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

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Abstract. *In this article, we examine how technology is associated with self-employment dynamics using worker-level data from 30 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 the risk of unemployment 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.*

Keywords: *automation, artificial intelligence, self-employment, occupations, tasks, technological change, technology, Europe.*

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1. Introduction

Technological advancements in artificial intelligence (AI), digital platforms and robotics, among others, are transforming the labour market, with important effects on all employment types. In particular, self-employment is likely to be strongly affected (Fossen, McLemore and Sorgner 2024). 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, Wright and Feldman 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 endeavours alongside traditional employment (Pouliakas and Ranieri 2022). At the same time, digital technologies can make self-employment less attractive if they lead to higher productivity and higher pay in paid employment.

On the other hand, technology can also worsen labour market prospects in dependent employment. Labour-saving technologies, such as advanced robotics, which automate tasks and reduce the need for human labour, 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 individuals with higher levels of education, and *solo self-employment*, which may often result from a lack of better employment options, particularly among those with lower levels of education.

This study therefore answers the following research questions for Europe:

1. How is technological progress, and particularly exposure to labour-augmenting and labour-saving technologies, related to workers' transitions into and out of self-employment?
2. Do these effects of technological progress differ between solo self-employment and self-employment with employees?
3. Do these effects 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 2014–19. These data allow us to identify annual transitions between labour market statuses. 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 for the 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 almost 23 million solo self-employed individuals were recorded in the European Union (EU), which was a 15 per cent increase since 2002 and represented about 10 per cent of total employment and 72 per cent of all self-employed workers.[1] The historical occupational composition of self-employment is also changing, with a growing

[1] In 2019, self-employed workers accounted for around 14 per cent of total employment in the EU. See Eurostat, "Employment by Sex, Age and Professional Status (1 000)", LFS Series – Detailed Annual Survey Results, 2021. https://doi.org/10.2908/LFSA_EGAPS.

share of high-skilled individuals in technical, professional and managerial roles – up from 36 per cent in 2012 to 42 per cent in 2019 in the EU.[2]

This article contributes to the literature in this area 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 period 2014–19, whereas evidence on such transitions is currently only available for the United States. Second, we examine the relationship between technological progress and worker-level transitions into and out of self-employment. We thus complement evidence for the United States on entries into self-employment (Fossen and Sorgner 2021) and we add to the literature with an analysis of the relationship between technological progress and exits from solo self-employment. Third, we explore the heterogeneity of the effect of exposure to technology across different groups of workers with respect to characteristics such as age, educational attainment and income, as well as between solo self-employed workers and self-employed workers with employees.

Our findings with respect to labour-augmenting technologies are as follows. First, workers who are more exposed to such technologies are more likely to transition between paid employment and solo self-employment than less exposed workers. Yet, the probability of switching from paid employment to solo self-employment is higher for workers who are in occupations that require lower levels of education and earn relatively low wages. 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 tertiary education and for prime age workers (aged 30–54). Third, older exposed workers (aged 55–65) also enter self-employment with employees or inactivity. Overall, these results suggest that labour-augmenting technologies such as AI 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 that these technologies have particularly adverse effects on the labour prospects of workers exposed to them – in other words, we do not find a significantly higher probability of workers moving 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 need to design targeted skill development programmes, particularly for low-skilled workers, in order to facilitate their adaptation to labour-augmenting technologies. They also advocate for the adoption of these technologies in the workplace owing 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 those most affected by labour-saving technologies. This should be complemented by strategies that promote technology integration, for the benefit of both high- and low-skilled workers, and by addressing socio-demographic disparities and ensuring equitable access to the advantages offered by technological progress.

The remainder of this article is organized as follows. The second section outlines the theoretical framework for this study and reviews existing empirical evidence relating to our research questions. The third section presents our data and methodology. The fourth section provides an overview of labour market dynamics in Europe over the period of our study. The fifth section provides the results of our main analyses, while the sixth considers those of our robustness tests. We formulate some conclusions in the seventh section.

[2] Our own calculations based on Eurostat data on "Self-employment by occupation" (variable code: LFSA_ESGAIS).

2. Theoretical framework and existing empirical evidence

The task-based approach (Autor, Levy and Murnane 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. those requiring manual dexterity) are usually performed in unstructured environments and are therefore difficult to automate. Accordingly, machines are less likely to replace workers in these areas, supplementing them instead (Autor, Levy and Murnane 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 they do not destroy jobs but rather change job profiles and induce positive employment effects (Felten, Raj and Seamans 2018; Gmyrek, Berg and Bescond 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, Mitchell and Rock 2018; Fernández-Macías et al. 2023).

We investigate our research questions empirically following the theoretical framework provided by Fossen and Sorgner (2021) and complementing it by developing hypotheses on mechanisms behind the transitions from solo self-employment to paid employment. A theoretical framework that focuses on the impact of digitalization on entrepreneurship entry (and exits), through its influence on the opportunity costs of remaining in a specific labour market status, seems particularly apt for developing 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.

Fossen and Sorgner (2021) have made an 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. Based on this distinction, studying the situation in the United States, Fossen and Sorgner (2022) find that workers in occupations that are more susceptible to destructive digitalization – and hence more at risk of unemployment – are more likely to become entrepreneurs by 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.

We follow the distinction between labour-saving and labour-augmenting technologies and find that both types of technology can have positive and negative effects on the likelihood of paid employees moving 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, keep abreast of new entrepreneurship-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. information and communications technology professionals) that are exposed to labour-augmenting technologies are typically easier to carry out remotely (Rodrigues, Fernández-Macías and Sostero 2021). This could provide incentives for workers seeking greater autonomy and flexibility to move into self-employment, while 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 when 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 could thus be more likely to become (solo) self-employed out of necessity – in other words, they might be “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 entrepreneurship 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 of developing 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 of switching 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 status as a result of poor wage employment opportunities in their occupation (Milasi and Mitra 2022). Furthermore, a significant proportion of solo self-employed workers in advanced countries move to dependent employment once an opportunity presents itself (Boeri et al. 2020).

With respect to labour-augmenting technologies, we might expect, on the one hand, that individuals in solo self-employment in exposed and therefore highly productive occupations are more likely to hire employees. 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.

We expect solo self-employed workers exposed to labour-saving technologies to be 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 they may instead be more likely to exit solo self-employment and become unemployed.

Overall, although the theoretical considerations examined above create expectations on the effects of technology on the entry into and exit from self-employment, these often remain 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 sex, formal education, age and income level.

3. Data and methodology

3.1. Measuring labour market transitions

Our analyses are based on EU-SILC micro data for the years 2014–19. Given that we are examining labour market transitions, we use the longitudinal version of these data. For Germany, EU-SILC data are not available as a panel. Instead, we use the EU-SILC clone provided by the German Socio-Economic Panel (SOEP).[3] In total, our analysis covers 30 European countries.[4]

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.[5] The data, provided by national statistical offices, are based on personal interviews or they are drawn from administrative data sources. They are representative of the population in the countries covered and comparable across Europe.

For most countries, the longitudinal version of the EU-SILC is based on a four-year rotating panel. Under this system, 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 individuals 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 data sets 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 labour market status at times 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.

In the case of Germany, we use the long format of the EU-SILC clone based on data from the SOEP (v37) – a representative annual survey that provides detailed labour market information on the individuals in the sampled households (Bartels, Nachtigall and Göth 2021). We restrict the resulting sample from the EU-SILC and SOEP to individuals aged 16–65 with valid data for the crucial variables. Furthermore, we exclude individuals working in the armed forces and in agricultural occupations. Since 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 purposes of our analysis, occupations are classified according to the 2008 International Standard Classification of Occupations (ISCO-08), allowing us to exploit the variation across 40 different occupations. Given that we are analysing labour market transitions from one year to the next, we further restrict the sample to individuals with valid information on their economic status in two consecutive years.

We differentiate between five labour market statuses: employment, self-employment with employees, solo self-employment, unemployment and inactivity. Labour market status is based on the respondents' self-reported current main economic status (variable pl031 in EU-SILC). To distinguish between solo self-employment and self-employment with employees, this information on the main current economic status is complemented with information on respondents' current activity status in their main job (variable pl040 in EU-SILC). According to the EU-SILC guidelines (Eurostat 2020), solo self-employed workers are self-employed individuals who work in their own business, professional practice, or farm for the purpose of earning 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 our analysis. We examine how exposure to technology in the current occupation is associated with transitions into and out of (solo) self-employment. Therefore, we focus on (1) transitions from employment to (solo) self-employment and other labour market statuses and (2) exits from (solo) self-employment to any other labour market status.

[3] See https://www.diw.de/en/diw_01.c.615551.en/research_infrastructure__socio-economic_panel__soep.html.

[4] The analysis includes Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, Serbia, Slovenia, Slovakia, Spain, Sweden, Switzerland and the United Kingdom. See supplementary online Appendix A for details.

[5] For further details, see Eurostat (2020).

3.2. Measuring technology and job tasks

In order to investigate whether exposure to a particular technology in the current job shapes individuals' probability of moving from one labour market status to another, and notably from paid employment to self-employment and vice-versa, we use several measures of exposure to technology 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. In line with the literature discussed in section 2, we focus on labour-saving and labour-augmenting technologies.

In order to operationalize 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 supplementary online Appendix A 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: (i) the routine manual 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 and assembling); (ii) the routine cognitive indicator, which measures an occupation's exposure to computerization and (unsophisticated) machine learning; and (iii) the overall routine task 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 that are not occupation-specific (e.g. Acemoglu and Autor 2011; Autor, Levy and Murnane 2003; Spitz-Oener 2006). Furthermore, the measures we use relate to the ISCO-08 classification, which allows for a direct match with European micro data.

We operationalize the concept of labour-augmenting technology following Fossen and Sorgner (2021) and use a measure of advances in AI by occupation estimated by Felten, Raj and Seamans (2018), who link these advances to skills specified in the US Occupational Information Network (O*Net) database of occupational contents to describe job requirements. In contrast to other existing measures of AI exposure (e.g. Brynjolfsson, Mitchell and Rock 2018; Tolan et al. 2021), Felten, Raj and Seamans (2018) provide a comprehensive measure of current (rather than potential future) AI developments (see supplementary online Appendix A for details). Moreover, using this index allows for a more straightforward comparison between our results and those obtained by Fossen and Sorgner (2021).

Lastly, we complement the above measures of labour-saving and labour-augmenting technologies with measures of the intensity of physical, intellectual and social tasks drawn from a set of task-specific indicators in the JRC-Eurofound European Tasks database (Bisello et al. 2021). This database is constructed 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 2017), the *Indagine Campionaria sulle Professioni* (an Italian version of O*NET) and the Programme for the International Assessment of Adult Competencies (PIAAC) survey of the Organisation for Economic Co-operation and Development (OECD).

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

3.3. Empirical methodology

In order to model alternative pathways into and out of self-employment, we consider labour market transitions from the original statuses of self-employment and paid employment to the five destination statuses of paid employment, self-employment with employees, solo self-employment, unemployment and inactivity. Accordingly, we study an individual choice between five discrete, unordered alternatives. The dependent variables take on the value *m* if the *m*th alternative is chosen, $m = 1, \ldots, j$. We control for various, alternative-invariant factors that might influence the decision to transition between labour market statuses (Wooldridge 2010; Cameron and Trivedi 2005). To this end, we use a multinomial logit model, which lets the regressors' coefficients β_m vary across alternatives *m*. The general form of the predicted probability from the multinomial logit model can be written as:

$$\Pr\left(y = m \middle| \boldsymbol{X}\right) = \frac{\exp\left(\boldsymbol{X}'^{\beta_{m|b}}\right)}{\sum_{j=1}^{J} \exp\left(\boldsymbol{X}'^{\beta_{j|b}}\right)}, \text{ with } m = 1, \ldots, j \tag{1}$$

where $\Pr(y = m \mid \boldsymbol{X})$ is the probability that alternative *m* is chosen conditional on the control variables in $\boldsymbol{X}$. The subscript *b* stands for the original status: paid employment or self-employment. $\boldsymbol{X}$ represents the vector of explanatory variables and captures individual characteristics such as sex, age, marital status, 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 per cent of the wage distribution. This allows us to control for individual- and job-specific factors. The coefficient $\beta_{m|b}$ varies across alternatives *m* and depends on the original status *m*. 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 – including business-cycle effects that are relatively similar between countries – that impact all individuals in a given year.

Since we want to examine the relationship 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 and 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.

In our baseline model, we perform separate regressions for the different measures of technology. This means that we run four different regression models, each with one of the following indicators at the occupation level: (i) the AI index as a measure for labour-augmenting technology; (ii) the intensity of total routine tasks as a measure of labour-saving technology; (iii) routine cognitive and routine manual task intensities as a variation of the previous model; and (iv) the intensity of physical, intellectual and social tasks. To facilitate the interpretation of the results, we standardize our technology and task measure and calculate marginal effects.

In order to analyse the heterogeneity of the relationship across different groups of workers, we interact our technology measure and the categorical variables for worker characteristics. In this model, the marginal effect of technology is a composite measure of the effect of the technology index and the interaction term.

A key assumption of this model is the independence of irrelevant alternatives, which posits that the probability of transitioning to one status 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 statuses are very distinct and are determined by significantly different factors (Cameron and Trivedi 2005). Since we are considering cross-sectional data, we are not able to capture the long-term effects of technology and adoption processes. Nevertheless, by studying labour market transitions we can gain insights into shorter-term adjustments in response to exposure to technology. Moreover, such short-term adjustments are particularly interesting when studying emergent technologies such as AI, which have experienced rapid growth in recent years and presented a shock to some occupations. An additional concern might be sample selection, such that individuals exposed to prior technology have already selected themselves into certain labour market statuses. However, we try to mitigate this concern by 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 analyse and do not extend to previous time periods.

Reverse causality is a potential concern with regard to our empirical model insofar as transitions into self-employment may increase demand for new tools and tailored solutions, thus driving technological innovation. However, this is unlikely to be the case for our technology measures for several reasons. First, they are not based on actual technology adoption across occupational tasks, but rather on standardized descriptions of occupations. Second, the measures are constructed based on job requirements defined prior to our sample period, making them relatively exogenous to changes in job demands during our study period. Third, given the highly innovative nature and scope of AI applications in a wide range of tasks, it is unlikely that solo self-employed workers (who are the bulk of self-employed workers and the focus of our study) can significantly drive advances in AI, which are more likely to be driven by large innovative firms.

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 over the 2014–19 period. Table 1 shows the average transition probabilities from one year to the next between the five labour market statuses considered in the analysis. A first observation is that paid employees are relatively unlikely to move to self-employment. However, since transitions out of paid employment are generally rather low, transitions to self-employment make up an economically relevant share of the total transitions out of paid employment. Self-employed workers are much more likely to move into paid employment than the opposite. On average, 8.0 per cent of solo self-employed workers move into paid employment in the following year – almost twice as many as those who transition to self-employment with employees. In contrast, while 7.3 per cent of self-employed workers with employees also switch to paid employment in the following year, and an even higher share switch from self-employment with employees to solo self-employment (10.7 per cent). Lastly, only a small proportion of the unemployed move to solo self-employment (2.2 per cent) and to self-employment with employees (0.3 per cent).

Table 1. Transition probabilities between labour market statuses, all countries (percentages)

Year *t*	Year *t+1*				
	Paid employment	**SE with employees**	**Solo SE**	**Unemployment**	**Inactivity**
Paid employment	92.35	0.27	0.79	2.81	3.79
Solo SE	7.97	4.94	80.77	2.35	3.96
SE with employees	7.25	78.66	10.70	1.06	2.33
Unemployment	24.55	0.31	2.15	56.73	16.26
Inactivity	9.94	0.10	0.78	5.30	83.89

Notes: Transition probabilities from year *t* to year *t*+1; averages for 2014–19. SE = self-employment.
Sources: EU-SILC 2014–19 and SOEP v37.

These observations generally hold across different groups of workers by sex, education and age (see supplementary online Appendix B, tables SB1, SB2, SB3, respectively). However, some differences are noteworthy: compared with men, women are less likely to make a transition from paid employment to self-employment (especially self-employment with employees) and from solo self-employment to self-employment with employees, and they are more likely to make a transition from self-employment to unemployment and (especially) to inactivity. This suggests that self-employment is a less favourable labour market status for women than for men. The same conclusion applies to workers with low qualification levels and to older workers.

Table 2 provides a full picture of the importance of different characteristics (e.g. individual, household, work and technology indicators) for transitions from paid employment and from solo self-employment to the different labour market statuses. With respect to the individual characteristics of sex, 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 of entering solo self-employment (around 21 per cent), but a relatively low probability of entering self-employment with employees. In contrast, workers in the top 20 per cent of the wage distribution are relatively likely to enter self-employment with employees (32 per cent), and much less likely to enter solo self-employment (19 per cent). 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 with employees are characterized by a (slightly) higher AI index and a lower intensity of routine manual tasks.

Table 2. Descriptive statistics by type of transition, 2014–19

From paid employment	**Destination status**				
	Paid employment	**SE with employees**	**Solo SE**	**Unemployment**	**Inactivity**
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

(*Cont.*)

Table 2. Descriptive statistics by type of transition, 2014–19 (*concl.*)

From paid employment	Destination status				
	Paid employment	**SE with employees**	**Solo SE**	**Unemployment**	**Inactivity**
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
From solo self-employment	**Solo SE**	**Paid employment**	**SE with employees**	**Unemployment**	**Inactivity**
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 wage 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

Notes: SE = self-employment. EU-SILC does not contain information on industry.
Source: Our own calculations based on EU-SILC data and SOEP v37.

As for the transitions from solo self-employment, workers in the top 20 per cent of the wage distribution display a relatively low probability of making a transition to paid employment (18 per cent), a relatively high probability of transitioning to self-employment with employees (33 per cent) and relatively low probabilities of transitioning to unemployment (13 per cent) or inactivity (19 per cent). 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 into 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 by Fossen and Sorgner (2021) for the United States. For example, the authors report that 58 per cent of transitions from paid employment to solo self-employment and 68 per cent of transitions from paid employment to self-employment with employees are made by male workers; we show that, for Europe, the corresponding figures amount to 60 per cent and 67 per cent, respectively.

5. Empirical analysis

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

The results in table 3 show that workers who are in occupations that are highly exposed to AI, as measured by the AI Felten index, have a higher, albeit small, probability of moving from paid employment to solo 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 transitioning from paid employment to solo self-employment by 0.05 percentage points (pp). This is equivalent to 12.5 per cent of the average probability of moving from paid employment to solo self-employment.[6]

This finding may reflect the fact that some employees in occupations with greater exposure to advances in AI are more likely to have the skills to develop innovative business ideas and therefore decide to become self-employed in order to implement them. This mechanism could be particularly at work during periods of economic expansion, such as the one analysed in this study (2014–19). According to the "prosperity pull" hypothesis of entry into entrepreneurship, the positive economic outlook and higher probabilities of success during these periods encourage more individuals to enter self-employment (Parker 2018). However, our findings could also indicate that workers in occupations more exposed to advances in AI may not fully benefit from its labour-augmenting effects 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 rather than an augmenting effect (Gmyrek, Berg and Bescond 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 2020). In order to explore this necessity-driven interpretation in terms of worker heterogeneity, in section 5.3, we interact the AI index with key socio-economic characteristics.

6 See table SC1 in supplementary online Appendix C for the results of the full regression analysis for the AI Felten index specification.

Table 3. Transition probabilities from paid employment: Technology indices

	Destination status				
	Paid employment	**SE with employees**	**Solo SE**	**Unemployment**	**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

*, ** 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. The full specification of the AI Felten Index regression is included in tables SB1 and SB2, in supplementary online appendix B.

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).

Turning to the measures of RTI, 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 0.07 pp. This accounts for 25 per cent of the mean transition probability to self-employment with employees and for 17.75 per cent of the mean 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 with 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.

Lastly, the results for task intensities suggest that employees in occupations with a higher intensity of social tasks are more likely to become self-employed with employees. 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 developing a business idea, which may eventually increase the probability of switching to self-employment.

5.2. Transitions from solo self-employment to other statuses

Turning to the econometric analysis of exits from solo self-employment, our main finding is that solo self-employed workers in occupations that are more exposed to advances in AI are more likely to switch to paid employment (table 4).[7] 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 7.3 per cent of the average 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 one's 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 relationships 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, solo self-employed workers in routine task-intensive occupations should have a low probability of moving to paid employment within their occupation, given that 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, solo self-employment in routine-intensive occupations is not associated with a higher probability of unemployment or inactivity. This may be caused by many of the solo self-employed workers 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 status, which at least provides them with some income.

Lastly, 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. However, workers with a high intensity of social tasks are less likely to remain in solo self-employment, but more likely to enter self-employment with employees. This finding could indicate that these workers are more likely to find an employee position in their professional domain that offers good working conditions (e.g. higher job stability). In contrast, workers in physical task-intensive occupations, similar to workers in routine task-intensive occupations, seem to have fewer opportunities to find an attractive job in paid employment.

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

The effects of exposure to technology are very likely to differ between groups of workers. We therefore examine potential differences between individuals, by educational attainment, age

[7] See table SC2 in supplementary online Appendix C for the results of the full regression analysis for the AI Felten index specification.

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

	Destination status				
	Solo SE	Paid employment	SE with employees	Unemployment	Inactivity
Labour-augmenting technology					
AI Felten index	−0.371	0.292*	0.269	0.055	−0.245
	(0.307)	(0.154)	(0.295)	(0.119)	(0.198)
Labour-saving technology					
Routine tasks	0.092	−0.012	0.054	−0.076	−0.058
	(0.483)	(0.306)	(0.307)	(0.115)	(0.226)
Routine cognitive tasks	0.136	0.036	0.001	−0.068	−0.105
	(0.504)	(0.331)	(0.340)	(0.104)	(0.248)
Routine manual tasks	−0.020	−0.093	0.104	−0.045	0.054
	(0.301)	(0.196)	(0.244)	(0.113)	(0.123)
Tasks					
Physical tasks	0.676	−0.392*	0.062	0.247	−0.594***
	(0.493)	(0.226)	(0.393)	(0.160)	(0.206)
Intellectual tasks	−0.269	0.412	0.283	0.204	−0.629*
	(0.425)	(0.281)	(0.394)	(0.125)	(0.327)
Social tasks	−1.133**	0.345	0.924*	−0.181	0.045
	(0.569)	(0.287)	(0.479)	(0.134)	(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

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.
Note: See notes and source information for table 3.

and income level. We do so for one of the most interesting results from the above section: the effect of exposure to advances in AI on individuals' probability of switching from paid employment to solo self-employment.

For the transitions out of paid employment (table 5), the interactions with the levels 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 exposure to advances in AI has a labour-augmenting effect.

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 by Fossen and Sorgner (2021), this may indicate 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 owing to longer work

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

	Destination status				
	Paid employment	**SE with employees**	**Solo SE**	**Unemployment**	**Inactivity**
AI Felten index × skill groups					
[1] (Pre-)primary and lower secondary education	−0.152	0.043	0.122**	−0.200	0.187**
	(0.185)	(0.033)	(0.050)	(0.175)	(0.078)
[2] (Upper) secondary and post-secondary education	0.285***	0.014	0.032	−0.387***	0.056
	(0.106)	(0.018)	(0.026)	(0.082)	(0.056)
[3] Tertiary education	0.394**	0.017	0.044	−0.361***	−0.094
	(0.188)	(0.027)	(0.058)	(0.103)	(0.084)
AI Felten index × age groups					
[1] Age 16–29	1.281***	0.005	0.106	−0.749***	−0.644***
	(0.233)	(0.022)	(0.071)	(0.119)	(0.192)
[2] Age 30–54	0.257**	0.014	0.024	−0.254***	−0.041
	(0.113)	(0.020)	(0.025)	(0.085)	(0.060)
[3] Age 55–65	−0.847***	0.054**	0.105	−0.093	0.781***
	(0.316)	(0.023)	(0.065)	(0.113)	(0.250)
AI Felten index × income groups					
[1] Bottom 80% of wage distribution	0.149	0.026	0.061*	−0.325***	0.088*
	(0.133)	(0.020)	(0.034)	(0.092)	(0.051)
[2] Top 20% of wage distribution	1.017***	−0.010	−0.017	−0.442***	−0.549**
	(0.309)	(0.022)	(0.079)	(0.164)	(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

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.
Note: See notes and source information for table 3.

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-driven entrepreneurs (Zhang, Stough and Gerlowski 2022).

Lastly, the positive associations between the AI index and the likelihood of switching to solo self-employment are significant only for low-skilled workers and workers in the bottom 80 per cent of the wage distribution. This may suggest that workers exposed to advances in AI who are in low-paid occupations and less educated may not actually benefit from the labour-augmenting effects of this technology. They may thus switch to solo self-employment out of necessity, lacking decent career prospects in the wage sector. In line with the previous section, these findings support the role of necessity-driven entrepreneurship. This result is

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

	Destination status				
	Solo SE	Paid employment	SE with employees	Unemploy-ment	Inactivity
AI Felten index × skill groups					
[1] (Pre-)primary and lower secondary education	−1.297*	−0.052	0.465	1.069**	−0.185
	(0.729)	(0.365)	(0.786)	(0.522)	(0.295)
[2] (Upper) secondary and post-secondary education	0.243	0.144	0.203	−0.060	−0.529*
	(0.495)	(0.317)	(0.369)	(0.170)	(0.279)
[3] Tertiary education	−0.642*	0.534**	0.244	−0.123	−0.012
	(0.386)	(0.262)	(0.327)	(0.150)	(0.215)
AI Felten Index × age groups					
[1] Age 16–29	0.578	−1.095	−0.394	0.247	0.664
	(1.278)	(0.837)	(0.452)	(0.464)	(0.584)
[2] Age 30–54	−0.703*	0.526***	0.395	0.046	−0.264
	(0.371)	(0.197)	(0.316)	(0.094)	(0.191)
[3] Age 55–65	0.233	0.103	0.104	−0.007	−0.432
	(0.615)	(0.248)	(0.473)	(0.232)	(0.345)
AI Felten Index × income groups					
[1] Bottom 80% of wage distribution	−0.455	0.435	0.357	0.156	−0.493*
	(0.399)	(0.295)	(0.311)	(0.162)	(0.295)
[2] Top 20% of wage distribution	0.026	0.137	−0.082	−0.201***	0.119
	(0.540)	(0.154)	(0.440)	(0.075)	(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

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.
Note: See notes and sources for table 3.

also consistent with Hyytinen and Rouvinen (2008), who find that the probability of entering entrepreneurship is negatively correlated with the unobserved ability and/or productivity of employees.

This argument is indirectly supported by the 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 are 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 workers who are engaged with digital technologies. Job offers with attractive working conditions, such as better job security and higher pay, might incentivize these workers to give up their own business and to transition into paid employment.

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 France, Germany and Italy because these countries account for a relatively large share of the European working population.[8]

For transitions from paid employment, we find that the overall pattern of our main results is robust to the exclusion of Germany, France or Italy from the regression, with only a slight change in the significance level of the coefficients for the AI index. We can also confirm the consistency of our main results for transitions from solo self-employment. The only small difference occurs when excluding Germany. In this case, the significance of AI exposure diminishes slightly, but the size of the coefficient remains qualitatively comparable. In order to take the impact of country-specific shocks over the years into account, we re-estimate the model with the interaction of country and year variables (see tables SD3 and SD4 in supplementary online Appendix D). The results obtained from this specification do not deviate from our primary findings, nor do they significantly influence the magnitudes of our coefficients. In essence, incorporating the additional interaction terms does not affect the conclusions drawn from our analysis.

Lastly, in order to investigate the quality of each of the separate regression models for the different technology indicators in the multinomial logit regressions in section 5, we compute the Akaike information criterion (AIC) for each regression. The results indicate that the AIC estimates do not differ strongly between the models, providing robustness to our analysis.[9]

7. Conclusions

In this article, we have examined the dynamics of self-employment for 30 countries in Europe over the period 2014–19 to answer three research questions: (i) How are labour-saving and labour-augmenting technologies related to worker transitions into and out of self-employment? (ii) Do these effects differ between transitions into and out of solo-self-employment and self-employment with employees? and (iii) Do these effects differ between worker groups?

Our results can be summarized as follows. 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 advances in AI 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 the interpretation pointing to necessity-driven entrepreneurship.

The above would indicate that AI is more of a risk than an opportunity for some workers. This appears to be 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 materialize 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, the results

[8] The results for the exclusion of France and Italy are available from the authors upon request. The results excluding Germany are presented in supplementary online Appendix D.

[9] Results available from the authors upon request.

indicate that high-skilled and high-paid workers have greater stability of paid employment in occupations strongly exposed to AI – in other words, they seem to benefit from this exposure. This is consistent with the higher transition rates that we observe 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. As a result, they are likely to remain in stable and (relatively) protected paid employment.

Our results for Europe therefore differ from those for the United States to some extent. In their study, Fossen and Sorgner (2021) find 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, including differences between country samples, different time periods (2014–19 vs 2011–18), the different intervals considered (annual vs quarterly) and the different level of detail in the occupational classification (2-digit ISCO-08 vs 5-digit Standard Occupational Classification). In addition, it is likely that these differences reflect the fact that the institutional, regulatory and business environment, as well as several cultural dimensions, are more conducive to the creation of larger ventures in the United States than in most European countries (Dheer and Treviño 2022). Indeed, solo self-employment is much less common in the United States than in Europe.[10] Furthermore, employees are more likely to select negatively into self-employment – where the likelihood of entering (and exiting) entrepreneurship correlates negatively with unobserved ability and/or in-paid-employment productivity – in Europe than in the United States (Hyytinen and Rouvinen 2008).

More broadly, these results on AI seem to be consistent with the literature on the impact of robots, which have generally been found to be detrimental for employment in the United States (Acemoglu and Restrepo 2020), but neutral or even positive for employment in Europe (Dauth et al. 2021; Bachmann et al. 2024). It is also consistent with the findings of Albanesi et al. (2023), who show that AI exposure is positively associated with employment at the occupation level for a large number of European countries.

In other respects, our results on advances in AI and transition patterns are in line with those of Fossen and Sorgner (2021) – we also find that employees in occupations that are more exposed to these 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 to be a labour-augmenting technology, which makes employees exposed to it more productive and therefore less likely to exit employment or lose their jobs.

Our analysis has important policy implications. First, if exposure to technology increases workers' entrepreneurial opportunities, public policies that support transitions to self-employment may be economically and socially beneficial. In the long term, however, facilitating transitions 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 an attempt to escape strict employment protection legislation.

Second, as some workers are likely to have been pushed into self-employment because of a lack of attractive alternatives in paid employment, public policies aimed at

[10] According to data from ILOSTAT, the share of solo self-employed workers in total employment in the United States was just below 4 per cent in 2019, against 10 per cent in the EU-27.

encouraging self-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 particularly concerns digital skills, found 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 businesses to improve their labour market opportunities.

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Competing interests

The authors declare that they have no competing interests.

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