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Technological progress and the dynamics of self-employment: Worker-level evidence for Europe

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**Technological Progress and the Dynamics
of Self-Employment: Worker-level Evidence
for Europe**

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Technological Progress and the Dynamics of Self-Employment: Worker-level Evidence for Europe

Abstract

We examine how technology is associated with self-employment dynamics using worker-level data from 31 European countries. We find that while employees exposed to labour-augmenting technologies are more likely to move from paid-employment to solo self-employment and vice-versa, employees exposed to labour-saving technologies are less likely to become self-employed. We identify important differences with respect to workers' socio-demographic characteristics. The results suggest that while labour-augmenting technologies promote workers' mobility and reduce unemployment risks for high-skilled workers, they have the opposite effect for low-skilled workers. Furthermore, labour-saving technologies worsen labour market outcomes particularly for low-skilled and routine workers.

JEL-Codes: J62, J63, J31

Keywords: : Solo self-employment; occupations; tasks; technology; Europe

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1. Introduction

Technological advancements, such as artificial intelligence (AI), digital platforms, and robotics, are transforming the labour market, with important effects on all employment types. Self-employment is likely to be particularly strongly affected. On the one hand, labour-augmenting technologies, such as AI and digital platforms, can enable self-employment, particularly among high-skilled workers. This empowerment stems from the emergence of new business opportunities, the expansion of customer reach, and the provision of efficient tools for essential tasks such as communication and marketing (Berger et al. 2021; Nambisan et al. 2019). Furthermore, digital platforms have streamlined the process of securing freelance opportunities and launching service-oriented ventures (Kässi and Lehdonvirta, 2018), offering flexibility to pursue these endeavors alongside maintaining traditional employment (Pouliakas and Ranieri, 2022). At the same time, digital technologies can reduce the attractiveness of self-employment if they lead to higher productivity and higher pay, thus increasing the attractiveness of paid employment.

On the other hand, technology can worsen labour-market prospects in dependent employment as labour-saving technologies, such as advanced robotics, which automate tasks and reduce the need for human labor, can lead to job displacement, particularly among low-skilled workers, and may therefore push individuals towards self-employment. Consequently, a critical distinction must be made between self-employment with employees, typically driven by entrepreneurial ambition and more common among higher-educated individuals, and solo self-employment, which may often arise due to a lack of better employment options, particularly for those with lower levels of education.

This study therefore answers the following research questions for Europe:

1. How is technological progress, and particularly the exposure to labor-augmenting and labour-saving technologies, related to workers transitions into and out of self-employment?
2. Do these effects of technological progress differ between transitioning into and out of solo-self-employment and self-employment with employees?

3. Do these effects of technological progress differ between worker groups according to their level of education, age, or income?

In our analysis, we use micro data from the European Union Statistics on Income and Living Conditions (EU-SILC) for the period 2014-2019. These data allow us to identify annual transitions between labour market states. We measure workers' exposure to technological progress and digital technologies at the occupational level, distinguishing between labour-augmenting and labour-saving technologies. We proxy labour-augmenting technologies with an indicator for the use of AI, and labour-saving technologies with an indicator of routine-task intensity (RTI) of an occupation. These indicators capture the potentially different effects of technology on the costs and opportunities of entering or leaving (self-)employment, depending on the type of technology, and the labour market transition considered.

The focus on solo self-employment (self-employment without employees) is also relevant since in 2019, the EU saw nearly 23 million solo self-employed individuals, a 15% increase since 2002, representing about 10% of total employment and 72% of all self-employed workers.¹ The sector is also evolving its historical occupational composition, with a growing number of high-skilled individuals in technical, professional, and managerial roles; their share increased from 36% in 2012 to 42% in 2019 in the EU.²

This study contributes to the literature in three ways. First, we present evidence on the extent of transitions into and out of self-employment across a large number of European countries for the time period 2014-19; corresponding evidence is currently only available for the US. Second, we examine the relation between technological progress and worker-level transitions into and out of self-employment. We thus complement evidence for the US on entries into self-employment (Fossner and Sorgner, 2021), and we add to the literature an analysis of the relation between technological progress

¹ In 2019, self-employed accounted for around 14 % of total employment in the EU in 2019 (Eurostat, 2021).

² Authors' calculations based on Eurostat data on "Self-employment by occupation" (variable code: LFSA_ESGAIS).

and exits from solo self-employment. Third, we explore the heterogeneity of the effect across different groups of workers with respect to characteristics such as age, educational attainment and income, as well as between solo-self-employed and self-employed with employees.

Our findings with respect to labour-augmenting technologies are as follows. First, workers more exposed to such technologies are more likely to transition between paid employment and solo self-employment than less exposed workers. Yet, the probability to switch from paid employment to solo self-employment is higher for workers who are in occupations that require lower levels of education and feature relatively low wages, whereas workers who are highly educated and earn relatively high wages are instead more likely to remain in paid employment and less likely to end up unemployed. Second, for strongly exposed workers, the probability of moving out of solo self-employment into paid employment is higher for those with a tertiary education and for prime age workers (aged 30-54). Third, exposed workers also enter self-employment with employees. Overall, these results suggest that technologies such as AI are in general labour-augmenting, but may also have some displacement effects, potentially resulting in solo self-employment out of necessity.

Concerning the effects of labour-saving technologies, our results are less clear-cut, and somewhat less in line with expectations. We find that employees exposed to these technologies have a reduced tendency to become self-employed (solo and with employees). However, we do not find particularly adverse effects of these technologies on labour prospects of exposed workers to them, i.e. we do not find a significantly higher probability to move to unemployment or inactivity.

Our findings have crucial implications for the role of public policy in sustaining employment amid rapid technological advancements. They highlight the necessity to design targeted skill development programs, particularly for low-skilled workers, to facilitate their adaptation to labour-augmenting technologies. Encouraging the adoption of these technologies in workplaces is also recommended, due to their positive impact on employment dynamics, especially benefiting high-skilled workers. Moreover, it is essential to provide protection for routine and low-skilled workers who are most

affected by labour-saving technologies. This should be complemented by strategies that promote technology integration, benefiting both high- and low-skilled workers, and by addressing socio-demographic disparities and ensuring equitable access to the advantages offered by technological progress.

2. Theoretical framework and existing empirical evidence

The task-based approach (Autor et al., 2003) has been pivotal in understanding the impact of technological progress on labour markets. This framework posits that jobs involve routine and non-routine tasks, both manual and cognitive. Routine manual tasks (e.g. repetitive movements in structured environments) and routine cognitive tasks (e.g. arithmetic calculations) can be relatively easily codified and therefore are more susceptible to automation by technologies such as computers and robots. By contrast, non-routine cognitive tasks (e.g. abstract and interpersonal tasks) and non-routine manual tasks (e.g. manual dexterity) are usually performed in unstructured environments and are therefore difficult to automate. Thus, machines are less likely to replace workers in these areas, but rather supplement them (Autor et al., 2003; Acemoglu and Autor, 2011; Autor, 2015).

The new wave of transformative technologies, with AI and machine learning at the forefront, have added complexity to the conventional hypothesis on the effects of new technologies on employment. Some studies, recognizing the transformative potential of these new digital technologies, suggest that these technologies do not destroy jobs but rather change job profiles and induce positive employment effects (Felten et al. 2019, Gmyrek et al. 2023). Other studies suggest that advanced technologies have been increasingly able to perform non-routine cognitive and manual tasks, making some occupations more repetitive and dependent on quality standards, and therefore more susceptible to the destructive effects of digitalization (Brynjolfsson et al., 2018; Fernández-Macías et al, 2023).

We investigate our research questions empirically following the theoretical framework of Fossen and Sorgner (2021) and complementing it by also developing hypotheses on mechanisms behind the transitions from solo self-employment to paid employment. A theoretical framework which focuses

on the impact of digitalization on entrepreneurship entry (and exits), through its influence on opportunity costs of remaining in a specific labour-market state, seems particularly apt to develop hypotheses on the mechanisms behind the association between digitalization in an employee's current job and the likelihood of entering (exiting) entrepreneurship.

Empirical studies have consistently highlighted the significance of opportunity costs as a determinant of the decision to transition from wage employment to entrepreneurship. For instance, higher wages (Berkhout, Hartog, and van Praag 2016), better job security (Sorgner and Fritsch 2018) and better career prospects (Sorgner 2017) have been shown to reduce the probability of workers' switching from paid employment to self-employment.

The important distinction between labour-augmenting technologies, which lead to improvements at the worker-level, and labour-saving technologies which worsen labour-market prospects, in terms of wages and employment, has been made by Fossen and Sorgner (2021). Based on this distinction, Fossen and Sorgner (2022) find for the US that workers in occupations that are more susceptible to destructive digitalization – and hence more at risk of unemployment – are more likely to become entrepreneurs setting up unincorporated businesses. In addition, they find that workers in occupations exposed to “transformative” technology, notably to advances in AI, are less likely to become solo self-employed, but more likely to become self-employed with employees instead.

We follow the distinction between labour-saving and labour-augmenting technologies and acknowledge that both types of technology can have positive and negative effects on the likelihood that paid employees move into self-employment. As for labour-augmenting technologies on the one hand, workers exposed to these technologies are expected to experience growing employment, rising productivity and higher wages. Therefore, these workers face higher opportunity costs of leaving their current jobs and should be less inclined to switch to self-employment.

On the other hand, workers in these occupations should also be better able to identify business opportunities, get in touch with new entrepreneurial-relevant digital technologies, and have access to

information and financial resources, which may ultimately increase their chances of becoming self-employed. Moreover, several occupations (e.g. ICT professionals) that are exposed to labour-augmenting technologies are typically easier to carry out remotely (Rodrigues et al. 2021). This could provide incentives for workers seeking greater autonomy and flexibility to move into self-employment, whilst also encouraging firms to outsource work. As a result, workers in these occupations are more likely to switch to self-employment within the same occupation, either by choice or because they may be forced by their employers to reclassify as external contractors.

As for labour-saving technologies, on the one hand, paid employees exposed to these technologies face higher risks of unemployment and slower wage growth, and thus could be more likely to become (solo) self-employed out of necessity, i.e. they are “forced” to start their own business to avoid unemployment and loss of income. This is consistent with the finding that a high occupation-specific risk of unemployment is associated with a higher probability of entrepreneurial entry (Sorgner and Fritsch 2018). On the other hand, workers exposed to these technologies tend to have lower levels of education, limited access to financial resources, and fewer possibilities to develop managerial skills, creativity, and strong social networks – all aspects that are positively associated with the odds of entering self-employment. Therefore, from a theoretical point of view, the exposure to labour-saving technologies can either increase or decrease employees’ odds to switch to self-employment.

Both labour-augmenting and labour-saving technologies are also likely to influence the probability of leaving solo self-employment, either for paid employment or for self-employment with employees. Focusing on exits from solo self-employment is of particular interest because individuals can often be found in this labour market state as the result of poor wage and employment opportunities in their occupation (Milasi and Mitra, 2022). Furthermore, a significant fraction of the solo self-employed in advanced countries move to dependent employment once an opportunity presents itself (Boeri et al. 2020).

With respect to labour-augmenting technologies, on the one hand, one could expect that individuals in solo self-employment in exposed and therefore highly productive occupations are more likely to become employers. On the other hand, the high labour demand and wages in exposed occupations may act as an incentive to move into paid employment and to give up self-employment completely. This could be particularly the case for those who entered solo self-employment involuntarily in the first place, namely because they could not find a decent job in their preferred occupation.

With respect to labour-saving technologies, we expect that exposed individuals working as solo self-employed are less likely to move into paid employment, as job vacancies in these occupations tend to be scarce. For similar reasons, we do not expect them to expand their business by hiring employees, but rather they may be more likely to exit solo self-employment and become unemployed.

Overall, the theoretical considerations yield expectations on the effects of technology on the entry into and exit from self-employment. However, these effects are often theoretically ambiguous, making empirical analysis all the more important. Furthermore, the extent to which each of the above hypotheses may hold varies according to how workers' socio-economic and demographic characteristics interact with different types of technology, and how this affects the incentives to enter or exit self-employment. This observation motivates our analyses of whether and how labour-market transitions into and out of self-employment differ by gender, formal education, age, and income level.

3. Data and methodology

3.1. Measuring labour market transitions

Our analyses are based on micro data from the European Union Statistics on Income and Living Conditions (EU-SILC) for the years 2014 to 2019. As we examine labour market transitions, we use the longitudinal version of the EU-SILC data. For Germany, EU-SILC data are not available as a panel.

Therefore, we use the EU-SILC clone provided by the German Socio-Economic Panel (SOEP) for Germany. In total our analysis covers 31 European countries.³

EU-SILC data are based on household surveys and provide annual cross-sectional and longitudinal information on socio-demographic characteristics, employment, income, poverty, household composition, and other living conditions for all EU member states and a number of other countries (see Eurostat 2020 for details). The data are provided by national statistical offices through personal interviews or by administrative data sources and are representative of the population in the countries covered and comparable across Europe.

To study labour market transitions, we use the longitudinal version of the EU-SILC data. For most countries, the longitudinal version of the EU-SILC is based on a four-year rotating panel, i.e. each household in the sample participates in the survey for four years and each year a quarter of the households surveyed are replaced by new households. The longitudinal version only includes persons who participated in the survey for at least two consecutive years. In order to construct a representative database with a maximum number of observations for the period under consideration, the longitudinal datasets are combined following Berger and Schaffner (2015). We use the data to construct labour market transitions from one year to the next, using individual-level information on the labour market state at time t and $t+1$. For our analyses, we use the longitudinal weights provided in EU-SILC for panel data of two years duration and we adjust the weights to reflect the population size of the countries in our sample.

For Germany, the analyses are based on data from the SOEP. This representative annual survey provides detailed labour-market information on the individuals in the sampled households. We use the long format of the EU-SILC clone provided with the SOEP v36 (Bartels et al. 2021). We restrict the resulting sample from the EU-SILC and SOEP to individuals aged 16- 65 with valid data for the crucial

³ The analysis includes Austria, Belgium, Bulgaria, Switzerland, Croatia, Cyprus, Czech Republic, Germany, Denmark, Estonia, Finland, Greece, Hungary, Ireland, Iceland, Italy, Lithuania, Luxembourg, Latvia, Netherlands, Norway, Poland, Portugal, Romania, Serbia, Sweden, Slovenia, Slovakia, Spain, United Kingdom. See appendix C for details.

variables. Furthermore, we exclude individuals working in the armed forces and in agricultural occupations. As we merge the technology measure at the 2-digit level, we also drop individuals for whom information on occupation is not available or only available at the 1-digit level. For the analysis, occupations are classified according to the ISCO-08 standard, allowing us to exploit the variation across 40 different occupations. Since we are analysing labour market transitions from one year to the next, we further restrict the sample to individuals with an available economic state for two consecutive years.

We differentiate between five labour market states: employment, self-employment (SE) with employees, solo self-employment (SE), unemployment and inactivity. The employment state is based on the current main economic state (variable p1031 in EU-SILC) as reported by the respondent. To distinguish between solo self-employment and self-employment with employees, this information on the main economic state is complemented with information on the current activity state in the main job (variable p1040 in EU-SILC). According to the EU-SILC guidelines (Eurostat 2020) solo self-employed are self-employed individuals who have their own business, professional practice, or farm for the purpose of making a profit, and who have no employees. The same definition applies to self-employed persons with employees, except that they employ at least one person. Family workers are excluded from the analysis. Our analysis examines how exposure to technology in the current occupation is associated with transitions into and out of (solo) self-employment. Therefore, we focus on transitions from (1) employment to (solo) self-employment and other labour market states and (2) exits from (solo) self-employment to any other labour market state.

3.2. Measuring technology and job tasks

To investigate whether exposure to a particular technology in the current job shapes individuals' probability of moving from one labour market state to another, and notably from paid employment to self-employment and vice-versa, we use several measures of technology exposure at the occupational level. This approach is based on the notion that the effect of technology on workers' transition

probabilities may depend on the type of technology and also on the task content of their occupations. Following the literature discussed in Section 2, we focus on labour-saving and labour-augmenting technologies.

To operationalise the concept of occupational exposure to labour-saving technologies, we use the measures of RTI developed by Mihaylov and Tijdens (2019) which are based on task descriptions at a detailed occupational level (see Appendix C for technical details). Tasks are classified as routine or non-routine and as cognitive or manual, based on whether a specific task can be replaced by computer-controlled technology and whether the performance of the task requires cognitive or manual skills. We use three of their indicators. First, the routine manual (RM) indicator which captures 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, assembling). Second, the routine cognitive (RC) indicator which measures an occupation's exposure to computerisation and (unsophisticated) machine-learning. Third, the overall routine task (RT) intensity of occupations. These measures have the advantage of being based on occupation-specific descriptions of tasks and duties, which allow for a more precise assessment of the routine content of occupations than other task measures which are not occupation-specific (e.g. Acemoglu and Autor 2011, Autor et al. 2003, Spitz-Oener 2006). Furthermore, the measures we use are provided for the ISCO classification which allows for a direct match with European micro data.

To operationalise the concept of labour-augmenting technology, we follow Fossen and Sorgner (2021) and use a measure of advances in AI by occupation estimated by Felten et al. (2018). To estimate advances in AI at the occupational level, Felten et al. (2018) link the advances in AI to skills specified in O*Net to describe job requirements. In contrast to other existing measures of AI exposure, e.g. Brynjolfsson et al. (2018) and Tolan et al. (2020), Felten et al. (2018) provide a comprehensive measure of current (rather than potential future) AI developments (see Appendix C for

details). Moreover, using this index allows for a more straightforward comparison between this paper's results and the ones by Fossen and Sorgner (2021).

Finally, we complement the above measures of labour-saving and labour-augmenting technologies with a set of task-specific indicators gathered from the JRC-Eurofound European Tasks database. This database is based on a comprehensive theoretical framework (Fernández-Macías and Bisello 2020) and provides indices at the 2-digit ISCO-08 level that directly capture the task content of an occupation using detailed information on the content of work from the European Working Conditions Survey (Eurofound 2016), the Indagine Campionaria delle Professioni (an Italian version of the O*NET database of occupational contents), and the OECD PIAAC survey. From this database, we extract information on the intensity of physical, intellectual, and social tasks.

These task-intensity measures allow us to shed further light on the differences between the technology exposure measures discussed above. In fact, unlike the measures by Mihaylov and Tijdens (2019) and Felten et al. (2018) which are constructed using standardised descriptions of the job content at the occupational level, these task indices are based on individuals' assessment of the types of tasks they perform in their jobs, and therefore they also capture the variation of task composition across workers within the same occupation.

3.3. Empirical methodology

To model alternative pathways into and out of self-employment, we consider labour market transitions from the origin states self-employment and paid employment to the five destination states paid employment, self-employment with employees, solo self-employment, unemployment, and inactivity. We use a multinomial logit model which allows us to capture an individual choice between discrete, unordered alternatives, while controlling for various factors that might influence the decision to transition between labour market states. A key assumption of this model is the independence of irrelevant alternatives which posits that the probability to transition to one state should not be affected by the availability of other options. While this is quite a restrictive assumption, we view this as

reasonable in the case of labour market transitions since labour market states are very distinct and are determined by significantly different factors. The general form of the predicted probability from the multinomial logit model can be written as

$$\Pr(y = m|X) = \frac{\exp(\mathbf{X}'\beta_{m|b})}{\sum_{j=1}^J \exp(\mathbf{X}'\beta_{j|b})}, \text{ with } m = 1, \dots, j,$$

where y is one of the five destination states and b stands for the state of origin: paid employment or self-employment. \mathbf{X} is the vector of explanatory variables controlling for individual characteristics such as gender, age, marital state, number of children, and educational attainment. For transitions from paid employment, we also account for job characteristics such as income, job tenure, and contract type (part-time vs. full-time). To capture high-paying jobs, we create an indicator measuring whether the current job is in the top 20% of the wage distribution. This allows us to control for individual- and job-specific factors. We include country fixed effects to capture level differences between countries that can come from country-specific institutional, cultural, and policy-related factors that are likely to affect labour market transitions. As we pool the data across years, we include year fixed effects to account for trends over time and time-specific shocks that impact all individuals in a given year.

Since we want to examine the relation between technology and labour market transitions into and out of self-employment, our main variables of interest are the measures for labour-augmenting and labour-saving technologies as well as for task intensities. These measures vary across occupations but are assumed to be constant over time and across countries for the period that we analyse. Thus, the coefficients are identified using the variation across occupations within a year and country.

In our baseline model, we perform separate regressions for the main variables of interest. This means that we run four different regression models including different indicators at the occupation level: first, the AI-index as a measure for labour-augmenting technology; second, the intensity of total routine tasks as a measure of labour-saving technology; third, routine-cognitive and routine-manual

task intensities as a variation of the previous model; and fourth, the intensity of physical, intellectual, and social tasks. To facilitate the interpretation of the results, we standardise our technology and task measure and calculate marginal effects.

To analyse the heterogeneity of the relation across different groups of workers, we interact our technology measure and the categorical variables for worker characteristics, i.e. education level, age group, and income group. In this model, the marginal effect of technology is a composite measure of the effect of the technology index and the interaction term.

Since we consider a cross-section of two-year longitudinal data, we are not able to capture long-term effects of technology and adoption processes. Nevertheless, by studying labour-market transitions we can gain understandings about shorter-term adjustments in response to technology exposure. Moreover, such short-term adjustments are particularly interesting when studying emergent technologies such as AI which experienced rapid growth in the last years and presented a shock to some occupations. An additional concern might be sample selection, such that individuals exposed to prior technology already selected themselves into certain labour market states. However, we try to mitigate this concern using a rich set of control variables and looking at labour market transitions not only from paid employment to self-employment, but also into unemployment and inactivity. Moreover, we emphasize that our results are only specific to the time-period and indicators that we analyze and do not extend to previous time periods.

4. Labour market dynamics in Europe: Descriptive evidence

This section provides an overview of the extent and direction of the labour market transitions observed in Europe for the time period 2014 to 2019. Table 1 shows the average transition probabilities from one year to the next between the five labour market states considered in the analysis. A first observation is that paid employees are relatively unlikely to move to self-employment. However, the transitions out of paid employment are generally rather low. Therefore, transitions from paid employment to self-employment make up an economically relevant share of the total transitions out of paid employment.

Self-employed persons are much more likely to move into paid employment. On average, 8.0% of solo self-employed move into paid employment in the following year – almost twice as many as those who transition to self-employment with employees. However, 7.3% of all self-employed with employees also switch to paid employment in the following year, and even a higher share switches from self-employment with employees to solo self-employment (10.7%). Finally, only a small proportion of the unemployed move to solo self-employment (2.2%) and to self-employment with employees (0.3%).

Table 1: Transitions between labour market states, all countries

Transition probabilities from year t to year $t+1$ (in %)

<i>Year t</i>	<i>Year t+1</i>				
	PEmpl	SE wE	Solo SE	Unemp	Non-act
PEmpl	92.35	0.27	0.79	2.81	3.79
Solo SE	7.97	4.94	80.77	2.35	3.96
SE wE	7.25	78.66	10.70	1.06	2.33
Unempl	24.55	0.31	2.15	56.73	16.26
Non-act	9.94	0.10	0.78	5.30	83.89

Source: EU-SILC 2014-2019, SOEP v.37. – Notes: Averages for the time period 2014-19. Abbreviations used in the table: PEmpl: paid employment; SE wE: self-employment with employees; Solo SE: solo self-employment; Unemp: unemployment; Non-act: non-activity.

These observations generally hold across different groups of workers, as shown in the tables in the appendix where transition probabilities are reported by gender, education, and age (Table A 1, A 2, and A 3, respectively). However, some differences are noteworthy: women are less likely to make a transition from paid employment to self-employment (especially self-employment with employees), from solo self-employment to self-employment with employees, and more likely to make a transition from self-employment to unemployment and (especially) to non-activity than men. This suggests that self-employment is a less favourable labour market state for women than for men. The same conclusion applies to workers with a low qualification level and to older workers.

We now provide a full picture of the importance of different characteristics (individual, household, work, technology indicators) for transitions from paid employment and from solo self-employment to the different labour market states (Table 2). With respect to the individual characteristics gender, age,

and education, the results mirror those discussed in the preceding paragraph. In addition, it becomes apparent that workers in part-time paid employment or on a temporary contract have a relatively high probability to enter solo self-employment (around 21%), but a relatively low probability of entering self-employment with employees. On the contrary, workers in the top 20% of the wage distribution are relatively likely to enter self-employment with employees (32%), and much less likely to enter solo self-employment (19%). Not controlling for individual-level characteristics, the technology and task indicators are relatively similar for the different transitions from paid employment, with two noteworthy exceptions: transitions into self-employment are characterized by a (slightly) higher AI index, and a considerably lower intensity of routine-manual tasks.

Table 2: Descriptive statistics by type of transition

From paid employment					
	stays in PEmpl	entry into SE wE	entry into solo SE	entry into Unempl	entry into Non-act
Individual characteristics					
Men	50.3	67.1	60.2	51.1	38.6
Age 16-29	13.2	9.3	15.3	25.1	24.2
Age 30-54	68.8	74.6	68.8	58.7	31.2
Age 55-65	18.0	16.2	15.9	16.2	44.6
(Pre-)primary and lower secondary education	14.2	15.1	16.4	27.0	21.7
(Upper) secondary and post- secondary education	48.6	46.2	42.8	50.6	49.7
Tertiary education	37.2	38.6	40.8	22.4	28.6
Married	59.6	65.3	56.2	45.4	56.9
No. of children in household	0.6	0.7	0.6	0.5	0.4
Work characteristics					
Part-time	14.5	8.0	21.5	21.1	31.6
Temporary work contract	11.7	9.8	21.0	43.4	19.9
Top 20% of wage distribution	21.4	31.7	19.0	9.8	18.2
AI index:					
AI Felten index	0.58	0.62	0.6	0.49	0.53
Task intensities					
Routine tasks	0.27	0.23	0.22	0.29	0.28
Routine-cognitive tasks	0.21	0.19	0.17	0.2	0.21
Routine-manual tasks	0.07	0.04	0.05	0.09	0.07

Physical tasks	0.33	0.32	0.34	0.39	0.34
Intellectual tasks	0.5	0.55	0.51	0.41	0.47
Social tasks	0.39	0.44	0.41	0.33	0.39
Observations	635.931	2.529	5.552	20.421	26.168

Transition from solo self-employment	stays solo SE	entry into PEmpl	entry into SE wE	entry into Uempl	entry into Non-act
Individual characteristics					
Men	62.7	60.7	70.7	62.9	44.9
Age 16-29	6.6	12.9	5.4	14.3	10.1
Age 30-54	68.8	70.5	72.2	64.1	37.3
Age 55-65	24.6	16.7	22.4	21.6	52.6
(Pre-)primary and lower secondary education	18.7	16.4	15.3	29.6	23.6
(Upper) secondary and post-secondary education	45.5	44.1	48.5	46.0	45.8
Tertiary education	35.8	39.4	36.2	24.4	30.6
Married	64.4	56.9	70.4	52.1	65.5
No. of children in household	0.6	0.6	0.6	0.5	0.4
Work characteristics					
Top 20% of earned income distribution	25.4	18.3	33.3	12.6	18.5
AI index:					
AI Felten index	0.61	0.6	0.63	0.55	0.56
Task intensities:					
Routine tasks	0.22	0.21	0.22	0.23	0.23
Routine-cognitive tasks	0.18	0.17	0.18	0.17	0.18
Routine-manual tasks	0.05	0.04	0.04	0.05	0.05
Physical tasks	0.36	0.34	0.35	0.38	0.35
Intellectual tasks	0.49	0.51	0.52	0.45	0.48
Social tasks	0.4	0.41	0.42	0.36	0.4
Observations	48.413	5.485	3.410	1.749	2.452

Source: EU-SILC, own computation. Averages for the time period 2014-19. EU-SILC does not contain information on industry.

As for the transitions from solo self-employment, workers in the top 20% of the earned income distribution display a relatively low probability to make a transition to paid employment (18%), a relatively high probability to make a transition to self-employment with employees (33%), and relatively low probabilities to make transitions to unemployment (13%) or inactivity (19%).

Furthermore, AI exposure is higher for those staying in solo self-employment and workers transitioning into paid employment and into self-employment with employees. The same holds for social and intellectual task intensity. However, the routine and manual task intensities hardly differ between labour market transitions. This is the case because entries to self-employment itself are relatively homogeneous with respect to these intensities (not controlling for individual-level factors), as witnessed by the descriptive evidence on inflows into self-employment.

These descriptive results are very similar to the results found in Fossen and Sorgner (2021) for the US. For example, Fossen and Sorgner (2021) report that 58% of transitions from paid employment to solo self-employment and 68% of transitions from paid employment to solo self-employment are made by male workers; we show that for Europe, the corresponding figures amount to 60% and 67%, respectively.

5. Empirical analysis

5.1. Transitions from paid employment to self-employment and other states

In this section, we analyse transitions from paid employment to five different destination states: paid employment (i.e. no transition), self-employment with employees, solo self-employment, unemployment, and inactivity. The results in Table 3 show that workers who are in occupations highly exposed to AI, as measured by the AI Felten index, have a higher, albeit small, probability of moving from paid employment to self-employment. This result shows that an increase in the Felten index by one standard deviation is associated with an increase in the probability of transition from paid employment to self-employment by 0.05 percentage point (pp). This is equivalent to 12.5% of the average probability of moving from paid employment to solo self-employment.

This finding may reflect that some of the employees in occupations more exposed to AI advances are more likely to have the skills to develop innovative new business ideas and therefore decide to

Table 3: Transition probabilities from paid employment: Technology indices

Multinomial logit regressions by technology index

	stays employed	entry into SE w/employees	entry into solo SE	entry into unemployment	entry into inactivity
Labour-augmenting technology:					
AI Felten index	0.234*	0.018	0.051**	-0.331***	0.028
	(0.123)	(0.018)	(0.024)	(0.089)	(0.040)
Labour-saving technology:					
Total routine tasks	0.084	-0.026	-0.079*	0.076	-0.054
	(0.097)	(0.017)	(0.045)	(0.066)	(0.048)
Routine-cognitive tasks	0.083	-0.010	-0.059	0.044	-0.058
	(0.093)	(0.013)	(0.039)	(0.065)	(0.052)
Routine-manual tasks	0.056	-0.050**	-0.071**	0.078	-0.013
	(0.122)	(0.020)	(0.032)	(0.072)	(0.037)
Tasks:					
Physical tasks	-0.012	0.004	0.082	-0.083	0.009
	(0.204)	(0.022)	(0.074)	(0.126)	(0.081)
Intellectual tasks	0.189	-0.003	0.099	-0.156	-0.129
	(0.223)	(0.025)	(0.064)	(0.137)	(0.105)
Social tasks	0.071	0.079***	0.013	-0.298*	0.134*
	(0.219)	(0.028)	(0.053)	(0.163)	(0.074)
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

Source: EU-SILC 2014-2019, SOEP v.37, 2-year longitudinal sample, AI and task indices: Felten et al. (2018), Mihaylov & Tijdens (2019), European tasks database & JRC Eurofound (2021). – Notes: Marginal effects from separate (by technology index) regressions, two-year longitudinal weights used. Coefficients standardized and displayed in per centage points. Robust standard errors in parentheses, clustered at two-digit occupational level with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The full specification of the AI Felten Index regression is included in the online appendix Table B 1.

become self-employed to implement these ideas. This mechanism could be particularly at work during a period of economic expansion as the one analysed in this study (2014-2019). In fact, in accordance with the “prosperity pull” hypothesis of entry into entrepreneurship, during periods of economic expansion more individuals are encouraged to enter self-employment given the positive economic outlook and higher probabilities of success (Parker, 2018). However, our findings could also indicate

that workers in occupations more exposed to AI advances may not fully benefit from the labour-augmenting effects of AI in terms of higher wages and better career prospects in their current occupation. For workers in some low- and medium-skilled occupations, a greater exposure to AI may even have a displacing effect, rather than an augmenting effect (Gmyrek et. al, 2023). As a result workers in these occupations have a lower opportunity cost of switching to solo self-employment in search of higher earnings, autonomy, and more flexible working conditions. To the extent that there is a strong association between solo self-employment and necessity-driven entrepreneurship, this second interpretation seems more plausible than the one suggested by the “prosperity pull” hypothesis. Indeed, if entry into solo self-employment were mainly opportunity-driven, we should also have found a positive and significant relationship between AI exposure and the likelihood of switching to self-employment with employees – which is more typically associated with opportunity-driven entrepreneurship (Fairlie and Fossen, 2019). In section 5.3, we interact the AI-index with key socio-economic characteristics to investigate worker heterogeneity.

Turning to the measures of routine task-intensity, which we use as a proxy for exposure to labour-saving technologies (see Section 3.2), Table 3 shows that employees who are more exposed to this type of technology are in fact less likely to become self-employed, with or without employees. This is particularly the case for employees in occupations with a higher intensity of routine manual tasks. A one standard deviation increase in routine-manual task intensity reduces the probability of a worker moving to self-employment with employees by 0.05 pp and to self-employment without employees by 0.08 pp. This accounts for 25% of the average transition probability to self-employment with employees and for 20% of the average transition probability into solo self-employment.

This result may indicate that employees in routine occupations, and especially in those involving intensive routine manual work, tend to have limited access to financial resources, and fewer opportunities to develop managerial skills, creativity, and strong social networks – all aspects that are positively associated to the odds of entering self-employment. Furthermore, in contrast to workers

exposed to AI, workers with high RTI are less likely to have business opportunities as solo self-employed workers. This is especially the case for workers in occupations intensive in routine manual tasks.

Finally, the results for task intensities suggest that employees in occupations with a higher intensity of social tasks carried out in an occupation increases employees' probability to become employers. This is in line with the argument that employees in occupations that are more intensive in these tasks may develop skills and social networks that are conducive to the development of a business idea, which may eventually increase the probability of switching to self-employment.

5.2. Transitions from solo self-employment to other states

Turning to the econometric analysis of exits from solo self-employment, the main finding is that solo self-employed working in occupations that are more exposed to advances in AI are more likely to switch to paid employment (Table 4). The results show that a one standard deviation increase in the AI Felten-index increases the probability of moving from solo self-employment to paid employment by 0.29 pp. This accounts for 7.5% of the probability of moving from solo self-employment to paid employment. However, we do not find that exposure to AI increases the probability of remaining in solo self-employment or of expanding the business and moving to self-employment with employees. This is consistent with the argument that solo self-employed workers in occupations exposed to AI might give up self-employment to enter more secure and stable paid employment relationship when a viable job opportunity arises.

Looking at the coefficients on the different measures of RTI, there are no statistically significant findings. This is in line with our theoretical expectations. In fact, individuals working as solo self-employed in routine task intensive occupation should have a low probability of moving to paid employment within their occupation, as job vacancies for these occupations are typically scarce. For similar reasons, we do not expect them to have a higher probability of expanding their business by hiring employees. However, working as a solo self-employed in routine-intensive occupations is not

associated with a higher probability of becoming unemployed or inactive. This may be caused by many of the solo self-employed in Europe having limited or no access to unemployment benefits or other forms of social protection. This means that they avoid becoming unemployed or inactive even if they have low earnings and little business activity. Instead, they may prefer to remain in their current occupational state, which at least provides them with some income.

Table 4: Transition probabilities from solo self-employment: Technology indices

Multinomial logit regressions by technology index

	stays solo SE	entry into employment	entry into SE w/employees	entry into unemployment	entry into inactivity
Labour-augmenting technology:					
AI Felten index	-0.371 (0.307)	0.292* (0.154)	0.269 (0.295)	0.055 (0.119)	-0.245 (0.198)
Labour-saving technology:					
Routine tasks	0.092 (0.483)	-0.012 (0.306)	0.054 (0.307)	-0.076 (0.115)	-0.058 (0.226)
Routine-cognitive tasks	0.136 (0.504)	0.036 (0.331)	0.001 (0.340)	-0.068 (0.104)	-0.105 (0.248)
Routine-manual tasks	-0.020 (0.301)	-0.093 (0.196)	0.104 (0.244)	-0.045 (0.113)	0.054 (0.123)
Tasks:					
Physical tasks	0.676 (0.493)	-0.392* (0.226)	0.062 (0.393)	0.247 (0.160)	-0.594*** (0.206)
Intellectual tasks	-0.269 (0.425)	0.412 (0.281)	0.283 (0.394)	0.204 (0.125)	-0.629* (0.327)
Social tasks	-1.133** (0.569)	0.345 (0.287)	0.924* (0.479)	-0.181 (0.134)	0.045 (0.275)
Year FE	yes	yes	yes	yes	yes
Country FE	yes	yes	yes	yes	yes
Mean Transition Probability	0.865	0.04	0.059	0.014	0.022
Observations	43,626	43,626	43,626	43,626	43,626

Note: See notes to Table 3.

Finally, our results on the specific task intensity measures show that solo self-employed workers with a higher intensity of physical tasks are less likely to enter paid employment. Conversely, workers

with a high intensity of social tasks are less likely to remain in solo self-employment, but more likely to become entrepreneurs, i.e. self-employed workers with employees. This finding could reflect that these workers are more likely to find an employee position in their professional domain which offers good working conditions, e.g. higher job stability. In contrast, workers in occupations intensive in physical tasks, similarly to workers in occupations intensive in routine tasks, seem to have less opportunities to find an attractive job in paid employment.

5.3. Worker heterogeneity for transitions between paid employment and solo self-employment

The effects of technology exposure are very likely to differ between worker groups. We therefore examine potential differences between individuals with different levels of formal education, age, and income level. We do so for one of the most interesting results from the above section, the effect of exposure to AI advances on individuals' probability to switch between paid employment to solo self-employment.

For the transitions out of paid employment (Table 5), the interactions for the level of education show that the positive association of the AI index with the probability of remaining in the current paid job becomes stronger with increasing levels of education. The AI index is also consistently associated with a lower probability of moving into unemployment for all levels of education. Taken together, these two results once again support the interpretation that AI reflects labour-augmenting effects of technology.

Looking at the interaction between the AI index and the age groups, the main result that emerges is that the positive association between the AI index and the probability of switching to self-employment with employees is stronger for individuals aged 55 and older. In line with findings from Fossen and Sorgner (2021), this may reflect that the group of older employees in occupations exposed to advances in AI may be better able to take advantage of entrepreneurial opportunities arising from new digital technologies due to their longer work experience, wider social networks, and greater availability of financial capital. This result is also consistent with findings that older workers with high

digital exposure in their occupation are more likely to be opportunity entrepreneurs (Zhang et al. (2022)).

Table 5: Transition probabilities from paid employment: Felten digitisation index, different worker groups

Multinomial logit regressions

	stays employed	entry into SE w/employees	entry into solo SE	entry into unemployment	entry into inactivity
AI Felten Index x Skill groups					
[1] (Pre-)primary and lower secondary education	-0.152 (0.185)	0.043 (0.033)	0.122** (0.050)	-0.200 (0.175)	0.187** (0.078)
[2] (Upper) secondary and post- secondary education	0.285*** (0.106)	0.014 (0.018)	0.032 (0.026)	-0.387*** (0.082)	0.056 (0.056)
[3] Tertiary education	0.394** (0.188)	0.017 (0.027)	0.044 (0.058)	-0.361*** (0.103)	-0.094 (0.084)
AI Felten Index x Age groups					
[1] Age 16-29	1.281*** (0.233)	0.005 (0.022)	0.106 (0.071)	-0.749*** (0.119)	-0.644*** (0.192)
[2] Age 30-54	0.257** (0.113)	0.014 (0.020)	0.024 (0.025)	-0.254*** (0.085)	-0.041 (0.060)
[3] Age 55-65	-0.847*** (0.316)	0.054** (0.023)	0.105 (0.065)	-0.093 (0.113)	0.781*** (0.250)
AI Felten Index x Income groups					
[1] Bottom 80% of wage Distribution	0.149 (0.133)	0.026 (0.020)	0.061* (0.034)	-0.325*** (0.092)	0.088* (0.051)
[2] Top 20% of wage distribution	1.017*** (0.309)	-0.010 (0.022)	-0.017 (0.079)	-0.442*** (0.164)	-0.549** (0.220)
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

Note: See notes to Table 3.

Finally, the positive associations between the AI index and the likelihood of switching to solo self-employment are stronger only for low-skilled workers and workers in the bottom 80% of the wage distribution. This may suggest that workers exposed to AI advances who are in low-paid occupations

and less educated, may not actually benefit from the labour-augmenting effects of this technology and may switch to solo self-employment out of necessity because they do not have decent career prospects in the wage sector. In line with the previous section, these findings support the role of necessity entrepreneurship. This result is also consistent with findings by Hyytinen and Rouvinen (2008) that the probability of entering entrepreneurship is negatively correlated with the unobserved ability and/or productivity of the employed.

Table 6: Transition probabilities from solo self-employment: Felten digitisation index, different worker groups

Multinomial logit regressions

	stays solo SE	entry into employment	entry into SE w/employees	entry into unemployment	entry into inactivity
AI Felten Index x Skill groups					
[1] (Pre-)primary and lower secondary education	-1.297* (0.729)	-0.052 (0.365)	0.465 (0.786)	1.069** (0.522)	-0.185 (0.295)
[2] (Upper) secondary and post-secondary education	0.243 (0.495)	0.144 (0.317)	0.203 (0.369)	-0.060 (0.170)	-0.529* (0.279)
[3] Tertiary education	-0.642* (0.386)	0.534** (0.262)	0.244 (0.327)	-0.123 (0.150)	-0.012 (0.215)
AI Felten Index x Age groups					
[1] Age 16-29	0.578 (1.278)	-1.095 (0.837)	-0.394 (0.452)	0.247 (0.464)	0.664 (0.584)
[2] Age 30-54	-0.703* (0.371)	0.526*** (0.197)	0.395 (0.316)	0.046 (0.094)	-0.264 (0.191)
[3] Age 55-65	0.233 (0.615)	0.103 (0.248)	0.104 (0.473)	-0.007 (0.232)	-0.432 (0.345)
AI Felten Index x Income groups					
[1] Bottom 80% of cash income Distribution	-0.455 (0.399)	0.435 (0.295)	0.357 (0.311)	0.156 (0.162)	-0.493* (0.295)
[2] Top 20% of cash income Distribution	0.026 (0.540)	0.137 (0.154)	-0.082 (0.440)	-0.201*** (0.075)	0.119 (0.102)
Year FE	yes	Yes	yes	yes	yes
Country FE	yes	Yes	yes	yes	yes
Mean Transition Probability	0.865	0.040	0.059	0.014	0.022
Observations	43,626	43,626	43,626	43,626	43,626

Note: See notes to Table 3.

This argument is indirectly supported by results for transitions out of solo self-employment presented in Table 6, which shows that the positive relationship between the AI index and the probability of moving out of solo self-employment into paid employment is higher for those with a tertiary education and for prime age workers (aged 30-54). This suggests that the incentives to move to paid employment are greater for highly educated solo self-employed who are engaged with digital technologies. Job offers with attractive working conditions, such as more secure working conditions and a higher pay, might incentivise these workers to give up their own business and to transition into paid employment. However, the positive relationship between the AI index and the likelihood of entering paid employment for those with lower cash income also reflects that less successful self-employed workers are more likely to return to paid employment. One reason for this could be that these solo self-employed workers entered self-employment involuntarily, either because they did not find a viable job in paid employment or because they were forced by their current employer to reclassify as a contractor.

It is also interesting to note that the probability to transition from solo self-employment to self-employment with employees does not significantly differ with respect to educational level, age, or income group.

6. Robustness checks

As we pool the data across a large number of European countries, there may be heterogeneity in the estimated coefficients across countries. To ensure that our results are not driven by specific countries, we run additional regressions excluding individual countries from the regressions. We focus on Germany, Italy, and France because these countries have a larger working population and a strong economy in Europe⁴.

⁴ The results are available from the authors upon request.

For transitions from paid employment, we find that the overall pattern of the results and the size of the coefficients stays the same when we exclude one of the countries, Germany, France, or Italy, from the regression. However, the significance level of the coefficients for the AI index changes slightly. Besides, the coefficient of RTI on remaining in paid employment becomes negative for Germany. However, the results are not significant.

For transitions from solo self-employment, we can also confirm that the pattern of the results and the size of the coefficients do not change significantly when leaving one of the countries out of the regression. However, for Germany, the AI coefficient is no longer significant for the transition to paid employment.

7. Conclusions

We have examined the dynamics of self-employment for 31 countries in Europe over the period 2014-2019, answering three research questions. First, how are labour-saving and labour-augmenting technologies related to worker transitions into and out of self-employment? Second, do these effects differ between transitions into and out of solo-self-employment and self-employment with employees? Third, do these effects differ between worker groups?

Our results can be summarised as follows. First, we find a positive correlation between labour-augmenting technologies (exposure to AI advances in the current occupation) and the probability of transitioning from paid employment to solo self-employment. This could have two non-mutually exclusive interpretations: workers could either be trying to benefit more fully from the labour-augmenting effects of AI advances by moving to solo self-employment, or they could be moving to solo self-employment because their opportunities in paid employment have diminished. Indeed, we find more support for necessity-driven entrepreneurship.

Therefore, AI is more of a risk than an opportunity for some workers. This is particularly the case for low-skilled workers who are more likely to leave paid employment and transition to inactivity or to (solo) self-employment. In these cases, solo self-employment seems to materialise because there are

no better options in paid employment. The same is true for low-paid workers who are more likely to become self-employed if they work in occupations strongly exposed to AI. Older workers also display higher transitions out of paid employment, but a higher transition rate to self-employment with employees, which may indicate better labour-market outcomes. In contrast, high-skilled workers and high-paid workers display a higher stability of paid employment in occupations strongly exposed to AI, i.e. they seem to benefit from higher AI exposure. This is consistent with higher transition rates from solo self-employment to paid employment for these two groups of workers.

Labour-saving technologies, as measured by the intensity of routine tasks in the current job, are negatively correlated with entry into self-employment. This is in line with theoretical expectations, as workers in occupations with a high RTI are likely to be negatively affected by technological progress. Therefore, they are likely to remain in stable and (relatively) protected paid employment.

Our results for Europe therefore differ from those for the US to some extent. Fossen and Sorgner (2021) find for the US that higher exposure to advances in AI reduces the probability of switching to unincorporated business, while increasing the likelihood of starting an incorporated business. These results suggest that workers who experience productivity gains in their occupations due to advances in AI technologies have more opportunities for growth-oriented entrepreneurship, but also higher opportunity costs of switching to less ambitious entrepreneurship. The difference between the results could reflect a host of factors, notably the different country samples, different time periods (2014-2019 vs 2011-2018), the different time horizon of the transitions considered (annual vs. quarterly), and the different level of detail of the occupational classification (2-digit ISCO-08 vs 5-digit SOC). In addition, it is likely that these differences reflect that the institutional, regulatory, and business environment, as well as several cultural dimensions, are more conducive to the creation of larger ventures in the US than in most European countries (Dheer and Treviño 2022). Indeed, working solo self-employed is

much less common in the US than in Europe.⁵ Furthermore, employees are more likely to negatively select into self-employment in Europe than in the US (Hyytinen and Rouvinen, 2008).

More broadly, these results on AI seem to be consistent with the literature on the impact of robots, which generally have been found to be detrimental for employment in the US (Acemoglu and Restrepo, 2019), but neutral or even positive for employment in Europe (Dauth et al., 2021; Bachmann et al., 2022). It is also consistent with findings of Albanesi et al. (2023), who show that AI exposure is positively associated with employment at the occupation level for a larger number of European countries.

In other respects, our results on AI advances and transition patterns are in line with those of Fossen and Sorgner (2021): we also find that employees in occupations more exposed to AI advances are more likely to remain in paid employment and less likely to become unemployed. These results support the argument that AI can be considered a labour-augmenting technology, which makes employees exposed to AI advances in their occupations more productive, and therefore less likely to exit employment and lose their jobs.

Our analysis has important policy implications. First, as exposure to technology may increase workers' entrepreneurial opportunities, public policies that support transitions to self-employment may be economically and socially beneficial. Looking into the future, however, facilitating the transition to self-employment might have important repercussions for countries' fiscal capacity and the sustainability of their social protection systems. This could be further exacerbated by firms' increased tendency to outsource work to external contractors or to reclassify employees as consultants in the attempt to escape strict employment protection legislation.

Second, as some workers are likely to have been pushed into self-employment because there are too few attractive alternatives in paid employment, public policies aimed at encouraging self-

⁵ According to data from ILOSTAT, the share of solo self-employed in total employment in the US was just below 4% in 2019, against 10% in the EU-27. In the same year, the share of self-employed with employees was instead 2.1% in the US against 4.3% in the EU-27.

employment among ill-prepared and poorly resourced workers can be counterproductive. Rather, public policy should first aim at providing workers with adequate skills to be able to benefit from technological advances. This concerns particularly digital skills, which have been shown to be unequally distributed between different worker groups (Bachmann and Hertweck, 2023). Indeed, our results suggest that training and upskilling, especially for workers with lower levels of education, might help them to start or expand their own business to improve their labour market opportunities.

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Online Appendix

Appendix A

Table A 1: Transitions between labour market states, all countries by gender

Transition probabilities from year t to year t+1 (in %)

<i>Year t</i>	<i>Year t+1</i>				
	employment	SE with employees	solo SE	unemployment	non-activity
Women					
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
non-activity	9.72	0.10	0.76	5.10	84.33
Men					
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
non-activity	10.32	0.09	0.81	5.62	83.16

Source: EU-SILC, own computation. Averages for the time period 2014-19.

Table A 2: Transitions between labour market states, all countries by skill group

Transition probabilities from year t to year t+1 (in %)

<i>Year t</i>	<i>Year t+1</i>				
	employment	SE with employees	solo SE	unemployment	non-activity
(Pre-)primary and lower secondary education:					
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
non-activity	6.80	0.05	0.41	5.72	87.02
(Upper) secondary and post-secondary education:					
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
non-activity	10.11	0.09	0.74	4.74	84.32
Tertiary Education:					
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
non-activity	17.28	0.24	1.96	5.73	74.79

Source: EU-SILC, own computation. Averages for the time period 2014-19.

Table A 3: Transitions between labour market states, all countries by age

Transition probabilities from year t to year t+1 (in %)

Year t	Year t+1				
	employment	SE with employees	solo SE	unemployment	non-activity
Age 16-29					
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
non-activity	15.28	0.07	0.54	6.68	77.43
Age 30-54					
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
non-activity	11.94	0.18	1.56	7.68	78.63
Age 55-65					
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
non-activity	2.20	0.06	0.45	1.84	95.45

Source: EU-SILC, own computation. Averages for the time period 2014-19.

Appendix B

Table B 1: Transition probabilities from paid employment: Felten digitisation index, all control variables

Multinomial logit regressions

	stays employed	entry into SE w/employees	entry into solo SE	entry into unemployment	entry into inactivity
AI Felten index	0.234* (0.123)	0.018 (0.018)	0.051** (0.024)	-0.331*** (0.089)	0.028 (0.040)
Women	-0.713*** (0.216)	-0.042** (0.018)	-0.242*** (0.055)	-0.353** (0.173)	1.350*** (0.120)
Age 16-29	-3.390*** (0.450)	-0.010 (0.027)	0.122 (0.083)	0.468*** (0.157)	2.810*** (0.351)
Age 55-65	-5.977*** (0.419)	-0.038* (0.022)	-0.112* (0.060)	0.347** (0.151)	5.780*** (0.347)
(Pre-)primary and lower secondary education	-1.193*** (0.253)	-0.032 (0.024)	0.077 (0.054)	0.581*** (0.181)	0.566*** (0.177)
Tertiary education	0.750*** (0.220)	0.038* (0.023)	0.225*** (0.073)	-0.684*** (0.140)	-0.329*** (0.126)
Married	0.120 (0.148)	0.022 (0.022)	-0.017 (0.036)	-0.861*** (0.077)	0.736*** (0.115)
No. of children in household	-0.076 (0.136)	0.001 (0.009)	0.077** (0.031)	0.096 (0.060)	-0.098 (0.115)
Part-time	-2.028*** (0.269)	-0.037 (0.026)	0.254*** (0.090)	0.413*** (0.127)	1.398*** (0.223)
Temporary work contract	-6.213*** (0.314)	0.003 (0.027)	0.538*** (0.111)	4.268*** (0.251)	1.404*** (0.119)
Top 20% of wage distribution	0.790** (0.329)	-0.019 (0.025)	-0.101 (0.097)	-0.900*** (0.148)	0.230 (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

Source: EU-SILC 2014-2019, SOEP v.37, 2-year longitudinal sample, AI and task indices: Felten et al. (2018), Mihaylov & Tijdens (2019), European tasks database & JRC Eurofound (2021). – Notes: Marginal effects from separate (by technology index) multinomial logit regressions, two-year longitudinal weights used. Coefficients standardized and displayed in percentage points. Robust standard errors in parentheses, clustered at two-digit occupational level with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The reference group is employed, male, not-married, age 30-55, has (upper) secondary and post-secondary education, has no children, works fulltime, has a permanent job, and is in the lower 80% of the wage distribution.

Table B 2: Transition probabilities from solo self-employment: Felten digitisation index, all control variables

Multinomial logit regressions

	stays solo SE	entry into employment	entry into SE w/employees	entry into unemployment	entry into inactivity
AI Felten index	-0.371 (0.307)	0.292* (0.154)	0.269 (0.295)	0.055 (0.119)	-0.245 (0.198)
Women	0.111 (1.055)	-0.401 (0.477)	-1.541*** (0.461)	0.421* (0.229)	1.409*** (0.423)
Age 16-29	-3.947*** (1.094)	2.021** (1.029)	-1.355** (0.536)	1.602*** (0.577)	1.679** (0.698)
Age 55-65	-0.020 (0.789)	-2.370*** (0.407)	-0.919*** (0.341)	0.219 (0.204)	3.089*** (0.419)
(Pre-)primary and lower secondary education	0.421 (0.827)	-0.555 (0.572)	-0.712* (0.381)	1.127** (0.465)	-0.282 (0.403)
Tertiary education	-0.267 (0.872)	0.868* (0.469)	-0.174 (0.523)	-0.033 (0.138)	-0.395 (0.277)
Married	-1.127* (0.664)	-0.175 (0.242)	1.430*** (0.387)	-0.587*** (0.199)	0.459 (0.316)
No. of children in household	-0.316 (0.338)	0.259 (0.214)	0.011 (0.201)	0.079 (0.126)	-0.033 (0.182)
Top 20% of cash income distribution	12.650*** (2.190)	-10.067*** (1.561)	2.758*** (0.371)	-1.760*** (0.463)	-3.582*** (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

Source: EU-SILC 2014-2019, SOEP v.37; Felten-index by Felten et al. (2018). Notes: - Marginal effects from separate (by technology indicators) multinomial logit regressions with five outcomes. Coefficients in per centage points. Robust standard errors in parentheses, clustered at two-digit occupational level with * $p < 0,1$, ** $p < 0,05$, *** $p < 0,01$. 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 fulltime, has a permanent job, and is in the lower 80% of the cash distribution. Country and year fixed-effects. Based on the two-year longitudinal sample.

Appendix C: Technical details

EU-SILC coverage

For Switzerland, Germany, Iceland, and the UK, the analysis covers the period 2014 – 2017, for Slovakia 2014 – 2015. When we consider occupational information, the analysis is further restricted: Slovenia only provides 2-digit occupational codes for 2014 and occupational codes are missing for Iceland in 2014 and 2015.

Malta is not included in the analysis since occupational codes are only provided at the 1-digit ISCO level.

Technology indicators

Table C provides an overview of the technology exposure indicators used in this paper.

Table C 1: 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 four-digit occupations in the ISCO-08 classification system	Range from 0 (min intensity) to 1 (max intensity)	From 4 digits ISCO-08 to 2 digits ISCO-08
Advances in AI	Felten et al. (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-digits SOC to 2-digits ISCO-08
Intensity of physical/intellectual/social tasks	JRC-Eurofound European Tasks database (see Bisello et al (2021) for details)	Indices are built using detailed information on the content of work of occupations from the EWCS 2015, the Italian ICP, and OECD's PIAAC Survey.	Normalised scores for all tasks. For each task, the score's value range from 0 to 1, taking value =1 for the occupation in the highest percentile of task intensity.	Already provided at 2-digits ISCO-08

Source: Own representation.

Measuring labour-saving technologies

The measures of RTI developed by Mihaylov and Tijdens (2019) are based on information on 3,264 tasks that are described for 427 four-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.⁶ 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, assembling). The RC indicator is intended to provide a measure of an occupation's exposure to computerisation and (unsophisticated) machine-learning. These RC technologies have the potential to perform standardised cognitive tasks which are easier to codify with programmed rules (e.g. counting, basic text writing, 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 2-digit by calculating the average weighted by the employment level of 3-digit occupations in the EU as provided by Eurostat.

⁶ One limitation of the measures of routine task-intensity 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.

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 SOC occupational classification, 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 et al. 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 et al. (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 to 4-digit ISCO-08. Then, we 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 the exposure to AI at the occupational level. The most prominent ones are those developed by Brynjolfsson et al. (2018) and Tolan et al. (2020). 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. (2020) identify potential AI exposure 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. (2020) is more of a measure of exposure to future AI developments, rather than a measure of existing AI benchmarks like the index by Felten et al. (2018). The index by Brynjolfsson et al. (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 et al. (2018) index best captures existing advances in AI and is therefore most suitable for our analysis, which focuses on recent trends in labour market transitions.

Technology and task measures: descriptive evidence

Table C 2: Average exposure to technology and task intensities at the 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 specialised services managers	0.78	0.02	0.02	0.00	0.22	0.81	0.63
Hospitality, retail and other services managers, PT:11,12 and 13 into 14	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, wood working, 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

Correlations between the technology measures

Table C 3 shows the correlation coefficients between the different measures of technology exposure and task intensity at the 2-digit ISCO-08 occupational level⁷. 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 C 3 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

⁷ Table C 1 displays the average technology exposure and task intensities for all indices at the two-digits level of the ISCO-08 classification.

in AI tend to be very low in routine intensive 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 worker.

Table C 3: 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 on data from Mihaylov and Tijdens (2019); JRC-Eurofound European Tasks database; Felten et al. (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.