# Supplementary online appendices

## Appendix A: Technical details

EU-SILC coverage

For Germany, Iceland, Switzerland and the United Kingdom, the analysis covers the period 2014–17, and for Slovakia 2014–15. When we consider occupational information, the analysis is further restricted: Slovenia only provides 2-digit occupational codes for 2014, and the 2014 and 2015 occupational codes are missing for Iceland.

Malta is not included in the analysis since occupational codes are only provided at the 1-digit International Standard Classification of Occupations (ISCO) level.

Technology indicators

Table A1 provides an overview of the technology exposure indicators used in this article.

Table A1. Overview of the task and technology measures used in the analysis

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Index** | **Source** | **Measurement** | **Scale** | **Our transformation** |
| Intensity of routine tasks (total/manual/cognitive) | Mihaylov and Tijdens (2019) | Information on 3 264 tasks that are described for 427 4-digit occupations in the ISCO-08 classification system | Range from 0 (min. intensity) to 1 (max. intensity) | From 4-digit ISCO-08 to 2-digit ISCO-08 |
| Advances in AI | Felten, Raj and Seamans (2018) | AI advances measured by the Electronic Frontier Foundation, mapped to 52 job requirements from O\*NET and then aggregated to occupational level | Scores ranging from 0 (min. exposure to AI advances) to 5 (max. exposure) | From 6-digit SOC to 2-digit ISCO-08 |
| Intensity of physical/intellectual/social tasks | Bisello et al. (2021)  | Indices are built using detailed information on the content of work of occupations from the EWCS 2015, the Italian ICP and the OECD’s PIAAC Survey. | Normalized scores for all tasks. For each task, the score’s value ranges from 0 to 1, taking value = 1 for the occupation in the highest percentile of task intensity. | Already provided at 2-digit ISCO-08  |

Notes: SOC = Standard Occupational Classification; EWCS = European Working Conditions Survey; ICP = *Indagine Campionaria sulle Professioni*; PIAAC = Programme for the International Assessment of Adult Competencies.

Source: Our own compilation.

Measuring labour-saving technologies

The measures of routine task intensity (RTI) developed by Mihaylov and Tijdens (2019) are based on information on 3,264 tasks that are described for 427 4-digit occupations in the ISCO-08 classification system. They classify tasks as routine or non-routine and as cognitive or manual, based on their own judgment of whether a specific task can be replaced by computer-controlled technology and whether the performance of the task requires cognitive or manual skills.[[1]](#footnote-2) They then calculate indicators for routine manual tasks (RM) and routine cognitive tasks (RC) by dividing the number of tasks in each task category by the total number of tasks in each occupation.

We use the RM indicator to capture an occupation’s exposure to traditional automation technologies, such as industrial production machinery and autonomous robots that are able to perform routine manual and physical tasks (e.g. lifting and assembling). The RC indicator is intended to provide a measure of an occupation’s exposure to computerization and (unsophisticated) machine-learning. These RC technologies have the potential of performing standardized cognitive tasks that are easier to codify with programmed rules (e.g. counting, basic text writing and translation). As several occupations require the performance of both routine manual and routine cognitive tasks, we also employ a third measure providing information on the overall routine task (RT) intensity of occupations.

These measures of RTI were originally provided by Mihaylov and Tijdens (2019) at the 4-digit ISCO-08 level. Since EU-SILC provides information on individuals’ occupation at the 2-digit level, we need to aggregate them to the more general occupational classification to match them with our individual-level data. To do this, we first average the indicators from Mihaylov and Tijdens (2019) at the 3-digit level and then we convert them to the 2-digit level by calculating the average, weighted by the employment level of 3-digit occupations in the European Union (EU) as provided by Eurostat.

The measures of exposure to automation technologies developed by Mihaylov and Tijdens (2019) have two key advantages for our analysis. First, unlike other measures such as the one developed by Frey and Osborne (2017), which are based on the US Standard Occupational Classification (SOC), these measures are constructed by assessing the descriptions of a set of 3,264 occupation-specific tasks according to the ISCO-08 classification. As ISCO-08 is the international classification system of occupations used by European countries, this allows us to establish a more direct link between the task intensity indices and the worker-level micro data set used in our analysis, the EU-SILC. Second, most existing task measures (e.g. Acemoglu and Autor 2011; Autor, Levy and Murnane 2003; Spitz-Oener 2006) are constructed on the basis of a limited set of common variables that are not occupation-specific, whereas the Mihaylov and Tijdens’ (2019) indices are developed on the basis of occupation-specific descriptions of tasks and duties, which allow for a more precise assessment of the routine content of occupations.

Measuring labour-augmenting technologies

The original Felten, Raj and Seamans (2018) index is available at the 6-digit SOC level. Therefore, to match it with EU-SILC individual level data, we perform a crosswalk from 6-digit SOC codes to 4-digit ISCO-08 codes. We then calculate the average of the index at the 3-digit level and convert it to the 2-digit level by weighting the values at the 3-digit level by the employment level of the occupation in the EU.

The literature offers alternative indicators measuring exposure to AI at the occupational level. The most prominent ones are those developed by Brynjolfsson, Mitchell and Rock (2018) and Tolan et al. (2021). These indicators, although similar in spirit, use different methodologies and a different underlying theoretical framework to measure the exposure of occupations to AI. Tolan et al. (2021) identify potential exposure to AI by including AI applications that have not been explicitly created yet, but which are currently being researched. As such, the AI exposure index by Tolan et al. (2021) is more of a measure of exposure to future AI developments, rather than a measure of existing AI benchmarks like the index by Felten, Raj and Seamans (2018). The index by Brynjolfsson, Mitchell and Rock (2018) captures the suitability of an occupation’s tasks for machine learning – a subfield of AI that aims to replace routine cognitive tasks. As such, it can be seen as an indicator of labour-saving technologies rather than labour-augmenting ones. These conceptual considerations imply that the Felten, Raj and Seamans (2018) index best captures existing advances in AI and is therefore the most suitable index for our analysis, which focuses on recent trends in labour market transitions.

Technology and task measures: Descriptive evidence

Table A2. Average exposure to technology and task intensities at the 2-digit occupation level (ISCO-08)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Occupation (ISCO-08)** | **AI-Felten index** | **Routine TI** | **Routine cognitive TI** | **Routine manual TI** | **Physical TI** | **Intellectual TI** | **Social TI** |
| Chief executives, senior officials and legislators | 0.79 | 0.00 | 0.00 | 0.00 | 0.14 | 0.75 | 0.64 |
| Administrative and commercial managers | 0.75 | 0.01 | 0.01 | 0.00 | 0.10 | 0.79 | 0.56 |
| Production and specialized services managers | 0.78 | 0.02 | 0.02 | 0.00 | 0.22 | 0.81 | 0.63 |
| Hospitality, retail and other services managers | 0.67 | 0.25 | 0.25 | 0.00 | 0.33 | 0.58 | 0.56 |
| Science and engineering professionals | 0.99 | 0.02 | 0.02 | 0.00 | 0.25 | 0.79 | 0.44 |
| Health professionals | 1.00 | 0.08 | 0.08 | 0.00 | 0.37 | 0.62 | 0.67 |
| Teaching professionals | 0.63 | 0.01 | 0.01 | 0.00 | 0.29 | 0.64 | 0.59 |
| Business and administration professionals | 0.65 | 0.06 | 0.06 | 0.00 | 0.12 | 0.76 | 0.53 |
| Information and communications technology professionals | 0.71 | 0.08 | 0.08 | 0.00 | 0.09 | 0.73 | 0.40 |
| Legal, social and cultural professionals | 0.72 | 0.06 | 0.06 | 0.00 | 0.13 | 0.61 | 0.50 |
| Science and engineering associate professionals | 0.87 | 0.24 | 0.21 | 0.03 | 0.33 | 0.65 | 0.37 |
| Health associate professionals | 0.74 | 0.16 | 0.15 | 0.01 | 0.44 | 0.52 | 0.57 |
| Business and administration associate professionals | 0.50 | 0.40 | 0.40 | 0.00 | 0.14 | 0.70 | 0.49 |
| Legal, social, cultural and related associate professionals | 0.55 | 0.21 | 0.21 | 0.00 | 0.42 | 0.51 | 0.52 |
| Information and communications technicians | 0.71 | 0.47 | 0.47 | 0.00 | 0.20 | 0.66 | 0.34 |
| General and keyboard clerks | 0.28 | 0.94 | 0.87 | 0.06 | 0.14 | 0.65 | 0.36 |
| Customer services clerks | 0.33 | 0.65 | 0.62 | 0.03 | 0.13 | 0.49 | 0.46 |
| Numerical and material recording clerks | 0.38 | 0.82 | 0.79 | 0.03 | 0.22 | 0.61 | 0.29 |
| Other clerical support workers | 0.32 | 0.77 | 0.70 | 0.07 | 0.21 | 0.48 | 0.34 |
| Personal service workers | 0.34 | 0.22 | 0.18 | 0.05 | 0.42 | 0.36 | 0.45 |
| Sales workers | 0.48 | 0.48 | 0.47 | 0.00 | 0.30 | 0.35 | 0.41 |
| Personal care workers | 0.43 | 0.09 | 0.09 | 0.00 | 0.44 | 0.29 | 0.39 |
| Protective services workers | 0.87 | 0.00 | 0.00 | 0.00 | 0.52 | 0.46 | 0.46 |
| Building and related trades workers (excluding electricians) | 0.60 | 0.02 | 0.01 | 0.01 | 0.62 | 0.36 | 0.20 |
| Metal, machinery and related trades workers | 0.70 | 0.31 | 0.00 | 0.31 | 0.49 | 0.44 | 0.25 |
| Handicraft and printing workers | 0.60 | 0.61 | 0.17 | 0.44 | 0.44 | 0.45 | 0.27 |
| Electrical and electronic trades workers | 0.85 | 0.18 | 0.18 | 0.00 | 0.49 | 0.54 | 0.35 |
| Food processing, woodworking, garment and other craft and related trades workers | 0.48 | 0.60 | 0.18 | 0.42 | 0.45 | 0.42 | 0.30 |
| Stationary plant and machine operators | 0.53 | 0.87 | 0.06 | 0.81 | 0.43 | 0.30 | 0.13 |
| Assemblers | 0.49 | 0.27 | 0.00 | 0.27 | 0.38 | 0.28 | 0.10 |
| Drivers and mobile plant operators | 0.68 | 0.29 | 0.29 | 0.00 | 0.64 | 0.24 | 0.18 |
| Cleaners and helpers | 0.00 | 0.00 | 0.00 | 0.00 | 0.40 | 0.10 | 0.20 |
| Agricultural, forestry and fishery labourers | 0.51 | 0.15 | 0.03 | 0.12 | 0.62 | 0.28 | 0.15 |
| Labourers in mining, construction, manufacturing and transport | 0.40 | 0.31 | 0.04 | 0.27 | 0.50 | 0.25 | 0.09 |
| Food preparation assistants | 0.13 | 0.11 | 0.11 | 0.00 | 0.44 | 0.15 | 0.19 |
| Street and related sales and service workers | 0.06 | 0.15 | 0.15 | 0.00 | 0.34 | 0.22 | 0.29 |
| Refuse workers and other elementary workers | 0.44 | 0.14 | 0.10 | 0.04 | 0.50 | 0.20 | 0.24 |

Source: Our own calculations based on data from Mihaylov and Tijdens (2019); Bisello et al. (2021); Felten, Raj and Seamans (2018).

Correlations between the technology measures

Table A3 shows the correlation coefficients between the different measures of technology exposure and task intensity at the 2-digit ISCO-08 occupational level.[[2]](#footnote-3) Each of the measures is statistically significantly correlated with one another (all with *p*-values < 0.01), although with varying intensity. The first and most important observation to be made from table A3 is that the various measures of the intensity of routine tasks – and thus of the exposure to labour-saving technologies – are strongly and negatively correlated with advances in AI. This suggests that occupations experiencing advances in AI tend to be very low in routine intensive tasks and therefore less exposed to labour-saving technologies. Such differences are crucial when analysing the correlation between technology measures and transition probabilities for subgroups of workers.

Table A3. Correlation coefficients between technology measures, 2-digit ISCO-08 occupations

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | **RT** | **RM** | **RC** | **Phy** | **Int** | **Soc** | **AI\_Fe** |
|  Total intensity of routine tasks (RT) | 1.00 |   |   |   |   |   |   |
|  Intensity of routine-manual tasks (RC) | 0.48 | 1.00 |   |   |   |   |   |
|  Intensity of routine-cognitive tasks (RC) | 0.81 | –0.13 | 1.00 |   |   |   |   |
|  Intensity of physical tasks (Phy) | –0.15 | 0.26 | –0.34 | 1.00 |   |   |   |
|  Intensity of intellectual tasks (Int) | –0.11 | –0.29 | 0.07 | –0.74 | 1.00 |   |   |
|  Intensity of social tasks (Soc) | –0.33 | –0.49 | –0.04 | –0.58 | 0.71 | 1.00 |   |
|  AI Felten index (AI\_Fe) | –0.40 | –0.11 | –0.38 | 0.01 | 0.55 | 0.39 | 1.00 |

Source: Authors’ calculations based on data from Mihaylov and Tijdens (2019); Bisello et al. (2021); Felten, Raj and Seamans (2018).

The correlations between the measures of technology exposure and the task indices further highlight the importance of considering different types of technology exposure. The AI Felten index is positively and strongly associated with the intensity of intellectual and social tasks, which are notably less suitable for automation. Conversely, the overall intensity of routine tasks (RT) is negatively related to these tasks. Taken together, these correlations suggest that workers in occupations with a high importance of social and intellectual tasks are less exposed to labour-saving technologies, but more likely to work with AI technologies.

## Appendix B

Table B1. Transition probabilities between labour market statuses, all countries by gender (percentages)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Year *t*+1** |  |  |  |  |
| **Year *t*** | **Paid employment** | **SE with** **employees** | **Solo SE** | **Unemployment** | **Inactivity** |
| **Women** |   |   |   |   |   |
| Paid employment | 91.54 | 0.18 | 0.63 | 2.77 | 4.88 |
| SE with employees | 8.46 | 75.53 | 11.17 | 1.19 | 3.66 |
| Solo SE | 8.40 | 3.91 | 78.91 | 2.54 | 6.23 |
| Unemployment | 23.70 | 0.22 | 1.55 | 53.50 | 21.03 |
| Inactivity | 9.72 | 0.10 | 0.76 | 5.10 | 84.33 |
|   |   |   |   |   |   |
| **Men** |   |   |   |   |   |
| Paid employment | 93.11 | 0.34 | 0.94 | 2.84 | 2.77 |
| SE with employees | 6.77 | 79.90 | 10.51 | 1.01 | 1.81 |
| Solo SE | 7.73 | 5.53 | 81.83 | 2.24 | 2.67 |
| Unemployment | 25.35 | 0.39 | 2.70 | 59.73 | 11.84 |
| Inactivity | 10.32 | 0.09 | 0.81 | 5.62 | 83.16 |

Notes: Transition probabilities from year *t* to year *t*+1; averages for 2014–19. SE = self-employment.

Source: Our own calculations based on EU-SILC and SOEP data.

Table B2. Transition probabilities between labour market statuses, all countries by skill group (percentages)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Year *t*+1** |  |  |  |  |
| **Year *t*** | **Paid employment** | **SE with employees** | **Solo SE** | **Unemployment** | **Inactivity** |
| **(Pre-)primary and lower secondary education** |   |   |   |   |   |
| Paid employment | 88.28 | 0.27 | 0.87 | 5.28 | 5.30 |
| SE with employees | 5.73 | 77.33 | 11.06 | 1.90 | 3.98 |
| Solo SE | 7.08 | 3.79 | 81.06 | 3.62 | 4.45 |
| Unemployment | 19.02 | 0.23 | 1.45 | 61.04 | 18.27 |
| Inactivity | 6.80 | 0.05 | 0.41 | 5.72 | 87.02 |
|   |   |   |   |   |   |
| **(Upper) secondary and post-secondary education** |   |   |   |   |   |
| Paid employment | 92.42 | 0.25 | 0.63 | 2.83 | 3.87 |
| SE with employees | 7.22 | 78.39 | 10.77 | 1.20 | 2.41 |
| Solo SE | 7.63 | 5.30 | 80.72 | 2.26 | 4.09 |
| Unemployment | 25.95 | 0.33 | 2.10 | 56.11 | 15.50 |
| Inactivity | 10.11 | 0.09 | 0.74 | 4.74 | 84.32 |
|   |   |   |   |   |   |
| **Tertiary education** |   |   |   |   |   |
| Paid employment | 94.08 | 0.28 | 0.96 | 1.73 | 2.96 |
| SE with employees | 7.90 | 79.59 | 10.37 | 0.60 | 1.54 |
| Solo SE | 8.54 | 5.21 | 81.16 | 1.74 | 3.36 |
| Unemployment | 33.05 | 0.42 | 3.69 | 49.15 | 13.69 |
| Inactivity | 17.28 | 0.24 | 1.96 | 5.73 | 74.79 |

Notes: Transition probabilities from year *t* to year *t*+1; averages for 2014–19. SE = self-employment.

Source: Our own calculations based on EU-SILC and SOEP data.

Table B3. Probability of transition between labour market statuses, all countries by age (percentages)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Year *t*+1** |  |  |  |  |
| **Year *t*** | **Paid employment** | **SE with****employees** | **Solo SE** | **Unemployment** | **Inactivity** |
| **Age 16–29** |   |   |   |   |   |
| Paid employment | 88.11 | 0.19 | 0.93 | 4.69 | 6.09 |
| SE with employees | 14.45 | 59.46 | 19.37 | 2.63 | 4.09 |
| Solo SE | 12.55 | 3.11 | 73.71 | 4.75 | 5.88 |
| Unemployment | 30.16 | 0.33 | 1.55 | 52.26 | 15.70 |
| Inactivity | 15.28 | 0.07 | 0.54 | 6.68 | 77.43 |
|   |   |   |   |   |   |
| **Age 30–54** |   |   |   |   |   |
| Paid employment | 94.64 | 0.30 | 0.79 | 2.45 | 1.82 |
| SE with employees | 7.45 | 80.44 | 10.11 | 0.99 | 1.01 |
| Solo SE | 8.29 | 5.33 | 81.90 | 2.10 | 2.38 |
| Unemployment | 25.92 | 0.35 | 2.56 | 57.85 | 13.32 |
| Inactivity | 11.94 | 0.18 | 1.56 | 7.68 | 78.63 |
|   |   |   |   |   |   |
| **Age 55–65** |   |   |   |   |   |
| Paid employment | 87.46 | 0.23 | 0.62 | 2.32 | 9.37 |
| SE with employees | 5.21 | 76.90 | 10.84 | 0.97 | 6.08 |
| Solo SE | 5.02 | 4.51 | 80.20 | 2.13 | 8.14 |
| Unemployment | 11.83 | 0.15 | 1.78 | 60.07 | 26.17 |
| Inactivity | 2.20 | 0.06 | 0.45 | 1.84 | 95.45 |

Notes: Averages for 2014–19.

Source: Our own calculations based on EU-SILC and SOEP data.

## Appendix C

Table C1. Transition probabilities from paid employment: Felten digitization index, all control variables

|  |  |
| --- | --- |
|  | **Destination status** |
|  | **Paid employment** | **SE with employees** | **Solo SE** | **Unemployment** | **Inactivity** |
|  AI Felten index | 0.234\* | 0.018 | 0.051\*\* | –0.331\*\*\* | 0.028 |
|  | (0.123) | (0.018) | (0.024) | (0.089) | (0.040) |
|  Women  | –0.713\*\*\* | –0.042\*\*  | –0.242\*\*\* | –0.353\*\*  |  1.350\*\*\* |
|  |  (0.216)  |  (0.018)  |  (0.055)  |  (0.173)  |  (0.120)  |
|  Age 16–29  | –3.390\*\*\* | –0.010  |  0.122  |  0.468\*\*\* |  2.810\*\*\* |
|  |  (0.450)  |  (0.027)  |  (0.083)  |  (0.157)  |  (0.351)  |
|  Age 55–65  | –5.977\*\*\* | –0.038\* | –0.112\* |  0.347\*\*  |  5.780\*\*\* |
|  |  (0.419)  |  (0.022)  |  (0.060)  |  (0.151)  |  (0.347)  |
|  (Pre-)primary and lower | –1.193\*\*\* | –0.032  |  0.077  |  0.581\*\*\* |  0.566\*\*\* |
| secondary education  |  (0.253)  |  (0.024)  |  (0.054)  |  (0.181)  |  (0.177)  |
|  Tertiary education |  0.750\*\*\* |  0.038\* |  0.225\*\*\* | –0.684\*\*\* | –0.329\*\*\* |
|  |  (0.220)  |  (0.023)  |  (0.073)  |  (0.140)  |  (0.126)  |
|  Married  |  0.120  |  0.022  | –0.017  | –0.861\*\*\* |  0.736\*\*\* |
|  |  (0.148)  |  (0.022)  |  (0.036)  |  (0.077)  |  (0.115)  |
|  No. of children in household | –0.076  |  0.001  |  0.077\*\*  |  0.096  | –0.098  |
|  |  (0.136)  |  (0.009)  |  (0.031)  |  (0.060)  |  (0.115)  |
|  Part-time | –2.028\*\*\* | –0.037  |  0.254\*\*\* |  0.413\*\*\* |  1.398\*\*\* |
|  |  (0.269)  |  (0.026)  |  (0.090)  |  (0.127)  |  (0.223)  |
|  Temporary work contract  | –6.213\*\*\* |  0.003  |  0.538\*\*\* |  4.268\*\*\* |  1.404\*\*\* |
|  |  (0.314)  |  (0.027)  |  (0.111)  |  (0.251)  |  (0.119)  |
|  Top 20% of wage distribution |  0.790\*\*  | –0.019  | –0.101  | –0.900\*\*\* |  0.230  |
|  |  (0.329)  |  (0.025)  |  (0.097)  |  (0.148)  |  (0.248)  |
| Year FE  | yes | yes | yes | yes | yes |
| Country FE  | yes | yes | yes | yes | yes |
| Mean transition probability  | 0.944 | 0.002 | 0.004 | 0.024 | 0.027 |
| Observations  |  514 445  |  514 445  |  514 445  |  514 445  |  514 445  |

\*, \*\* and \*\*\* indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.

Notes: Marginal effects from separate multinomial logit regressions (by technology index), using two-year longitudinal weights. Coefficients standardized and displayed in percentage points. Robust standard errors in parentheses, clustered at 2-digit occupational level. The reference group is employed, male, not-married, age 30–55, has (upper) secondary and post-secondary education, has no children, works full-time, has a permanent job and is in the lower 80 per cent of the wage distribution.

Sources: EU-SILC 2014–19, SOEP v37, 2-year longitudinal sample; AI and task indices: Felten, Raj and Seamans (2018); Mihaylov and Tijdens (2019); Bisello et al. (2021).**Table C2. Transition probabilities from solo self-employment: Felten digitization index, all control variables**

|  |  |
| --- | --- |
|  | **Destination status** |
|  | **Solo SE** | **Paid employment** | **SE with employees** | **Unemployment** | **Inactivity** |
|  AI Felten index |  –0.371  |  0.292\*  |  0.269  |  0.055  |  –0.245  |
|  |  (0.307)  |  (0.154)  |  (0.295)  |  (0.119)  |  (0.198)  |
|  Women  |  0.111  | –0.401  | –1.541\*\*\* |  0.421\* |  1.409\*\*\* |
|  |  (1.055)  |  (0.477)  |  (0.461)  |  (0.229)  |  (0.423)  |
|  Age 16–29  | –3.947\*\*\* |  2.021\*\*  | –1.355\*\*  |  1.602\*\*\* |  1.679\*\*  |
|  |  (1.094)  |  (1.029)  |  (0.536)  |  (0.577)  |  (0.698)  |
|  Age 55–65  | –0.020  | –2.370\*\*\* | –0.919\*\*\* |  0.219  |  3.089\*\*\* |
|  |  (0.789)  |  (0.407)  |  (0.341)  |  (0.204)  |  (0.419)  |
|  (Pre-)primary and lower |  0.421  | –0.555  | –0.712\* |  1.127\*\*  | –0.282  |
| secondary education  |  (0.827)  |  (0.572)  |  (0.381)  |  (0.465)  |  (0.403)  |
|  Tertiary education | –0.267  |  0.868\* | –0.174  | –0.033  | –0.395  |
|  |  (0.872)  |  (0.469)  |  (0.523)  |  (0.138)  |  (0.277)  |
|  Married  | –1.127\* | –0.175  |  1.430\*\*\* | –0.587\*\*\* |  0.459  |
|  |  (0.664)  |  (0.242)  |  (0.387)  |  (0.199)  |  (0.316)  |
|  No. of children in household | –0.316  |  0.259  |  0.011  |  0.079  | –0.033  |
|  |  (0.338)  |  (0.214)  |  (0.201)  |  (0.126)  |  (0.182)  |
|  Top 20% of wage  | 12.650\*\*\* |  –10.067\*\*\* |  2.758\*\*\* | –1.760\*\*\* | –3.582\*\*\* |
| distribution |  (2.190)  |  (1.561)  |  (0.371)  |  (0.463)  |  (0.676)  |
| Year FE  | Yes | Yes | Yes | Yes | Yes |
| Country FE  | Yes | Yes | Yes | Yes | Yes |
| Mean transition probability  | 0.866 | 0.04 | 0.059 | 0.014 | 0.021 |
| Observations  | 43 626  | 43 626  | 43 626  | 43 626  | 43 626  |

\*, \*\* and \*\*\* indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.

Notes: Marginal effects from separate multinomial logit regressions (by technology indicators) with five outcomes. Coefficients in percentage points. Robust standard errors in parentheses, clustered at 2-digit occupational level. The observations are weighted using the two-year longitudinal weights. The reference group is self-employed, male, not-married, age 30–55, has (upper) secondary and post-secondary education, has no children, works full-time, has a permanent job and is in the lower 80 per cent of the wage distribution. Country and year fixed-effects. Based on the 2-year longitudinal sample.

Sources: EU-SILC 2014–19, SOEP v37; Felten index by Felten, Raj and Seamans (2018).

## Appendix D

Table D1. Transition probabilities from paid employment without Germany

|  |  |
| --- | --- |
|  | **Destination status** |
|  | **Paid employment** | **SE with employees** | **Solo SE**  | **Unemployment** | **Inactivity** |
| **Labour-augmenting technology:** |  |  |
|  AI Felten index | 0.342\*\* | 0.010 | 0.041\* | –0.342\*\*\* | –0.051 |
|  | (0.162) | (0.015) | (0.023) | (0.099) | (0.066) |
| **Labour-saving technology:** |  |  |  |  |  |
| Total routine tasks | –0.046 | –0.023\* | –0.075 | 0.068 | 0.076\* |
|  | (0.095) | (0.014) | (0.046) | (0.070) | (0.045) |
|  Routine cognitive tasks | –0.010 | –0.012 | –0.057 | 0.026 | 0.053 |
|  | (0.092) | (0.012) | (0.040) | (0.069) | (0.047) |
|  Routine manual tasks | –0.067 | –0.033\*\* | –0.064\* | 0.089 | 0.075\*\*\* |
|  | (0.116) | (0.016) | (0.033) | (0.082) | (0.023) |
| **Tasks:** |  |  |  |  |  |
|  Physical tasks  | –0.008 | –0.003 | 0.093 | –0.092 | 0.011 |
|  | (0.210) | (0.020) | (0.073) | (0.139) | (0.089) |
|  Intellectual tasks | 0.253 | –0.012 | 0.098\* | –0.181 | –0.158 |
|  | (0.258) | (0.022) | (0.059) | (0.150) | (0.126) |
|  Social tasks  | 0.153 | 0.066\*\*\* | 0.000 | –0.298\* | 0.080 |
|  | (0.245) | (0.024) | (0.054) | (0.180) | (0.081) |
| Year FE  | Yes | Yes | Yes | Yes | Yes |
| Country FE  | Yes | Yes | Yes | Yes | Yes |
| Mean transition probability  | 0.944 | 0.001 | 0.004 | 0.025 | 0.026 |
| Observations  | 472 350 | 472 350 | 472 350 | 472 350 | 472 350 |

\*, \*\* and \*\*\* indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.

Notes: Marginal effects from separate multinomial logit regressions (by technology index), using 2-year longitudinal weights. Coefficients standardized and displayed in percentage points. Robust standard errors in parentheses, clustered at 2-digit occupational level.

Sources: EU-SILC 2014–19, 2-year longitudinal sample; AI and task indices: Felten, Raj and Seamans (2018); Mihaylov and Tijdens (2019); Bisello et al. (2021).

Table D2. Transition probabilities from solo self-employment without Germany

|  |  |
| --- | --- |
|  | **Destination status** |
|  | **Solo SE** | **Paid employment** | **SE with employees** | **Unemployment** | **Inactivity** |
| **Labour-augmenting technology** |  |  |
|  AI Felten index | –0.262 | 0.205 | 0.354 | 0.116 | –0.412\* |
|  | (0.405) | (0.213) | (0.339) | (0.140) | (0.227) |
| **Labour-saving technology** |  |  |  |  |  |
| Total routine tasks | –0.143 | 0.118 | 0.019 | –0.035 | 0.041 |
|  | (0.491) | (0.273) | (0.352) | (0.136) | (0.221) |
|  Routine cognitive tasks | –0.021 | 0.074 | –0.050 | –0.031 | 0.029 |
|  | (0.525) | (0.299) | (0.404) | (0.125) | (0.235) |
|  Routine manual tasks | –0.253 | 0.125 | 0.112 | –0.020 | 0.036 |
|  | (0.294) | (0.179) | (0.208) | (0.129) | (0.138) |
| **Tasks** |  |  |  |  |  |
|  Physical tasks  | 0.682 | –0.530\*\* | 0.131 | 0.332\* | –0.615\*\*\* |
|  | (0.549) | (0.230) | (0.403) | (0.185) | (0.238) |
|  Intellectual tasks | –0.308 | 0.391 | 0.263 | 0.311\*\* | –0.657\* |
|  | (0.474) | (0.313) | (0.415) | (0.153) | (0.377) |
|  Social tasks  | –0.950 | 0.069 | 1.110\*\* | –0.195 | –0.034 |
|  | (0.625) | (0.238) | (0.480) | (0.156) | (0.349) |
| Year FE  | Yes | Yes | Yes | Yes | Yes |
| Country FE  | Yes | Yes | Yes | Yes | Yes |
| Mean transition probability  | 0.87 | 0.037 | 0.059 | 0.014 | 0.02 |
| Observations  | 41 125 | 41 125 | 41 125 | 41 125 | 41 125 |

\*, \*\* and \*\*\* indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.

Note: See notes and source information for table D1.

Table D3. Transition probabilities from paid employment with country and year fixed effects

|  |  |
| --- | --- |
|  | **Destination status** |
|  | **Paid employment** | **SE with employees** | **Solo SE**  | **Unemployment** | **Entry into inactivity** |
| **Labour-augmenting technology** |  |  |
|  AI Felten index |  0.234\*  |  0.019  |  0.050\*\*  |  –0.332\*\*\* |  0.029  |
|  |  (0.123)  |  (0.018)  |  (0.024)  |  (0.089)  |  (0.041)  |
| **Labour-saving technology** |  |  |  |  |  |
| Total routine tasks |  0.087  |  –0.027  |  –0.080\*  |  0.075  |  –0.055  |
|  |  (0.097)  |  (0.017)  |  (0.045)  |  (0.066)  |  (0.049)  |
|  Routine cognitive tasks |  0.084  |  –0.010  |  –0.059  |  0.043  |  –0.058  |
|  |  (0.093)  |  (0.013)  |  (0.039)  |  (0.065)  |  (0.052)  |
|  Routine manual tasks |  0.058  |  –0.050\*\*  |  –0.072\*\*  |  0.078  |  –0.014  |
|  |  (0.121)  |  (0.020)  |  (0.032)  |  (0.072)  |  (0.037)  |
| **Tasks** |  |  |  |  |  |
|  Physical tasks  |  –0.014  |  0.005  |  0.082  |  –0.083  |  0.011  |
|  |  (0.204)  |  (0.022)  |  (0.074)  |  (0.126)  |  (0.081)  |
|  Intellectual tasks |  0.188  |  –0.002  |  0.099  |  –0.158  |  –0.127  |
|  |  (0.224)  |  (0.025)  |  (0.063)  |  (0.137)  |  (0.105)  |
|  Social tasks  |  0.071  |  0.080\*\*\* |  0.014  |  –0.298\*  |  0.134\*  |
|  |  (0.219)  |  (0.028)  |  (0.053)  |  (0.163)  |  (0.075)  |
| Year FE  | Yes | Yes | Yes | Yes | Yes |
| Country FE  | Yes | Yes | Yes | Yes | Yes |
| Mean transition probability  | 0.94  |  0.002  |  0.004  |  0.024  |  0.027  |
| Observations  |  514 445  |  514 445  |  514 445  |  514 445  |  514 445  |

\*, \*\* and \*\*\* indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.

Note: See notes and source information for table D1.

Table D4. Transition probabilities from solo self-employment with country and year fixed effects

|  |  |
| --- | --- |
|  | **Destination status** |
|  | **Solo SE** | **Paid employment** | **SE with employees** | **Unemployment** | **Inactivity** |
| **Labour-augmenting technology** |  |  |
|  AI Felten index |  –0.411  |  0.289\*  |  0.312  |  0.060  |  –0.249  |
|  |  (0.297)  |  (0.153)  |  (0.279)  |  (0.120)  |  (0.202)  |
| **Labour-saving technology** |  |  |  |  |  |
| Total routine tasks |  0.038  |  –0.000  |  0.107  |  –0.077  |  –0.067  |
|  |  (0.452)  |  (0.298)  |  (0.290)  |  (0.115)  |  (0.226)  |
|  Routine cognitive tasks |  0.060  |  0.044  |  0.075  |  –0.072  |  –0.108  |
|  |  (0.471)  |  (0.324)  |  (0.322)  |  (0.104)  |  (0.248)  |
|  Routine manual tasks |  –0.009  |  –0.082  |  0.093  |  –0.040  |  0.037  |
|  |  (0.299)  |  (0.189)  |  (0.241)  |  (0.112)  |  (0.127)  |
| **Tasks** |  |  |  |  |  |
|  Physical tasks  |  0.636  |  –0.378\*  |  0.088  |  0.251  |  –0.597\*\*\* |
|  |  (0.480)  |  (0.224)  |  (0.402)  |  (0.158)  |  (0.208)  |
|  Intellectual tasks |  –0.264  |  0.420  |  0.266  |  0.210  |  –0.632\*  |
|  |  (0.413)  |  (0.277)  |  (0.372)  |  (0.131)  |  (0.328)  |
|  Social tasks  |  –1.128\*\*  |  0.314  |  0.946\*  |  –0.185  |  0.053  |
|  |  (0.569)  |  (0.282)  |  (0.499)  |  (0.134)  |  (0.273)  |
| Year FE  | Yes | Yes | Yes | Yes | Yes |
| Country FE  | Yes | Yes | Yes | Yes | Yes |
| Mean transition probability  |  0.87  |  0.04  |  0.059  |  0.014  |  0.022  |
| Observations  |  43 626  |  43 626  |  43 626  |  43 626  |  43 626  |

\*, \*\* and \*\*\* indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.

Note: See notes and source information for table D1.

**References**

Acemoglu, Daron, and David Autor. 2011. “Skills, Tasks and Technologies: Implications for Employment and Earnings”. In *Handbook of Labor Economics*, Vol. 4, Part B, edited by David Card and Orley Ashenfelter, 1043−1171. Amsterdam: North Holland.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. “The Skill Content of Recent Technological Change: An Empirical Exploration”. *Quarterly Journal of Economics* 118 (4): 1279−1333. <https://doi.org/10.1162/003355303322552801>.

Bisello, Martina, Marta Fana, Enrique Fernández-Macías, and Sergio Torrejón-Perez. 2021. “A Comprehensive European Database of Tasks Indices for Socio-economic Research”. JRC124124. Brussels: European Commission.

Brynjolfsson, Erik, Tom Mitchell, and Daniel Rock. 2018. “What Can Machines Learn, and What Does it Mean for Occupations and the Economy?” *AEA Papers and Proceedings* 108 (May): 43−47. <https://doi.org/10.1257/pandp.20181019>.

Felten, Edward W., Manav Raj, and Robert Seamans. 2018. “A Method to Link Advances in Artificial Intelligence to Occupational Abilities”. *AEA Papers and Proceedings* 108 (May): 54−57. <https://doi.org/10.1257/pandp.20181021>.

Frey, Carl Benedikt, and Michael A. Osborne. 2017. “The Future of Employment: How Susceptible Are Jobs to Computerisation?” *Technological Forecasting and Social Change* 114 (January): 254−280. <https://doi.org/10.1016/j.techfore.2016.08.019>.

Mihaylov, Emil, and Kea Tijdens. 2019. “Measuring the Routine and Non-Routine Task Content of 427 Four-Digit ISCO-08 Occupations”, Tinbergen Institute Discussion Paper No. 2019−035/V. Amsterdam and Rotterdam: Tinbergen Institute.

Spitz-Oener, Alexandra. 2006. “Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure”. *Journal of Labor Economics* 24 (2): 235−270. <https://doi.org/10.1086/499972>.

Tolan, Songül, Annarosa Pesole, Fernando Martínez-Plumed, Enrique Fernández-Macías, José Hernández-Orallo, and Emilia Gómez. 2021. “Measuring the Occupational Impact of AI: Tasks, Cognitive Abilities and AI Benchmarks”. *Journal of Artificial Intelligence Research* 71: 191−236. <https://doi.org/10.1613/jair.1.12647>.

1. One limitation of the measures of RIT developed by Mihaylov and Tijdens (2019) is that they are all based on the authors’ subjective judgment about which tasks are replaceable by technology, and which are not. This inevitably leaves some room for discretion when assigning tasks to different routine domains. However, the authors provide an extensive discussion on the possibility of misclassifying tasks, and show that subjectivity in their classification of tasks should not be a major concern. [↑](#footnote-ref-2)
2. Table A2 displays the average technology exposure and task intensities for all indices at the 2-digit level of the ISCO-08 classification. [↑](#footnote-ref-3)