newspaper and package deliverers and related workers	74.6
422	client information clerks	73.4
814	wood-processing- and papermaking-plant operators	72.5
711	miners, shot firers, stonecutters and carvers	72.2

341	finance and sales associate professionals	72.1
812	metal-processing-plant operators	71.9
919	other sales and services elementary occupations	71.1
932	manufacturing labourers	70.3
324	life science technicians	68.7
723	machinery mechanics and fitters	66.7
743	garment and related trades workers	65.5
515	protective services workers	65.4
912	helpers and cleaners	63.9
816	power-production and related plant operators	63.7
612	animal producers and related workers	63.4
613	crop and animal producers	63.4
822	chemical-products machine operators	63.2
615	fishery workers, hunters and trappers	62.4
511	travel attendants and related workers	62.3
611	market gardeners and crop growers	61.1
826	textile-, fur- and leather-products machine operators	60.5
734	craft printing and related trades workers	59.2
712	building frame and related trades workers	59.0
724	electrical and electronic equipment mechanics and fitters	57.2
311	physical and engineering science technicians	56.4
243	archivists, librarians and related information professionals	50.4
744	pelt, leather and shoemaking trades workers	50.3
713	building finishers and related trades workers	48.1
241	business professionals, such as accountants and organisational analysts	46.2
732	potters, glass-makers and related trades workers	42.9
731	precision workers in metal and related materials	42.4
315	safety and quality inspectors	40.5
733	handicraft workers in wood, textile, leather and related materials	37.2
313	optical and electronic equipment operators	36.6
817	industrial-robot operators	36.0
513	personal care and related workers	34.1
344	customs, tax and related government associate professionals	33.0
314	ship and aircraft controllers and technicians	32.1
312	computer associate professionals	30.2
514	other personal services workers, such as hairdressers and undertakers	29.0
322	health associate professionals (except nursing), such as dieticians, dental hygienists and physiotherapists	26.2
244	social science and linguistics professionals (except social work professionals)	25.5
247	public service administrative professionals	23.0
248	administrative professionals of special-interest organisations	23.0
123	other specialist managers	23.0
347	artistic, entertainment and sports associate professionals	22.8
211	physicists, chemists and related professionals	21.4

245	writers and creative or performing artists	18.9
212	mathematicians and statisticians	17.7
345	police officers and detectives	13.9
122	production and operations managers	13.0
332	other teaching associate professionals	13.0
131	managers of small enterprises	12.1
213	computing professionals	11.7
346	social work associate professionals	11.2
242	legal professionals, such as lawyers and judges	8.0
232	secondary education teaching professionals	6.4
233	primary education teaching professionals	5.6
331	pre-primary education teaching associate professionals	5.2
214	architects, engineers and related professionals	4.9
221	life science professionals	3.0
249	psychologists, social work and related professionals	3.0
348	religious associate professionals, such as pastors	2.5
222	health professionals (except nursing), such as medical doctors, dentists, veterinarians and pharmacists	1.5
121	directors and chief executives	1.5
112	senior officials of special-interest organisations	1.5
111	legislators and senior government officials	1.2
234	special education teaching professionals	1.1
235	other teaching professionals	0.9
246	religious professionals, such as priests	0.8
321	agronomy and forestry technicians	0.8

Table A.2: 2-digit occupation (sorted by probabilities)

Occupational code	Description	Aut. share
92	agricultural, fishery and related labourers	95.0
52	models, salespersons and demonstrators	94.4
41	office clerks	88.6
82	machine operators and assemblers	84.7
83	drivers and mobile-plant operators	83.0
74	other craft and related trades workers	82.2
42	customer services clerks	80.4
91	sales and services elementary occupations	75.7
93	labourers in mining, construction, manufacturing and transport	74.2
81	stationary-plant and related operators	72.0
72	metal, machinery and related trades workers	69.8
61	skilled agricultural and fishery workers	64.2
34	other associate professionals	63.3
71	extraction and building trades workers	56.2
73	precision, handicraft, craft printing and related trades workers	49.0
31	physical and engineering science associate professionals	47.9
51	personal and protective services workers	41.2
24	other professionals requiring theoretical specialist expertise	28.6
12	corporate managers in large and medium-sized companies etc.	15.6
32	life science and health associate professionals, requiring shorter college education	13.2
13	managers of small enterprises etc.	12.1
21	physical, mathematical and engineering science professionals	9.2
33	teaching associate professionals, requiring shorter college education	5.8
23	teaching professionals	4.2
11	legislators and senior officials	1.3
22	life science and health professionals	1.0