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

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Abstract

We investigate the extent, direction, and determinants of transitions in and out of self-employment across 31 European countries over the period 2014-2019. We focus on workers' transitions from solo self-employment to paid employment and vice-versa, as well as on transitions within self-employment. We are particularly interested in exploring how exposure to a certain type of technology in one's occupation affects the probability of moving in and out of solo self-employment, and how this effect differs across worker groups. To answer these questions, we match worker-level data from EU-SILC with indicators of exposures to AI advances and routine task-intensity at the occupational level. First, we use artificial intelligence (AI) indicators as a proxy for exposure to labour-augmenting technology. We find that employees who are more exposed to AI advances are more likely to move to solo self-employment. However, solo self-employment also seems to become more risky, as being exposed to AI advances also increases the probability of transitioning from solo self-employment to paid employment. Certain workers, particularly the ones with low education, may not fully benefit from the labour-augmenting effects of AI, and therefore switch between employment status in search of better career prospects. Second, we use measures of routine task-intensity (RTI) as a proxy for the exposure to labour-saving technologies. We find that employees with higher RTI are less likely to enter self-employment, be it with or without employees. This is particularly the case for employees in manual occupations. This result may reflect that employees in these types of occupations tend to have limited access to financial resources and skills that are positively associated with the odds of entering self-employment.

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

JEL: J62, J63, J31

1. Introduction

Self-employment makes up an important share of employment in most EU countries. In 2019, self-employed accounted for around 14 per cent of total employment in the EU (Eurostat, 2021). The share of solo self-employment, i.e. self-employment without employees, is high and growing: in 2019, there were close to 23 million solo self-employed in the EU - 15 per cent more than in 2002 - accounting for around 72 per cent of all self-employed workers and for about 10 per cent of total employment. Meanwhile, the occupational composition of solo self-employment has also changed, with many of the newly solo self-employed entering high-skilled occupations providing specialised intellectual or technical services. For instance, the share of solo self-employed in technical, professional and managerial occupations in the EU went from 36 per cent in 2012 to 42 per cent in 2019. Therefore, it seems plausible that self-employment contributes to and is affected by technological progress and the changing nature of jobs. While there is some evidence on this issue for the US (Fossner and Sorgner, 2021), there is no clear evidence for European countries.

This study therefore aims at partly filling this gap, by answering the following three research questions for Europe: First, what are the individual-level and occupation-level determinants of the transitions to and from (solo) self-employment? In this context, the level of educational attainment, and the demographic characteristics of individuals, notably age, gender and education, are of primary interest. Furthermore, this analysis aims to understand whether wages and the type of work contract play a role in this context. Second, how does technological progress, and particularly the substitutability or complementarity with digital technologies, affect the transitions from employment and self-employment? Third, do these effects of digitization differ between worker groups, depending on their level of education, age, or income?

In order to answer these questions, we use micro data from the European Union Statistics on Income and Living Conditions (EU-SILC) for the time period 2014-2019, supplemented with data from the German Socio-economic Panel. Furthermore, we use several external data sources to measure workers' exposure to technological progress and digital technologies.

To explore the many possible links between technology and self-employment dynamics, our analyses investigate both entries into and exits from solo self-employment, and their association with different measures of technology. In particular, we investigate how the exposure to technology in the current occupation is linked to the probability to: i) stay in paid employment or solo self-employment, ii) enter solo self-employment from unemployment and employment; and iii) exit from solo self-employment into all other labour market states.

Regarding the technology measures, we use indicators proxying for the occupation-specific exposure to labour-saving and labour-augmenting technologies. These indicators capture the potential 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. For instance, regarding entries into self-employment, one could expect that employees in routine-intensive occupations (i.e. in occupations that are presumably more exposed to labour-saving technologies such as industrial robots) are more likely to move to solo self-employment as a response to the lack of viable alternatives in wage employment, in comparison to employees in occupations facing a lower exposure. Conversely it could be possible that employees in occupations that are more exposed to labour-augmenting technologies, thus being more productive and gaining higher wages, have a higher opportunity cost of leaving their job, and as such they are less likely to switch to self-employment.

This study makes the following contributions to the literature, which is discussed in more detail in the next section. First, we present updated descriptive evidence of the extent of transitions into and out of self-employment across European countries for the time period 2014-19. Second, we analyse the individual- and occupation-specific determinants of these dynamics for 31 European countries by modelling transitions between five different labour market states - namely solo self-employment, self-employment with employees, paid employment, unemployment, and inactivity. This five-state categorization allows us to differentiate alternative pathways into, within, and out of self-employment. This type of evidence exists neither for a large sample of European countries nor for the described five-state categorization. Third, we are the first to examine the link between self-employment and indicators of technological change using European worker-level data.

Our results have important policy implications concerning the role of public policy in supporting self-employment, and which worker groups are most likely to benefit from this. Furthermore, our analysis provides evidence on how resilient and future-proof self-employment may be against the background of ongoing technological change.

The rest of the paper is structured as follows. In the next section, we present some of the theoretical considerations underlying the links between technology and self-employment dynamics and discuss why exploring these links empirically matters. In section 3, we present the data and methodology used. We first discuss the construction of labour market transitions using individual-level data from EU-SILC, and then we present the selected indicators of technology exposure at the occupational level, and the empirical strategy. In Section 4, we present our descriptive and empirical results. Section 5 concludes.

2. Theoretical considerations

Existing literature points to a wide range of factors explaining the rising prevalence of self-employment, and its changing composition across occupations. These include:

- Individual-level determinants such as growing shares of older workers who are more likely to opt for self-employment or changing preferences with workers valuing more work-time flexibility and autonomy;
- General labour market developments such as weak traditional labour markets leaving workers with little options for traditional wage employment and forcing them to enter self-employment; or the growth of digital labour platforms and the improvements in digital technologies that facilitate the online provision of digital services remotely from freelancers while reducing monitoring and supervisory costs for firms;
- Labour-market institutions such as strict labour market regulation, encouraging firms to contract out work and replacing paid employment with external consultants; or more favourable tax treatment of self-employment vis-à-vis paid employment that distorts individual incentives to sort into self-employment and firms' incentives to hire under traditional employment contracts.

In this study, we focus on the first two explanations, i.e. individual- and occupation-level determinants, as well as the impact of technology on the labour market.

Despite the importance of self-employment in Europe described above, relatively little attention has been paid to studying self-employment dynamics at the individual level across European countries, and especially so for transitions into and out of solo self-employment (Lechmann and Wunder 2017). This is surprising given that such an analysis can shed light on the importance of the role played by self-employment in the labour market and the factors contributing to its increasing importance.

Most of existing studies focus on single countries. One of the most important findings from these studies is that entries into self-employment often occur from unemployment, as showed for example by Glocker and Steiner (2007) for Germany, Carrasco (1999) for Spain, von Greiff (2009) and Andersson and Wadensjö (2007) for Sweden, and Taylor (2011) for a group of EU countries. By contrast, exits from self-employment mainly lead to transitions to paid employment or to non-employment (Boeri et al. 2020; Taylor 2011).

In explaining these transition patterns, most of these contributions focus on individual-level determinants such as: i) demographic characteristics (gender, age, and marital status and children); (ii) family background (parents and spouse); (iii) human capital (education and experience); (iv) nationality and ethnicity; (v) individual's income. This strand of literature has shown that workers' socio-economic and demographic characteristics are key factors explaining transitions in and out of self-employment.

What remains relatively underexplored is the role of occupation-specific characteristics in shaping incentives to enter in or exit from self-employment. In fact, only few studies have focused on these factors, and mostly to explain transitions from paid employment to self-employment. For instance, Taylor (2011) finds that employees in permanent jobs are less likely than those in temporary employment to enter self-employment. Andersson and Wadensjö (2007) show that employees in Sweden who are underpaid are more likely to enter self-employment. Sorgner and Fritsch (2018) show that the probability of switching from paid employment to self-employment in Germany is higher in occupations with a relatively high occupation-specific unemployment level. They also show that the failure to achieve an expected occupation-specific income, as well as a higher occupational earnings risk, increase the probability of entrepreneurial entry.

Moreover, only few studies have analysed the role of technology in shaping transitions across labour market states, which is of particular interest for our study. One of the few exceptions is Sorgner (2017) who shows that individuals' willingness to become an entrepreneur and their actual transition into self-employment in Germany are lower for those in occupations with a high risk of computerization. Fossen and Sorgner (2021) make the important distinction between "labour-saving" and "labour-augmenting" technologies.

According to the theoretical argument outlined in Fossen and Sorgner (2021), each of these types of technology can have both positive and negative effects on the probability that paid employees move to self-employment. On the one hand, paid employees who are exposed to labour-saving technologies, facing higher risks of unemployment and slower wage growth, could be more likely to become (solo) self-employed out of necessity, namely because they are “forced” to start their own business to avoid unemployment and loss of income. This would be consistent with the finding that high occupation-specific risk of unemployment is associated with higher probabilities of entrepreneurial entry (Sorgner and Fritsch, 2018). It is also in line with the finding for the US that employees 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 comparison to employees facing a lower risk (Fossen and Sorgner 2021).

On the other hand, workers in occupations exposed to labour-saving technology tend to have lower levels of education, limited access to financial resources, and less possibilities to develop managerial abilities, 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 extent to which being exposed to labour-saving technologies affects employees’ odds to switch to solo self-employment remains uncertain.

The predicted effect of being exposed to labour-augmenting technologies is equally ambiguous. Workers in occupations affected by these technologies are expected to see growing employment, rising productivity and higher wages in their current occupations. Therefore, these workers, facing higher opportunity costs of leaving their current job, should be less prone to switch to self-employment. However, workers in these occupations should be more able to recognize business opportunities, get in touch with new entrepreneurial-relevant digital technologies, and have access to information and financial resources which may ultimately increase their odds of entering self-employment. 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 in search of greater autonomy and flexibility to switch to self-employment, whilst also encouraging firms to outsource work. As a result, workers in these occupations have a higher probability to switch to self-employment while remaining in their occupational domain, either by choice or because they may be forced by their employers to reclassify as external contractors. This is in line with results for the US showing that employees in occupations that are exposed to labour-augmenting technology, notably to advances in AI, are less likely to become solo self-employed, but more likely to become self-employed with employees instead (Fossen and Sorgner, 2021).

Technology may matter not only for entries into self-employment, but also for exits out of self-employment. We expect that individuals who work as solo self-employed in occupations that are affected by labour-saving technologies are less likely to move to 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 might have a higher probability to exit solo self-employment and turn to unemployment.

Formulating hypotheses on the transition patterns of solo self-employed who are in occupations affected by labour-augmenting technology is particularly difficult. While one could expect that these entrepreneurs being active in highly productive occupations are more likely to grow and become employers, high labour demand and wages in occupations exposed to labour augmenting technology can act as an incentive to transition into paid employment and to give up self-employment. This could be particularly the case for those who entered solo self-employment in the first place involuntarily, namely because they could find a decent job in their preferred occupations.

Therefore, many of the effects of technology on the entry into and exit from self-employment are ambiguous from a theoretical point of view, which makes an empirical analysis all the more important. In the following, we therefore explain how we use the EU-SILC to identify worker’s labour market transitions, and their individual- and occupational level determinants. In what follows we also present the indicators used to capture the workers’ exposure to different types of technology.

3. Data and methodology

3.1. Individual-level data from the EU-SILC

Our analyses are based on micro data from the European Union Statistics on Income and Living Conditions (EU-SILC) for the years 2014 – 2019. As we investigate labour market transitions, we use the longitudinal version of the EU-SILC data. For Germany, EU-SILC data is not available as a panel. Therefore, we use data from the German Socio-Economic Panel (SOEP) for Germany.

EU-SILC data are based on household surveys and provide annual cross-sectional and longitudinal information on sociodemographic 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; they are representative for the population in the countries covered and comparable across Europe.

For investigating labour market transitions, we use the longitudinal version of the EU-SILC data, and construct transitions between labour-market states from one year to the next. 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 one quarter of the households surveyed are replaced by new households. The longitudinal version only contains persons who participated in the survey in at least two adjacent years. In order to construct a representative database with a maximum number of observations for the period under consideration, the longitudinal datasets are combined based on Berger and Schaffner (2015). As we analyse labour market transitions from one year to the next in the descriptive and empirical analysis, we use longitudinal weights provided in EU-SILC for panel data of two-year duration. We adjust the weights to represent the population size of the countries in our sample.

For Germany, the analyses are based on data from the SOEP. This representative annual survey includes detailed labour-market information on the individuals of the sampled households. We use the long format of the EU-SILC clone provided with the SOEP v36. A detailed description of the SOEP EU-SILC clone data set can be found in Bartels et al. (2021).

We restrict the resulting sample from the EU-SILC and SOEP to persons between 16 and 65 years of age who are in paid employment in two consecutive years between 2014 and 2019 and valid data for the crucial variables. Further, we exclude people working in armed forces and agricultural occupations. In total our analysis encompasses 31 European countries.[1]

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 status (variable pl031 in EU-SILC) as declared by the interviewed person. In order to differentiate between solo self-employment and self-employment with employees, we complement this information on the main economic status with information on the current activity status in the main job (variable pl040 in EU-SILC). According to the EU-SILC guidelines (Eurostat 2020) solo self-employed are self-employed individuals that have their own business, professional practice, or farm for the purpose of making a profit, and that do not have employees. For self-employed persons with employees, the same definition applies, except that they employ at least one person. We exclude family workers from the analysis.

The outcome variable in our analysis is the labour market transition of an individual between one year and the next. Therefore, a necessary condition for the analysis is that the economic status of an individual is available for two consecutive years. Otherwise, an individual cannot be included in the analysis. For our analysis, we are especially interested in the transitions into and out of (solo) self-employment. We consider the transitions from unemployment and employment to (solo) self-employment and to other labour market states, and exits from (solo) self-employment to any other labour market states

3.2. Measures of job tasks and technology

To investigate whether being exposed to a certain technology in the current occupation shapes individuals' probability of moving from one labour-market state to another, and notably to move from paid employment to self-employment and vice-versa, we use a range of different 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 the task content of their occupations. In particular, following the theoretical considerations in Section 2, we focus on labour-saving and labour-augmenting technologies.

To operationalize the concept of occupational exposure to labour-saving technologies, we use the measures of routine task intensity developed by Mihaylov and Tijdens (2019). We use three indicators capturing the intensity of routine tasks: routine manual tasks (RM), routine cognitive tasks (RC), and routine total (RT). The RM-indicator is expected to capture an

[1] The following countries are included in the analysis: 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. For Switzerland, Germany, Iceland, and the UK the analysis only encompasses the years 2014 to 2017. For Slovakia the analysis is restricted to the years 2014 and 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 dropped from the analysis since occupational codes are only provided at the 1-digit ISCO level.

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). Whereas the RC-indicator is expected to provide a measure of an occupation's exposure to computerization and machine-learning. These RC technologies have the potential to conduct standardized cognitive tasks which are easier to codify with programmed rules (e.g. counting, writing basic texts, translating).

Since several occupations require carrying out both routine manual and routine cognitive tasks, we also employ a third measure providing information on the overall intensity of routine tasks (RT) across occupations. These measures of routine task intensity were originally provided by Mihaylov and Tijdens (2019) at the 4-digit ISCO-08 level. Since EU-SILC report information on individuals' occupation at the 2-digit level, we need to aggregate them to the more general occupational classification to be able to match them with our individual-level data. To do so, we first average the indicators from Mihaylov and Tijdens (2019) at the 3-digits level, and then we convert them to 2-digits by computing the average weighted by the 3-digit occupations' employment levels in the EU as provided by Eurostat.

The measures of exposure to automation technologies developed by Mihaylov and Tijdens (2019) have two key advantages for our analysis. First, unlike other measures such as the one developed by Frey and Osborne (2017) which are based on the US SOC occupational classification, these measures are constructed by evaluating the descriptions of a set of 3,264 occupation-specific tasks according to the ISCO-08 classification. Since ISCO-08 is the international classification system of occupations used by European countries, this allows us to make a more direct link between the task intensity indices and the worker-level micro data set used in our analysis, the EU-SILC. Second, the majority of 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 specific to any occupation, while the Mihaylov and Tijdens (2019) indices are developed on the basis of occupation-specific data, which allows to capture the routine content of occupations more precisely.[2]

To operationalize the concept of labour-augmenting technology, we follow Fossen and Sorgner (2021) and use a measure of advances in AI by occupations estimated by Felten et al. (2019). To estimate advances in AI at the occupational level, Felten et al. (2019) link the advances in AI to abilities that are given in O*Net to describe job requirements. The original Felten et al. (2019) index is available at the 6-digits SOC level. Therefore, in order to match it with EU-SILC individual level data, we do a crosswalk from 6-digit SOC to 4-digits ISCO-08. Then, we compute the average of the index at the ISCO-08 3-digit level and convert it to the ISCO-08 2-digits by computing the average at 3-digits weighted by the occupations' employment levels 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 also considering 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 a measure of exposure to future AI developments, instead of a measure of existing AI benchmarks as the Felten et al. (2019) index. The index by Brynjolfsson et al. (2018) captures the suitability of an occupation's tasks for machine learning - a subfield of AI that is supposed to replace routine cognitive tasks. Therefore, it can be considered more indicative of labour-saving technologies rather than labour-augmenting ones. These conceptual considerations imply that the Felten et al. (2019) index best captures existing advances in AI and is therefore most suitable for our analysis which focuses on recent trends of labour market transitions. Moreover, using this index allows a more straightforward comparison between this paper's results and the ones by Fossen and Sorgner (2021) who also use the same index to operationalize the concept of labour-augmenting digitalization.

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, Fernández-Macías et al. 2016a, 2016b) and provides indices at the 2-digits 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

[2] 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. Mihaylov and Tijdens (2019) indeed classify 3,264 tasks as routine or non-routine and as cognitive or manual, on the basis of their own judgment on whether a specific tasks can be replaced by computer-controlled technology and whether the performance of the tasks requires cognitive or manual abilities. Whilst the authors show that subjectivity in their classification of tasks should not be a major concern, their approach inevitably leaves some room for discretion when assigning tasks to different routine domains.

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. (2019) which are constructed using standardized descriptions of the work content at the occupational level, these tasks indices are based on individuals' assessment of the type of tasks they do in their occupations, and therefore they also capture the variation of task composition across workers within the same occupation. **Erreur ! Source du renvoi introuvable.** provides an overview of the technology exposure indicators used in this paper.

Table 1 –Overview of the task and technology measures used in the analysis

Index	Source	Measurement	Measurement scale	Our transformation
Intensity of routine tasks (total/ manual/cognitive)	Mihaylov and Tijdens (2019)	Classification of 3,264 tasks as routine or non-routine, and as cognitive or manual, on the base of ISCO-08 occupation descriptions.	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 occupation level.	Scores ranging from 0 (min exposure to advances in AI) to 5 (max exposure to advances in AI)	From 6-digits SOC, to 2-digits ISCO-08
Intensity of physical/intellectual/social tasks	JRC-Eurofound European Tasks database (see Bisello at al. 2021 for details)	Indices are built using detailed information on the content of work of occupations from the EWCS 2015, Italian ICP, and the OECD´s PIAAC Survey.	Normalised scores for all tasks. For each of tasks, the score's value range from 0 to 1, taking values=1 for the occupation in the highest percentile of task intensity.	Already provided at 2-digits ISCO-08

Source: Own representation.

Erreur ! Source du renvoi introuvable. shows the correlations coefficients across the various measures of technology exposure and task intensity at the 2-digits ISCO-08 occupational level. Each of the measures are statistically significantly correlated with one another (all with p-values < 0.01), although with varying intensity. The first and most important observation coming from Table 2 is that the various measures of intensity of routine tasks – and therefore of the exposure to labour-saving technologies of a given occupation – are strongly and negatively correlated with advances in AI (see Table 2). This suggests that occupations experiencing advances in AI are typically very little routine intensive and therefore less subject to labour-saving technologies. Such differences will be crucial when analysing the correlation between technology measures and transition probabilities for worker sub-groups.

The correlations between the measures of technology exposures and the task indices shed further light on 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.

Table 2 –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)

3.3. Empirical methodology

Our empirical analysis focuses on labour market transitions from the origin states unemployment, paid employment and solo self-employment to the destination states paid employment, self-employment with employees, solo self-employment, unemployment, and inactivity. To econometrically investigate these transitions, for each of the three origin states, we run a multinomial logit model for the transitions out of the respective origin state to the five destination states. The general form of the predicted probability from the multinomial logit model can be written as:

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

where *y* is one of the five destination states and *b* stands for the state of origin, the base category. $\boldsymbol{X}$ is the vector of explanatory variables which controls for gender, age, marital status, number of children, education level, and work characteristics (for transitions from (self-)employment), i.e. income and contract type (part-time vs. full-time). For income, we use an indicator of whether the income of the current job is in the top 20 per cent of the wage distribution to capture high-paying jobs. We also include fixed effects for years and countries. These variables allow us to investigate the importance of individual- and job-specific factors. We present the results in the next section, 4.1.

In order to investigate the role of technology for labour market transitions into and out of self-employment, we additionally include as explanatory variables the technology and task indices described in Section 3.2. The results of this analysis are presented in Sections 4.2 and 4.3.

4. The Dynamics of Self-Employment in Europe

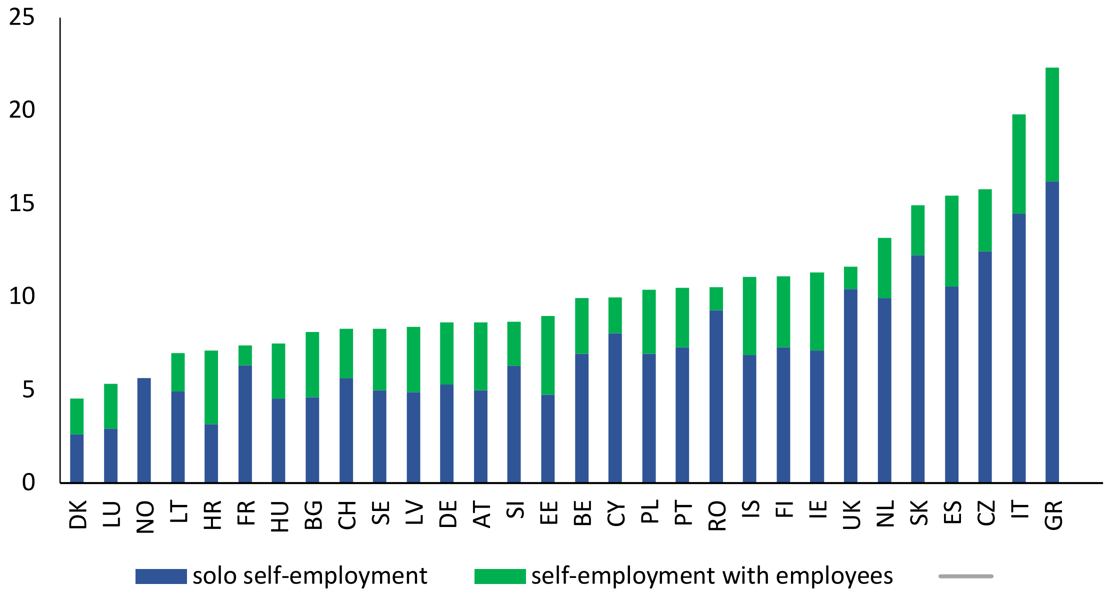
4.1. The role of individual-level and occupation-level determinants

In this section, we analyse the role played by individual- and occupation-level factors in shaping entries into and exits from self-employment. To put these transitions into perspective, we start by displaying the average stock of self-employed workers across European countries. Figure 1 shows the average share of self-employed workers with respect to the working population for the time period 2014-2019. Excluding agriculture, the share of self-employed amounts to 10.5 per cent in Europe as a whole.[3] There are great differences in the prevalence of self-employment across countries. Self-employment is most widespread in Greece where 22.6 per cent of the working population work in self-employment and least widespread in Denmark (4.6 per cent). When looking at country groups, it becomes apparent that self-employment is more common in Mediterranean countries than in Continental European, Scandinavian, Central and Eastern European (CEE) countries, or the UK and Ireland (see Figure A 2 in the appendix). Across all European countries, the share of solo

[3] The next section provides details on the data used and the sample construction.

self-employment is higher than the share of self-employed with employees. On average, just 31 per cent of the self-employed in our sample have employees, with the highest shares of around 50 per cent in Hungary and Estonia.[4]

Figure 1: Self-employment by country (Self-employment as % of total employment)



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

Next, we provide an overview of the extent and direction of labour market transitions observed in our sample. Table 1 shows the average transition probabilities from one year to the next between all labour market states for all countries in our sample over the period 2014 to 2018. Whilst showing transition probabilities across all the five labour market states considered, for the scope of this study we are most interested in discussing transitions from paid employment to self-employment, and vice versa. Table 3 shows that workers in paid employment are relatively unlikely to move to self-employment, especially with employees. However, the share of employees who transition into solo self-employment remains economically relevant, considering that the probability of staying in paid employment is extremely high. On the other hand, it is worth noting that a considerable share of (solo) self-employed move to paid employment. For instance, 8 per cent of solo self-employed on average switched to paid employment in the following year – twice as much as the fraction of those who remained self-employed and hired employees. Finally, we observe that only a small fraction of the unemployed transition into solo self-employment (2.2 per cent) and self-employment with employees (0.3 per cent).

Table 1: Transitions between labour market states, all countries

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

Year t	***Year t+1*** employment	SE with employees	solo SE	unemployment	non-activity
employment	92.34	0.27	0.81	2.85	3.73
SE with employees	7.26	78.33	10.95	1.10	2.36
solo SE	8.00	4.93	80.80	2.38	3.89
unemployment	24.46	0.30	2.18	56.90	16.16
non-activity	9.61	0.09	0.78	5.32	84.19

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

[4] Moreover, as shown in Figure A 1 only a small fraction of self-employed works part-time. Therefore, this aspect will not be analysed in more detail in the following.

The transition probabilities also display some differences between worker groups. For example, more men than women decide to enter self-employment with and without employees from employment and unemployment (Table A 1 in the appendix). The share of men that stays in self-employment is also slightly higher. Furthermore, workers with (pre-) primary, lower secondary- and tertiary education are more likely than workers with (upper-)secondary and post-secondary education to move from paid employment to solo self-employment (Table A 2). However, the probability to enter solo self-employment and self-employment with employees from unemployment is higher for medium- and high-skilled workers. The probability to transition from solo self-employment to self-employment with employees is also higher for medium- and high-skilled workers.

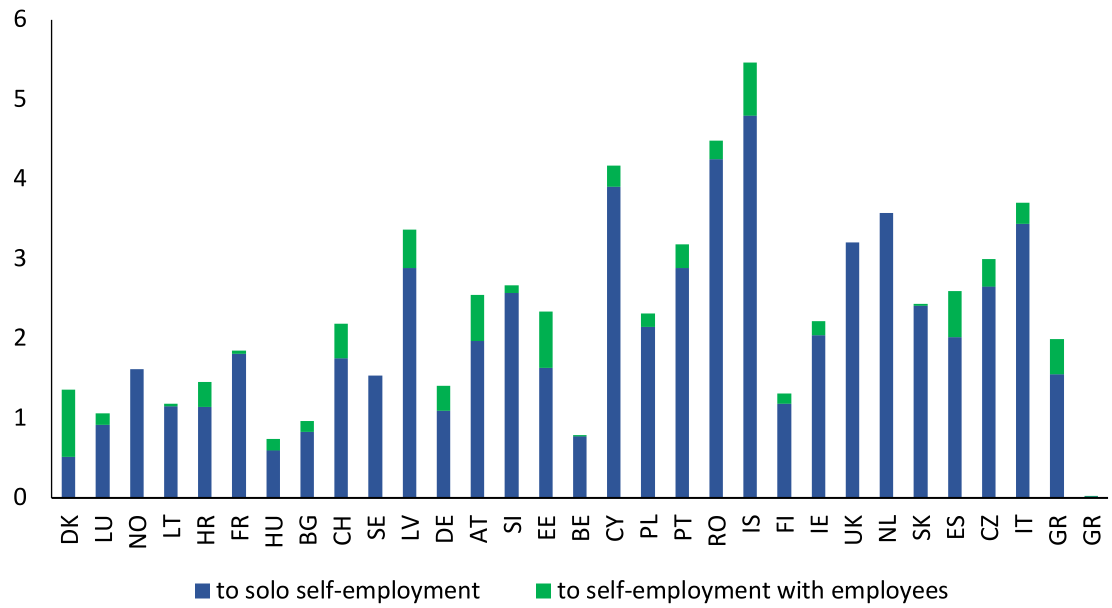
Looking at different age groups (Table A 3), younger workers between 16 and 29 are more likely to transition from paid employment to solo self-employed but less likely to transition into self-employment with employees than older age groups. It seems that younger workers are also less successful or take higher risks when expanding their own business since almost 20 per cent of those that are self-employed with employees move back to solo self-employment. From unemployment, workers between 30 and 54 are most likely to move into self-employment, with and without employees. They also have a higher likelihood of moving from solo self-employment to self-employment with employees.

Comparing country groups, the transition probability from employment and unemployment into solo self-employment is highest in the UK and Ireland (Table A). However, the percentage of people moving from employment and unemployment to self-employment with employees is highest in the Mediterranean countries. The probability to move from solo self-employment to self-employment with employees is higher in Scandinavian countries and in Continental Europe.

The differences between European countries become even more apparent when looking at individual countries. Figure 2 displays entries from unemployment into (solo) self-employment. The probability to transition into self-employment exceeds 4 per cent in countries such as Iceland, Romania, and Cyprus, and is less than 1 per cent in Belgium and Hungary. As the order of the countries on the horizontal axis is the same as in Figure 1, which displays the share of self-employment in total employment, it becomes obvious that the flow probability into self-employment is not increasing with the self-employment stock in a country. Therefore, the transition probability from unemployment to self-employment must be determined by other factors, which we explore later in this section.

Figure 2: Transitions from unemployment to self-employment

In % of unemployment stock

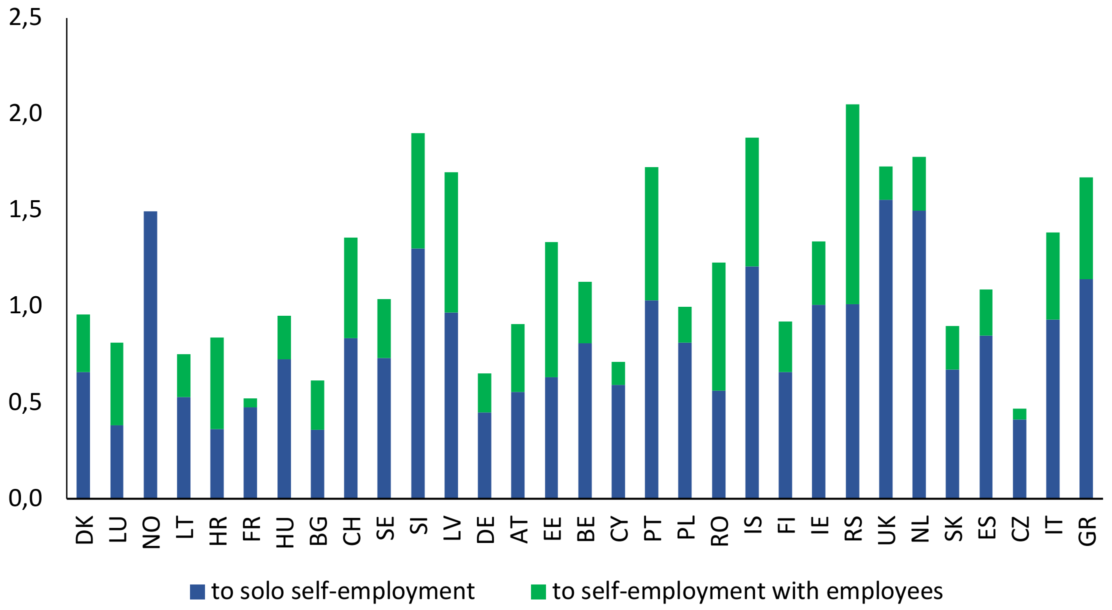


Source: EU-SILC, own computation. Averages for the time period 2014-19. Country ordering as in Figure 1.

Similarly to the transitions from unemployment to self-employment, the transitions from employment to self-employment display strong country heterogeneity. Figure 3 shows the transition rates from paid employment to (solo) self-employment across countries. The overall transition rate from paid employment to self-employment ranges from around 0.5 per cent in the Czech Republic, France, and Bulgaria to around 2 per cent in Serbia, Slovenia, and the Netherlands. Again, the order of the countries along the horizontal axis is the same as in Figure 1, which is ordered according to the importance of self-employment in a country. We can therefore infer from Figure 3 that the flow from paid employment to self-employment is not higher in countries with a higher share of self-employment.

Figure 3: Transitions from paid employment to self-employment

In % of total employment



Source: EU-SILC, own computation. Averages for the time period 2014-19. Country ordering as in Figure 1.

Lastly, we are also interested in exits from solo self-employment to self-employment with employees. On average 4.9 per cent of the solo self-employed employ workers in the next year (see Figure 4). However, we can see a strong variation in the transition probability across countries that is not correlated with the stock of self-employed in a country. In Serbia, Finland, Iceland, Hungary, and Croatia more than 10 per cent of the solo self-employed become an employer in the next year. However, in the Netherlands, Romania, Bulgaria, and Norway not even one per cent of the solo self-employed move into self-employment with employees from one year to the next.

Figure 4: Transitions from solo self-employment to self-employment with employees

In % of stock of solo self-employment

Source: EU-SILC, own computation. Averages for the time period 2014-19. Country ordering as in Figure 1.

After having described the extent and direction of labour market transitions and how these vary across countries and workers' characteristics, we now turn to a more elaborate empirical analysis which can help shed light on the determinants of the transitions described above. We first focus on the role played by individual- and occupation-specific characteristics. The descriptive statistics for the different groups are presented in Table A 4. The groups that move into self-employment with and without employees have a higher share of men, are on average older, are more educated than those staying in unemployment and moving into inactivity and are more likely to be married. To jointly take into account the various individual and occupation-specific characteristics, we run the multinomial logit (MNL) model described in Section 3.3, considering the five possible outcomes: i) stay unemployed, ii) enter employment, iii) enter self-employment with employees, iv) enter solo self-employment; v) move into inactivity.

First, we look at the transitions out of unemployment. The results from the MNL model show a number of significant correlations between individual and household characteristics on the one hand, and transitions rates from unemployment to self-employment on the other hand (Table 2). First, men are more likely to move into self-employment with and without employees. The probability to transition into self-employment with employees is 0.2 percentage points (pp) lower for women than for men; for transitions into solo self-employment, the probability is 1.47 pp lower. Second, the age group 30 to 55 is more likely than younger or older individuals to move into solo self-employment. For the older age group, the probability to enter self-employment with employees is significantly lower. Third, relative to workers with upper secondary and post-secondary education, workers with (pre-)primary and lower secondary education are less likely to enter self-employment with (-0.16 pp) and without employees (-0.94 pp) and workers with tertiary education are 1.78 pp more likely to enter solo self-employment. Fourth, married workers are more likely to move into self-employment with (0.22 pp) and without employees (0.39 pp). Fifth, unemployed individuals with children are 0.25 pp more like to enter solo self-employment than individuals without children. However, the number of children is not correlated with the probability to transition into self-employment with employees.

Table 2: Transition probabilities from unemployment: Individual characteristics

Multinomial logit regression

	stays unemployed	entry into employment	entry into SE w/employees	entry into solo SE	entry into inactivity
Women	-0.0542***	-0.0298***	-0.0022***	-0.0147***	0.1008***
	(0.0054)	(0.0048)	(0.0006)	(0.0015)	(0.0039)
Age 16-29	-0.0788***	0.0500***	0.0002	-0.0107***	0.0393***
	(0.0071)	(0.0067)	(0.0009)	(0.0017)	(0.0053)
Age 55-65	0.0259***	-0.1437***	-0.0020***	-0.0070***	0.1269***
	(0.0069)	(0.0051)	(0.0006)	(0.0020)	(0.0059)
(Pre-)primary and lower	0.0650***	-0.0709***	-0.0016**	-0.0094***	0.0169***
secondary education	(0.0062)	(0.0053)	(0.0008)	(0.0016)	(0.0046)
Tertiary education	-0.0492***	0.0595***	0.0008	0.0178***	-0.0288***
	(0.0076)	(0.0071)	(0.0010)	(0.0029)	(0.0052)
Married	-0.0720***	0.0163***	0.0022**	0.0039**	0.0497***
	(0.0059)	(0.0054)	(0.0009)	(0.0018)	(0.0044)
No. of children in household	-0.0063**	-0.0015	-0.0002	0.0025***	0.0055**
	(0.0031)	(0.0027)	(0.0004)	(0.0008)	(0.0024)
Year FE	yes	yes	yes	yes	yes
Country FE	yes	yes	yes	yes	yes
Mean Transition Probability	0.599	0.231	0.003	0.022	0.146
Observations	112,525	112,525	112,525	112,525	112,525

Source: EU-SILC 2014-2019, SOEP v.36. – Notes: Marginal effects from a multinomial logit regression with five outcomes. Robust standard errors in parentheses with * p < 0,1, ** p < 0,05, *** p < 0,01. The observations are weighted using the two-year longitudinal weights. The reference group is unemployed, male, not-married, age 30-55, has (upper) secondary and post-secondary education, has no children. Country and year fixed-effects. Based on the longitudinal sample of two year duration.

The coefficients for the other transitions also have the expected sign. Women, often due to caring responsibilities, and older workers, due to retirement, are more likely to enter inactivity. Also, workers with tertiary education are less likely to stay in unemployment and more likely to enter paid employment than workers with (upper-)secondary education. Instead, workers with (pre-)primary and lower secondary education have higher odds of staying unemployed and are less likely to move to paid employment.

In a next step, we conduct the same MNL analysis for labour market transitions from paid employment into (solo) self-employment. We thus again consider five different groups: individuals that stay in paid employed between one year and the next, individuals that enter self-employment with employees, individuals that enter solo self-employment, individuals that become unemployed and individuals that move into inactivity.

The results from the MNL regression are presented in Table 3. First, men are more likely to enter self-employment with (+0.06 pp) or without employees from employment than women (+0.26 pp). Second, older workers are 0.1 pp less likely to move into solo self-employment than middle-aged workers (30-54), but there is no significant difference for the younger age group (16-29). For transitions to self-employment with employees, no significant difference with respect to age can be observed. Third, a higher education level is associated with an increased likelihood of moving from paid employment to self-employment with employees and workers with tertiary education are also more likely to move to solo self-employment (+ 0.27 pp). Fourth, household characteristics, i.e. being married and having children, play a minor role for transitions from paid employment to self-employment. Fifth, more flexible work arrangements decrease the likelihood of staying in paid employment and increase the likelihood of transitioning into solo self-employment. The results show that workers with a temporary contract (+0.5 pp) and part-time workers (+0.24 pp) are more likely than full-time workers with a permanent contract to move into solo self-employment. Sixth, workers with a higher wage are less likely to move to unemployment and more likely to move to inactivity, but there is no significant correlation between the wage and the transition probability into self-employment.

The other coefficients are again in line with expectations. Women and older workers are more likely to move into unemployment and inactivity. The likelihood of staying employed increases with the education level while the probability to move into unemployment and inactivity decreases with the education level. In addition, full-time work and having a work contract of unlimited duration is positively related to the probability of staying employed and negatively correlated with the probability of moving into unemployment and inactivity.

Table 3: Transition probabilities from employment: Individual and job characteristics

Multinomial logit regression

	stays employed	**entry into SE w/employees**	**entry into solo SE**	**entry into unemployment**	**entry into inactivity**
Women	-0.0085***	-0.0006***	-0.0026***	-0.0014	0.0131***
	(0.0021)	(0.0002)	(0.0006)	(0.0016)	(0.0010)
Age 16-29	-0.0324***	0.0001	0.0012	0.0044***	0.0267***
	(0.0044)	(0.0003)	(0.0008)	(0.0016)	(0.0034)
Age 55-65	-0.0605***	-0.0003	-0.0010*	0.0041***	0.0577***
	(0.0039)	(0.0002)	(0.0006)	(0.0014)	(0.0034)
(Pre-)primary and lower	-0.0131***	-0.0004*	0.0007	0.0073***	0.0055***
secondary education	(0.0027)	(0.0002)	(0.0005)	(0.0018)	(0.0018)
Tertiary education	0.0101***	0.0004	0.0027***	-0.0091***	-0.0041***
	(0.0024)	(0.0002)	(0.0008)	(0.0015)	(0.0011)
Married	0.0018	0.0003	-0.0002	-0.0087***	0.0068***
	(0.0015)	(0.0002)	(0.0004)	(0.0008)	(0.0011)
No. of children in household	-0.0007	0.0000	0.0008**	0.0008	-0.0010
	(0.0014)	(0.0001)	(0.0003)	(0.0006)	(0.0011)
Part-time	-0.0235***	-0.0002	0.0024***	0.0062***	0.0152***
	(0.0023)	(0.0003)	(0.0009)	(0.0012)	(0.0020)
Temporary work contract	-0.0638***	-0.0001	0.0050***	0.0445***	0.0144***
	(0.0033)	(0.0003)	(0.0010)	(0.0025)	(0.0016)
Top 20% of wage distribution	0.0000	-0.0001	-0.0012	-0.0078***	0.0090***
	(0.0025)	(0.0002)	(0.0008)	(0.0013)	(0.0021)
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	0.026
Observations	527,359	527,359	527,359	527,359	527,359

Source: EU-SILC 2014-2019, SOEP v.36. – Notes: Marginal effects from a multinomial logit regression with five outcomes. 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 employed, male, not-married, age 30-55, has (upper) secondary and post-secondary education, has no children. Country and year fixed-effects. Based on the two-year longitudinal sample.

Finally, we conduct the MNL analysis for exits out of solo self-employment. We are particularly interested in the transition from solo self-employment to self-employment with employees since this can be seen as a sign of successful entrepreneurship. We obtain the following results (Table 4). First, men are more likely to expand their business and to become self-employed with employees (+1.45 pp). Second, solo self-employed workers between the age of 30 and 54 are more likely to transition to self-employment with employees than younger and older workers in solo self-employment.

Third, solo self-employed workers with a (pre-)primary and lower secondary education are less likely (-0.74 pp) to move into self-employment with employees than employees with at least (upper-)secondary and post-secondary education. Fourth, workers who are married more often move to self-employment with employees (+1.45 pp). Fifth, a high cash income from solo self-employment is strongly correlated with the probability to stay self-employed and the probability to transition to self-employment with employees. The estimated marginal effect shows that the likelihood to transition to self-employment with employees is 2.84 pp higher for self-employed with a high income. However, high income is negatively correlated with the likelihood of transitioning to paid employment. This is in line with the expectation that more successful entrepreneurs are more likely to expand their business and to employ workers.

Table 4: Transition probabilities from solo self-employment: Individual and job characteristics

Multinomial logit regression

	stays solo SE	**entry into employment**	**entry into SE w/employees**	**entry into unemployment**	**entry into inactivity**
Women	0.0025	-0.0056	-0.0145***	0.0044**	0.0131***
	-0.0103	-0.0048	-0.0045	-0.0022	-0.004
Age 16-29	-0.0409***	0.0212**	-0.0125**	0.0166***	0.0156**
	-0.0113	-0.0105	-0.0055	-0.0059	-0.0066
Age 55-65	-0.002	-0.0238***	-0.0090***	0.0017	0.0331***
	-0.008	-0.0041	-0.0033	-0.0021	-0.004
(Pre-)primary and lower	0.006	-0.0062	-0.0074**	0.0111**	-0.0036
secondary education	-0.008	-0.0057	-0.0035	-0.0047	-0.0033
Tertiary education	-0.0042	0.0104**	-0.0009	-0.0004	-0.0050*
	-0.0073	-0.0042	-0.0043	-0.0014	-0.0029
Married	-0.0103	-0.0026	0.0145***	-0.0055***	0.004
	-0.0067	-0.0023	-0.0037	-0.0019	-0.003
No. of children in household	-0.0037	0.0027	0.0001	0.0007	0.0002
	-0.0033	-0.0021	-0.002	-0.0013	-0.0018
Top 20% of cash income	0.0757***	-0.0672***	0.0284***	-0.0104***	-0.0265***
distribution	-0.0123	-0.0081	-0.0046	-0.0018	-0.0041
Year FE	yes	yes	yes	yes	yes
Country FE	yes	yes	yes	yes	yes
Mean Transition Probability	0.863	0.043	0.059	0.014	0.021
Observations	44,281	44,281	44,281	44,281	44,281

Source: EU-SILC 2014-2019, SOEP v.36. – Notes: Marginal effects from a multinomial logit regression with five outcomes. 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 percent of the cash income distribution. Country and year fixed-effects. Based on the two-year longitudinal sample.

In this section, we analysed the role of individual and occupational characteristics for the transitions into self-employment out of unemployment and paid employment. In addition, we were also interested in the determinants for transitions between solo self-employment and self-employment with employees.

The results show that men are more likely than women to move out of unemployment and employment into (solo) self-employment, and men are also more likely to transition from solo self-employment to self-employment with employees, i.e. to grow their business and employ workers. One reason could be a higher preference among men to become self-employed and to implement their own business idea (Verheul et al. 2012). Another reason could be that men work in different occupations that make a transition to self-employment easier or that they have a higher unemployment risk so that they are forced to move into self-employment out of necessity.

The results for age groups show that the likelihood to move from unemployment to self-employment is significantly higher for workers between ages 30 and 54. While older workers are less likely to move into solo self-employment, there is no significant difference between younger and middled aged workers in transitioning from paid employment to self-employment. However, middle-aged workers seem to be more successful entrepreneurs since they are more likely to expand their business and to become employers. These results indicate that self-employment is especially attractive for middled-aged workers who could already gain some work experience and establish a network.

Education also plays a key role for the probability to transition into self-employment. Workers with a tertiary education are more likely than workers with (upper-)secondary education to move from unemployment and employment to solo self-employment. This may suggest that for some of the highly educated individuals, solo self-employment represents an opportunity to implement a business idea or to work independently. For some, the switch to solo self-employment may be only temporary, as reflected by individuals with tertiary education being more likely to switch from solo self-employment to paid employment. Finally, it is worth noting that low educated solo self-employed workers are less likely to become employers, which supports the argument that some of these workers may be more necessity- than opportunity-driven entrepreneurs.

With respect to occupational characteristics, the results show that more vulnerable workers, part-time workers, and workers with a fixed-term contract are more likely to move into self-employment than full-time workers and workers with a permanent contract respectively. On the one hand this could reflect that the opportunity cost of switching to solo self-employment from paid employment is lower among workers with worse working conditions. On the other hand, workers who plan to transition into self-employment might voluntarily self-select into part-time jobs, as they might have a preference for greater working time flexibility, or because they are already running a business as a secondary job.

For paid employment, a higher wage is not correlated with the probability to transition into self-employment, which indicates that well-paid employees have a high opportunity cost of leaving their job for a riskier entrepreneurial activity, although the payoff in self-employment could be higher. However, solo self-employed who are in top 20 per cent of the income distribution – an indicator of the success of their business and of their financial capacity – show a significantly higher probability to stay in solo self-employment and to expand their business by employing workers.

4.2. The role of technology in explaining labour-market transitions in and out of self-employment and across other labour market states

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

In this section, we present the main results of the multinomial logit estimations on our measures of technology exposure and task intensity discussed in Section 3.2. We run the same MNL regression model used in Section 4.1, adding each of the technology measures in a separate regression. This means that we run seven different regression models, one for each of the technology-exposure and task measures separately. The cells show the marginal effects of a unit increase in these measures on the probability that an individual transitions from paid employment to a new labor market status in the following year.[5]

Looking at the transitions from paid employment to self-employment, the first observation coming from the regression results in Table 5 is that workers who are in occupations highly exposed to AI as measured by the AI Felten index have a higher, although small, probability to switch to self-employment. This result is statistically significant at the 10-per cent level only when transitions into solo self-employment are considered. This finding may reflect that some of the employees 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. As a consequence, they have a lower opportunity cost of switching to solo self-employment in search of a better wage. 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, in a period of economic expansion more individuals will be encouraged to enter self-employment given the positive economic outlook and higher probabilities of success (Parker, 2018).

[5] The following results tables only show the coefficients on the main technology-exposure and tasks intensity measures. The full regression results including the AI index are displayed in Tables A6 and A7 in the appendix. It becomes clear that the coefficients of the socio-demographic and occupation-specific variables do not change compared to results in Section 4.1. Full results using the other technology-exposure and tasks intensity measures are available upon request.

Furthermore, some of the workers in occupations highly exposed to AI may have the skills to develop innovative new business ideas and therefore decide to enter self-employment to implement these ideas.

Interestingly, our results and interpretation are at odds with those provided by Fossen and Sorgner (2021) for the US. They find that higher exposure to AI advancements reduces the probability of entering into solo self-employment. According to the authors, this suggests that employees who are experiencing productivity gains in their occupations due to advances in AI technologies have higher opportunity costs of switching to entrepreneurship. The difference between this study's results and those by Fossen and Sorgner (2021) 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 (yearly vs. quarterly), and the different level of detail of the occupational classification (2-digit ISCO-08 vs 5-digit SOC). Meanwhile, it is likely that these discrepancies also reflect the different nature of self-employment in the US with respect to Europe. In fact, working as a solo self-employed in the US is considerably less common than in Europe.

In other respects, our results on AI advances and transition patterns are in line with those of Fossen and Sorgner (2021). In particular, we also find that employees in occupations more exposed to AI advances are more likely to remain in paid employment and less likely to enter unemployment. Taken together, these two results support the argument according to which 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 job.

Turning to the measures of routine task-intensity, which we use as a proxy of the exposure to labour-saving technologies (see Section 3.2), Table 5 shows that employees who are more exposed to this type of technologies are in fact less likely to enter self-employment, be it with or without employees. This is particularly the case for employees in occupations with greater intensity of routine manual tasks.

This result may reflect that individuals employed in routine occupations, and especially in those intensive in routine manual tasks, tend to have limited access to financial resources, and less possibilities to develop managerial abilities, creativity, and strong social networks – all aspects that are positively associated to the odds of entering self-employment. Meanwhile, the results could also reflect that we analyse a time period of strong employment growth in Europe. In this period of high labour demand, employees in occupations with a higher risk of substitution are more likely to find new employment, and therefore less likely to switch to self-employment out of necessity. This interpretation is also indirectly supported by our findings showing an insignificant relationship between being in occupations more intense in routine tasks and the probability of transitioning to unemployment.

Finally, looking at the coefficients on the specific task intensity measures at the bottom of the table provides further insights and complements the results discussed above. In fact, these findings suggest that employees in occupations with higher intensity of intellectual or social tasks are more likely to remain in paid employment and less likely to switch to unemployment. More importantly, it appears that the extent of intellectual and social tasks carried out in an occupation increases employees' probability to switch to self-employment, and especially to become employers. This is in line with the argument that employees in occupations that are more intensive in these tasks may develop abilities and social networks that are conducive to the development of a business idea, which may eventually increase the probability of switching to self-employment.

Table 5: Transition probabilities from paid employment: Digitization indices

Multinomial logit regressions by digitization index

	stays employed	entry into SE w/employees	entry into solo SE	entry into unemployment	entry into inactivity
AI Felten index	0.00615**	0.00025	0.00090*	-0.00664***	-0.00066
	(0.00248)	(0.00029)	(0.00047)	(0.00163)	(0.00082)
Task intensity					
Routine tasks	0.00081	-0.00101*	-0.00283*	0.00306	-0.00003
	(0.00363)	(0.00061)	(0.00171)	(0.00260)	(0.00170)
Routine-cognitive tasks	0.00194	-0.00023	-0.00198	0.00111	-0.00083
	(0.00391)	(0.00051)	(0.00153)	(0.00276)	(0.00202)
Routine-manual tasks	-0.00069	-0.00276**	-0.00394**	0.00523	0.00215
	(0.00800)	(0.00112)	(0.00184)	(0.00474)	(0.00220)
Physical tasks	-0.01397	-0.00111	0.00026	0.01037	0.00446
	(0.00976)	(0.00112)	(0.00317)	(0.00654)	(0.00444)
Intellectual tasks	0.01929***	0.00183*	0.00275*	-0.01846***	-0.00541
	(0.00712)	(0.00105)	(0.00148)	(0.00435)	(0.00396)
Social tasks	0.02229**	0.00445***	0.00243	-0.02772***	-0.00144
	(0.00981)	(0.00142)	(0.00272)	(0.00672)	(0.00404)
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	505,499	505,499	505,499	505,499	505,499

Source: EU-SILC 2014-2019, SOEP v.36, AI and task indizes: Felten et al. (2018), Mihaylov & Tijdens (2019), European tasks database & JRC Eurofound (2021). – Notes: Marginal effects from multinomial logit regressions with five outcomes. Separate regressions for each technology indicator. 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 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 percent of the wage distribution. Country and year fixed-effects. Based on the two-year longitudinal sample.

4.2.2. Transitions from solo self-employment to other states

Next, we investigate the link between the transition probabilities of remaining in solo self-employment vis-à-vis switching to any of the other four labour market states considered and the technology and task intensity measures. We focus on the transitions out of solo self-employment because these transitions can shed light on the quality and growth prospects of solo self-employment.

The main finding that stands out from the results in Table 6 is that solo self-employed workers active in occupations that are more exposed to AI advances are more likely to switch to paid employment. However, we do not find that exposure to AI increases the probability to stay in solo self-employment or to expand the business and to transition and to become self-employed with employees. This is consistent with the argument that solo self-employed workers in occupations exposed to AI might give up self-employment to start working in a more secure and stable paid employment relationship once a viable job opportunity presents itself.

Looking at the coefficients on the various measures of routine task intensity, no statistically significant findings emerge. This is in line with our theoretical expectations. In fact, individuals who work as solo self-employed in occupations which are intensive in routine tasks should have a low probability to move to paid employment within their occupation, as job vacancies for those occupations are typically scarce. For similar reasons, we do not expect them to have a higher probability to expand their business by hiring employees. What is perhaps more surprising is that working as a solo self-employed worker in routine-intensive occupations is not associated with a higher probability to exit solo self-employment, and transition to unemployment or inactivity. This might be explained 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 poor revenues and little business activity. They may instead prefer to remain in their current professional status which provides them at least with some revenue.

Finally, our results on the specific task intensity measures show that solo self-employed workers with a greater intensity of physical tasks are more likely to remain in solo self-employment or to transition to unemployment. Conversely, those who are engaged in occupations requiring a more intensive use of intellectual and social tasks are less likely to remain in solo self-employment, but more likely to become paid employees or entrepreneurs, i.e. self-employed workers with employees. This finding could reflect that solo self-employed workers in occupations more intensive in intellectual and social tasks are more likely to find an employee position in their professional domain with good working conditions. Conversely, solo self-employed workers in occupations intensive in physical tasks, similarly to workers in occupations intensive in routine tasks, having less access to favorable opportunities in traditional paid employment, may have a preference to remain self-employed.

Table 6: Transition probabilities from solo self-employment: Digitization indices

Multinomial logit regressions by digitization index

	stays solo SE	**entry into employment**	**entry into SE w/employees**	**entry into unemployment**	**entry into inactivity**
AI Felten index	-0.00656	0.00630**	0.00575	0.00072	-0.00621*
	(0.00580)	(0.00287)	(0.00557)	(0.00229)	(0.00362)
Task intensity:					
Routine tasks	0.00264	-0.00012	0.00322	-0.00295	-0.00279
	(0.01866)	(0.01147)	(0.01158)	(0.00448)	(0.00877)
Routine-cognitive tasks	0.00634	0.00139	-0.00122	-0.00293	-0.00358
	(0.02144)	(0.01368)	(0.01469)	(0.00445)	(0.01041)
Routine-manual tasks	-0.00520	-0.00379	0.01065	-0.00160	-0.00005
	(0.01880)	(0.01188)	(0.01466)	(0.00696)	(0.00640)
Physical tasks	0.08606***	-0.05017***	-0.03311*	0.01551**	-0.01828*
	(0.02606)	(0.01052)	(0.01882)	(0.00678)	(0.01069)
Intellectual tasks	-0.07767***	0.05042***	0.04228**	-0.00679	-0.00824
	(0.02483)	(0.01217)	(0.02103)	(0.00493)	(0.01254)
Social tasks	-0.11022***	0.05770***	0.06804**	-0.01607***	0.00056
	(0.03612)	(0.01434)	(0.02715)	(0.00512)	(0.01694)
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	43,047	43,047	43,047	43,047	43,047

Source: EU-SILC 2014-2019, SOEP v.36, AI and task indizes: Felten et al. (2018), Mihaylov & Tijdens (2019), European tasks database & JRC Eurofound (2021). – Notes: Marginal effects from multinomial logit regressions with five outcomes. Separate regressions for each technology indicator. 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 percent of the cash distribution. Country and year fixed-effects. Based on the two-year longitudinal sample.

4.2.3 Interacting exposure to AI advancements with key socio-demographic factors

The most interesting and original results coming from the above section concerns the effect of exposure to AI advances on individuals' probability to switch from paid employment to solo self-employment and vice-versa. Moreover, these results seem to confirm that AI can be regarded as a labour-augmenting technology, given that employees in occupations more exposed to AI advances are more likely to remain employed, and less likely to become unemployed.

In order to better interpret and qualify our baseline results on the impact of labour-augmenting technology, in this section we explore whether and how these results differ between individuals with different levels of formal education, age, and income level. We investigate the interactions between these characteristics and our technology indicators both for transitions out of paid employment (Table 7) and for transitions out of solo self-employment (Table 8). To do so, we re-run the same regression models shown in Table 5 and Table 6, adding each time to the models the interactions between the AI advances index and dummy variables for the education level, the age group, and the income group.

The interactions for the education level show that the positive association of the AI index with the probability of remaining in the current wage occupation becomes stronger with increasing education levels. The AI index is also consistently associated with a decreased probability of switching to unemployment for all education levels. Taken together, these two results once again support the interpretation that AI reflect labour-augmenting effects of technologies. Yet, this effect appears to be slightly stronger for workers with higher levels of education. The labour-augmenting effect of technology is corroborated by two further findings for the interaction with the indicator for the wage level. First, the positive association of the AI index with the probability of remaining in paid employment is considerably higher among those at the top of the income distribution. Second, the negative association of the AI index with the probability of switching to unemployment is considerably lower among the same group.

When looking at the interaction between the AI index and the age group, 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 years old or more. 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 more able to exploit entrepreneurial opportunities arising from new digital technologies thanks to their longer work experience, wider social networks, and larger availability of financial capital.

Finally, it is interesting to see that the positive associations between the AI index and the probability to switch to solo self-employment is stronger only among low educated workers and workers in the bottom 20% of the wage distribution. This may suggest that workers exposed to AI advances who are in low-paid and little specialized occupations may not actually benefit from the labour-augmenting effects of this technology and may switch to solo self-employment in search of better employment prospects.

Table 7: Transition probabilities from employment: Felten digitization index, different worker groups

Multinomial logit regression

	stays employed	entry into SE w/employees	entry into solo SE	entry into unemployment	entry into inactivity
Skill groups					
[1] (Pre-)primary and lower	-0.00260	0.00073	0.00228**	-0.00365	0.00324**
secondary education	(0.00371)	(0.00061)	(0.00093)	(0.00327)	(0.00146)
[2] (Upper) secondary and post-	0.00741***	0.00009	0.00060	-0.00793***	-0.00017
secondary education	(0.00228)	(0.00030)	(0.00051)	(0.00164)	(0.00097)
[3] Tertiary education	0.00973***	0.00031	0.00071	-0.00729***	-0.00346**
	(0.00354)	(0.00043)	(0.00114)	(0.00187)	(0.00149)
Age groups					
[1] Age 16-29	0.02675***	-0.00014	0.00193	-0.01452***	-0.01403***
	(0.00424)	(0.00043)	(0.00133)	(0.00232)	(0.00302)
[2] Age 30-54	0.00575***	0.00025	0.00041	-0.00514***	-0.00127
	(0.00212)	(0.00035)	(0.00048)	(0.00160)	(0.00096)
[3] Age 55-65	-0.01196**	0.00064**	0.00186	-0.00233	0.01179**
	(0.00588)	(0.00030)	(0.00115)	(0.00195)	(0.00463)
Income groups					
[1] Bottom 80% of wage	0.00473*	0.00034	0.00112*	-0.00661***	0.00041
distribution	(0.00263)	(0.00031)	(0.00063)	(0.00172)	(0.00088)
[2] Top 20% of wage distribution	0.01926***	-0.00011	-0.00056	-0.00766**	-0.01092***
	(0.00528)	(0.00036)	(0.00128)	(0.00309)	(0.00341)
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	505,499	505,499	505,499	505,499	505,499

Source: EU-SILC 2014-2019, SOEP v.36; Felten-index by Felten et al. (2018). – Notes: Marginal effects from a multinomial logit regressions with five outcomes. Different regressions for skill, age, and income groups. 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 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 percent of the wage distribution. Country and year fixed-effects. Based on the two-year longitudinal sample.

Table 8 presents the results for the transitions out of solo self-employment The main finding coming from this analysis is that the positive relationship between the AI index and the probability of switching from solo self-employment to paid employment is higher for those with a tertiary level of education and for prime age workers (age 30-54). This suggests that the incentives to move to paid employment are greater for solo self-employed workers with a high level of education who are engaged with digital technologies. Vacancies offering attractive working conditions such as more secure working conditions and a higher pay might incentivize these workers to give up their own business and to transition into paid employment. However, the positive relation between the AI index and the probability to enter paid employment for the individuals with lower cash income also reflects that less successful self-employed workers are more likely to move back to paid employment. A reason could be that these solo self-employed workers entered their 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 external contractors.

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 education level, age, or income group.

Table 8: Transition probabilities from solo self-employment: Felten digitization index, different worker groups

Multinomial logit regressions

	stays solo SE	entry into employment	entry into SE w/employees	entry into unemployment	entry into inactivity
Skill groups					
[1] (Pre-)primary and lower	-0.02116*	-0.00235	0.00876	0.01981**	-0.00507
secondary education	(0.01281)	(0.00667)	(0.01432)	(0.00984)	(0.00491)
[2] (Upper) secondary and post-	0.00439	0.00444	0.00449	-0.00186	-0.01145**
secondary education	(0.00903)	(0.00637)	(0.00714)	(0.00304)	(0.00521)
[3] Tertiary education	-0.01229*	0.01089**	0.00548	-0.00227	-0.00180
	(0.00715)	(0.00452)	(0.00584)	(0.00277)	(0.00364)
Age groups					
[1] Age 16-29	0.01006	-0.01956	-0.00703	0.00452	0.01200
	(0.02388)	(0.01551)	(0.00834)	(0.00886)	(0.01057)
[2] Age 30-54	-0.01172*	0.01016***	0.00743	0.00109	-0.00697**
	(0.00702)	(0.00365)	(0.00581)	(0.00180)	(0.00304)
[3] Age 55-65	0.00178	0.00452	0.00487	-0.00244	-0.00873
	(0.01117)	(0.00487)	(0.00910)	(0.00382)	(0.00680)
Income groups					
[1] Bottom 80% of cash income	-0.00819	0.00905*	0.00700	0.00219	-0.01005*
distribution	(0.00707)	(0.00515)	(0.00578)	(0.00280)	(0.00521)
[2] Top 20% of cash income	0.00052	0.00281	0.00027	-0.00424**	0.00064
distribution	(0.01080)	(0.00301)	(0.00960)	(0.00186)	(0.00253)
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	43,047	43,047	43,047	43,047	43,047

Source: EU-SILC 2014-2019, SOEP v.36; Felten-index by Felten et al. (2018). – Notes: Marginal effects from a multinomial logit regressions with five outcomes. Different regressions for skill, age, and income groups. 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 percent of the cash distribution. Country and year fixed-effects. Based on the two-year longitudinal sample.

5. Conclusions

In this paper, we investigated the dynamics of self-employment for 31 countries in Europe in the time period 2014-2019. We aimed to answer three research questions. First, what are the individual-level and occupation-level determinants of the transitions to and from self-employment? Second, how does technological progress, and particularly the labour-saving and labour-augmenting technologies, affect the transitions from and into employment and self-employment? Third, do these effects of digitization differ between worker groups?

To answer these questions, we first estimate worker flow probabilities using data from the EU-SILC and different technology indicators. We then match these worker-level data with indicators of technology exposure at the occupational level. These indicators capture the two potential effects of technological progress on employment, namely its labour-saving effect (i.e. technology replaces human labour and thus reduces labour demand); and labour-augmenting, (i.e. technology complements human labour and thus increases labour demand and productivity).

Our findings can be summarised as follows. Regarding the first research question, we find that some individual-level characteristics are strongly correlated with the probability to become self-employed or leave self-employment: men, middle-aged workers, and employees with higher levels of education are more likely to transition to self-employment, particularly solo self-employment.

Occupational characteristics also play a role in this context: workers with part-time and with fixed-term contracts are more likely to become self-employed than workers with full-time and permanent contracts. For these worker groups, push factors, i.e. unattractive working conditions in paid employment, seem to be a decisive factor for taking up self-employment.

Regarding the second research question, the link between technology and self-employment dynamics, we find a positive correlation between being exposed to AI advances in the current occupation and the probability to transitions to self-employment. We interpret this as workers trying to benefit more fully from the labour-augmenting effects of AI advances by moving to self-employment. However, this is apparently not always successful, as there is also a positive correlation between the AI index and transitions from solo self-employment to paid employment. Therefore, advances in AI above all seem to be related to higher worker flows into and out of (solo) self-employment, i.e. higher churning.

The intensity of routine tasks in the current occupation is also an important determinant of transitions to and from self-employment. On the one hand, our measure of labour-saving effects, routine task-intensity, is negatively correlated with entries into self-employment. This is in line with theoretical expectations as workers performing high amounts of routine tasks are likely to be negatively affected by technological progress. On the other hand, a higher intensity of intellectual and social tasks, which are typically little routinized, is correlated with higher transitions to self-employment, particularly with employees.

Having established that our measures of technological progress are important predictors of transitions to and from self-employment, we turn to the third research question, i.e. which worker groups are particularly strongly affected by the labour-saving and labour-augmenting effects of technology. In doing so, we focus on transitions from paid employment and from solo self-employment.

Our findings identify some worker groups in paid employment for whom technological progress is more of a risk rather than an opportunity. This is the case for low-skilled workers and for older 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. By contrast, highly skilled workers and highly 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 transitions from solo self-employment to paid employment for these two worker groups.

Our analysis can provide some useful policy implications. First, it suggests that new technologies influence labour market dynamics not only by affecting the quantity and quality of employment, but also by shaping worker's incentives to sort into different professional status, and notably to enter self-employment. This suggests that being exposed to technology may increase workers' entrepreneurial opportunities, helping them to develop and expand their business, so creating more jobs. In this case public policy that supports transitions into self-employment may be economically and socially beneficial. Yet, looking forward, to the extent switching to self-employment will become easier, there might be important repercussions on 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 re-classify employees as consultants in the attempt to escape strict employment protection legislations.

These issues are becoming increasingly relevant in a post-COVID perspective. Post-COVID, the issue of self-employment, and transitions in and out of, is likely to remain high on the policy agenda. Self-employed workers, especially in certain sectors, appear to be more likely to have entered unemployment and inactivity during the pandemic. Others, mostly in high-skilled services, being able to continue their activity remotely, might however suffer less. In the longer term, the outbreak and ensuing sector-specific shocks and changes in working modes (e.g. telework) might affect workers' incentives to take up self-employment, and encourage firms to outsource work to external contractors.

Second, our results confirm that some of the most vulnerable solo self-employed are in poor quality employment with little probability to expand their business. This suggests that a fraction of these workers might be pushed into self-employment because of the absence of attractive alternatives in paid employment, resulting in short spells in self-employment followed by transitions to unemployment. If that is the case, public policy aiming to spur self-employment among ill-prepared and poorly resourced workers can be counterproductive. Yet, our results suggest that training and additional education especially for workers with lower education might help them to create or expand their own business to improve their labour market opportunities.

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Appendix A

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

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

	Year t+1				
Year t	**employment**	**SE with employees**	**solo SE**	**unemployment**	**non-activity**
Women					
employment	91.56	0.18	0.65	2.83	4.78
SE with employees	8.54	75.19	11.43	1.23	3.60
solo SE	8.45	4.00	78.94	2.61	5.99
unemployment	23.63	0.22	1.57	53.58	21.00
non-activity	9.38	0.10	0.76	5.12	84.64
Men					
employment	93.07	0.35	0.96	2.87	2.75
SE with employees	6.76	79.56	10.76	1.05	1.87
solo SE	7.74	5.45	81.85	2.26	2.70
unemployment	25.24	0.37	2.75	59.97	11.67
non-activity	10.01	0.09	0.80	5.64	83.46

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 %)

Year t	*Year t+1* employment	SE with employees	solo SE	unemployment	non-activity
(Pre-)primary and lower secondary education:					
employment	88.30	0.27	0.89	5.30	5.24
SE with employees	5.74	77.13	11.19	1.92	4.03
solo SE	7.07	3.82	81.08	3.64	4.39
unemployment	18.90	0.23	1.48	61.22	18.17
non-activity	6.55	0.05	0.42	5.68	87.30
(Upper) secondary and post-secondary education:					
employment	92.38	0.26	0.64	2.90	3.81
SE with employees	7.09	78.29	10.94	1.25	2.43
solo SE	7.74	5.28	80.67	2.30	4.02
unemployment	25.89	0.31	2.14	56.18	15.48
non-activity	9.80	0.09	0.72	4.81	84.58
Tertiary Education:					
employment	94.08	0.28	0.98	1.74	2.92
SE with employees	8.08	79.00	10.72	0.63	1.57
solo SE	8.61	5.18	81.15	1.76	3.31
unemployment	32.90	0.42	3.70	49.55	13.44
non-activity	16.97	0.23	2.00	5.82	74.98

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+1				
Year t	**employment**	**SE with employees**	**solo SE**	**unemployment**	**non-activity**
Age 16-29					
employment	88.18	0.19	0.96	4.81	5.86
SE with employees	13.39	60.32	19.87	2.70	3.72
solo SE	12.70	3.16	73.74	4.80	5.60
unemployment	30.11	0.28	1.59	52.58	15.45
non-activity	14.79	0.07	0.54	6.72	77.87
Age 30-54					
employment	94.62	0.30	0.81	2.48	1.79
SE with employees	7.54	80.00	10.40	1.03	1.03
solo SE	8.29	5.30	81.99	2.13	2.29
unemployment	25.77	0.35	2.61	57.89	13.37
non-activity	11.55	0.18	1.58	7.75	78.94
Age 55-65					
employment	87.29	0.23	0.64	2.35	9.49
SE with employees	5.19	76.70	10.90	1.01	6.20
solo SE	5.05	4.50	80.05	2.15	8.26
unemployment	11.78	0.15	1.77	60.36	25.94
non-activity	2.13	0.06	0.44	1.85	95.52

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

Table A 4: Transitions between labour market states by country group

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

	Year t+1				
Year t	**employment**	**SE with employees**	**solo SE**	**unemployment**	**non-activity**
Continental:					
employment	92.41	0.19	0.60	2.67	4.13
SE with employees	5.90	83.53	7.96	0.45	2.16
solo SE	8.37	5.64	80.30	1.70	3.98
unemployment	29.17	0.16	1.68	55.90	13.09
non-activity	12.51	0.09	0.72	3.34	83.34
Scandinavian:					
employment	92.26	0.24	0.86	1.94	4.70
SE with employees	8.69	76.40	11.70	0.83	2.39
solo SE	12.78	7.31	73.35	1.67	4.88
unemployment	31.22	0.26	1.17	47.46	19.89
non-activity	17.53	0.13	0.64	5.05	76.65
Mediterranean:					
employment	91.02	0.40	0.92	4.61	3.05
SE with employees	5.02	81.33	9.46	1.67	2.52
solo SE	6.41	4.76	81.59	3.61	3.62
unemployment	21.44	0.44	2.56	57.73	17.84
non-activity	6.16	0.14	0.83	9.09	83.78
Central and Eastern Europe:					
employment	93.73	0.36	0.67	2.43	2.82
SE with employees	10.82	73.15	12.81	1.38	1.85
solo SE	7.99	4.72	82.18	2.54	2.57
unemployment	22.73	0.26	2.00	62.75	12.26
non-activity	6.43	0.05	0.45	3.46	89.61
UK and Ireland:					
employment	92.20	0.19	1.51	1.40	4.70
SE with employees	16.02	49.75	30.02	0.14	4.07
solo SE	9.96	3.56	79.90	0.73	5.85

unemployment	29.13	0.03	3.00	35.78	32.06
non-activity	13.77	0.08	1.59	5.23	79.33

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

Table A 4: Descriptive statistics by type of transition

Flows from unemployment	stays unemployed	entry into employment	entry into SE w/employees	entry into solo SE	entry into inactivity
Individual characteristics					
Men	52.9	52.4	66.7	63.9	36.3
Age 16-29	22.7	32.4	18.2	19.4	22.5
Age 30-54	56.2	57.2	68.1	65.0	43.5
Age 55-65	21.0	10.4	13.7	15.5	34.0
(Pre-)primary and lower secondary education	36.1	26.4	24.4	25.2	39.6
(Upper) secondary and post-secondary education	48.7	50.8	51.6	45.8	46.4
Tertiary education	15.2	22.8	24.1	29.1	14.0
Married	44.1	39.6	53.4	47.5	52.7
No. of children in household	0.5	0.6	0.6	0.6	0.5
Observations	69,415	27,114	351	2,561	17,146

Flows from employment	stays employed	entry into SE w/employees	entry into solo SE	entry into unemployment	entry into inactivity
Individual characteristics					
Men	50.3	67.0	60.3	51.0	38.6
Age 16-29	13.2	9.2	15.4	25.0	24.0
Age 30-54	68.9	74.6	68.7	58.8	31.0
Age 55-65	18.0	16.2	15.9	16.2	45.0
(Pre-)primary and lower secondary education	14.3	15.2	16.5	26.9	21.9
(Upper) secondary and post-secondary education	48.5	46.2	42.7	50.7	49.6
Tertiary education	37.2	38.6	40.7	22.4	28.5
Married	59.6	65.3	56.1	45.5	57.0
No. of children in household	0.6	0.7	0.6	0.5	0.4
Work characteristics					
Part-time	14.1	7.6	21.1	20.8	30.9
Temporary work contract	11.6	9.8	21.0	43.4	19.6
Top 20% of wage distribution	21.5	31.5	18.9	10.0	19.2
AI index:					
AI Felten index	3.3	3.4	3.4	3.1	3.2
Task intensities					
Routine tasks	0.3	0.2	0.2	0.3	0.3
Routine-cognitive tasks	0.2	0.2	0.2	0.2	0.2
Routine-manual tasks	0.1	0.0	0.1	0.1	0.1
Physical tasks	0.3	0.3	0.3	0.4	0.3
Intellectual tasks	0.5	0.5	0.5	0.4	0.5

Social tasks	0.4	0.4	0.4	0.3	0.4
Observations	621,496	2,487	5,473	20,088	25,385

Flows from self-employment	**stays solo SE**	**entry into employment**	**entry into SE w/employees**	**entry into unemployment**	**entry into inactivity**
Individual characteristics					
Men	62.9	61.0	70.7	62.8	45.3
Age 16-29	6.6	12.9	5.4	14.3	10.0
Age 30-54	68.9	70.5	72.2	64.2	37.2
Age 55-65	24.5	16.5	22.3	21.5	52.8
(Pre-)primary and lower secondary education	18.9	16.6	15.5	29.7	23.8
(Upper) secondary and post-secondary education	45.6	44.2	48.6	46.1	45.7
Tertiary education	35.6	39.1	36.0	24.2	30.5
Married	64.5	56.8	70.4	52.2	65.6
No. of children in household	0.6	0.6	0.6	0.5	0.4
Work characteristics					
Part-time	15.7	23.2	6.8	29.9	41.1
Temporary work contract	23.4	22.4	10.3	27.3	43.3
Top 20% of cash income distribution	24.7	18.2	32.4	12.6	17.6
AI index:					
AI Felten index	3.4	3.4	3.5	3.3	3.3
Task intensities:					
Routine tasks	0.2	0.2	0.2	0.2	0.2
Routine-cognitive tasks	0.2	0.2	0.2	0.2	0.2
Routine-manual tasks	0.0	0.0	0.0	0.1	0.1
Physical tasks	0.4	0.3	0.3	0.4	0.3
Intellectual tasks	0.5	0.5	0.5	0.4	0.5
Social tasks	0.4	0.4	0.4	0.4	0.4
Observations	47,800	5,411	3,371	1,740	2,413

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

Table A 5: Transition probabilities from employment: Felten digitization index, all control variables

Multinomial logit regression

	stays employed	entry into SE w/employees	entry into solo SE	entry into unemployment	entry into inactivity
AI Felten index	0.00615**	0.00025	0.00090*	-0.00664***	-0.00066
	(0.00248)	(0.00029)	(0.00047)	(0.00163)	(0.00082)
Women	-0.00657***	-0.00053***	-0.00244***	-0.00360**	0.01313***
	(0.00229)	(0.00019)	(0.00053)	(0.00182)	(0.00108)
Age 16-29	-0.03298***	0.00016	0.00125	0.00469***	0.02688***
	(0.00447)	(0.00026)	(0.00085)	(0.00161)	(0.00337)
Age 55-65	-0.05996***	-0.00031	-0.00101*	0.00364**	0.05764***
	(0.00408)	(0.00022)	(0.00060)	(0.00147)	(0.00346)
(Pre-)primary and lower	-0.01167***	-0.00038	0.00087	0.00589***	0.00530***
secondary education	(0.00285)	(0.00025)	(0.00054)	(0.00193)	(0.00191)
Tertiary education	0.00862***	0.00028	0.00244***	-0.00739***	-0.00394***
	(0.00233)	(0.00020)	(0.00076)	(0.00145)	(0.00107)
Married	0.00162	0.00031	-0.00020	-0.00857***	0.00683***
	(0.00146)	(0.00021)	(0.00037)	(0.00080)	(0.00115)
No. of children in household	-0.00083	0.00002	0.00080**	0.00092	-0.00091
	(0.00137)	(0.00008)	(0.00031)	(0.00063)	(0.00114)
Part-time	-0.02188***	-0.00012	0.00253***	0.00451***	0.01496***
	(0.00250)	(0.00026)	(0.00091)	(0.00132)	(0.00202)
Temporary work contract	-0.06360***	-0.00005	0.00506***	0.04402***	0.01457***
	(0.00352)	(0.00026)	(0.00105)	(0.00251)	(0.00159)
Top 20% of wage distribution	0.00099	-0.00008	-0.00134	-0.00771***	0.00813***
	(0.00269)	(0.00020)	(0.00097)	(0.00177)	(0.00181)
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	505,499	505,499	505,499	505,499	505,499

Source: EU-SILC 2014-2019, SOEP v.36; Felten-index by Felten et al. (2018). – Notes: Marginal effects from a multinomial logit regression with five outcomes. 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 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 percent of the wage distribution. Country and year fixed-effects. Based on the two-year longitudinal sample.

Table A 7: Transition probabilities from solo self-employment: Felten digitization index, all control variables

Multinomial logit regression

	stays solo SE	entry into employment	entry into SE w/employees	entry into unemployment	entry into inactivity
AI Felten index	-0.00656	0.00630**	0.00575	0.00072	-0.00621*
	(0.00580)	(0.00287)	(0.00557)	(0.00229)	(0.00362)
Women	0.00161	-0.00427	-0.01353***	0.00454**	0.01165***
	(0.01058)	(0.00476)	(0.00471)	(0.00229)	(0.00406)
Age 16-29	-0.04053***	0.02100**	-0.01262**	0.01670***	0.01545**
	(0.01141)	(0.01062)	(0.00557)	(0.00598)	(0.00682)
Age 55-65	-0.00203	-0.02404***	-0.00912***	0.00161	0.03358***
	(0.00806)	(0.00411)	(0.00332)	(0.00209)	(0.00399)
(Pre-)primary and lower	0.00526	-0.00575	-0.00683*	0.01134**	-0.00402
secondary education	(0.00800)	(0.00594)	(0.00379)	(0.00482)	(0.00338)
Tertiary education	-0.00184	0.00825*	-0.00277	-0.00061	-0.00302
	(0.00814)	(0.00443)	(0.00495)	(0.00128)	(0.00278)
Married	-0.01040	-0.00261	0.01446***	-0.00550***	0.00405
	(0.00676)	(0.00227)	(0.00381)	(0.00195)	(0.00297)
No. of children in household	-0.00360	0.00269	0.00011	0.00068	0.00012
	(0.00334)	(0.00212)	(0.00204)	(0.00129)	(0.00178)
Top 20% of cash income	0.11687***	-0.09426***	0.02693***	-0.01387***	-0.03567***
distribution	(0.02026)	(0.01437)	(0.00374)	(0.00358)	(0.00696)
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	43,047	43,047	43,047	43,047	43,047

Source: EU-SILC 2014-2019, SOEP v.36; Felten-index by Felten et al. (2018). Notes: - Marginal effects from a multinomial logit regression with five outcomes. 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 percent of the cash distribution. Country and year fixed-effects. Based on the two-year longitudinal sample.

Appendix B: Additional results

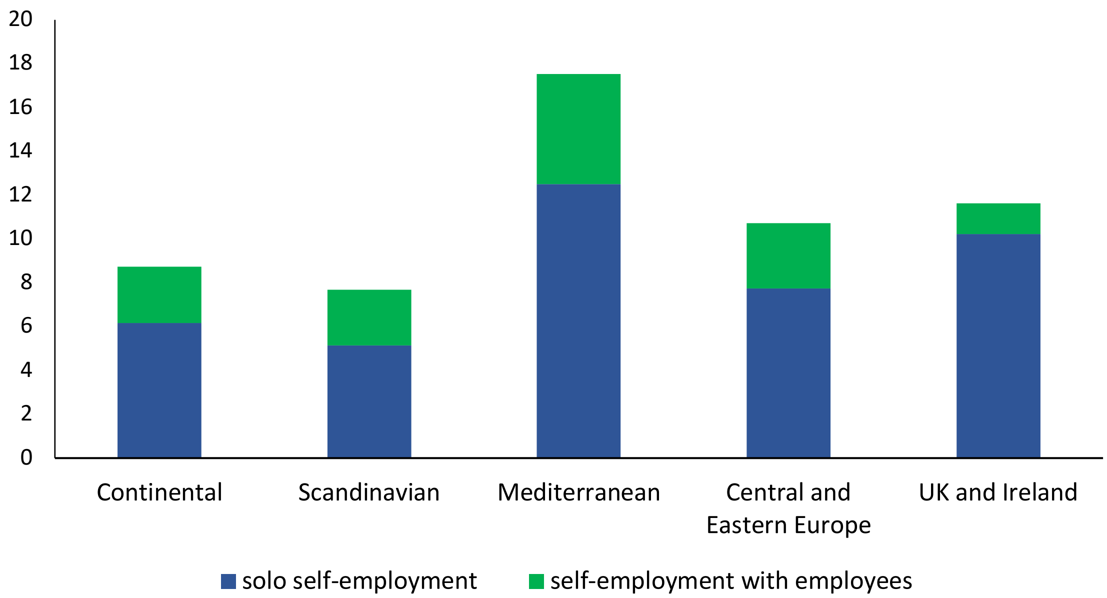
Figure A 1: Self-employment (detailed categorization) by country

In % of total employment

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

Figure A 2: Self-employment by country groups

In % of total employment



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

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