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**Conference Paper**

## Jobs at Risk!? Effects of Automation of Jobs on Occupational Mobility

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2017: Alternative Geld- und Finanzarchitekturen - Session: Labor Economics I, No. D04-V1

**Provided in Cooperation with:**

Verein für Socialpolitik / German Economic Association

*Suggested Citation:* Sorgner, Alina (2017) : Jobs at Risk!? Effects of Automation of Jobs on Occupational Mobility, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2017: Alternative Geld- und Finanzarchitekturen - Session: Labor Economics I, No. D04-V1, ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft, Kiel, Hamburg

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<https://hdl.handle.net/10419/168088>

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# **Jobs at Risk!?**

## **Effects of Automation of Jobs on Occupational Mobility**

Alina Sorgner

February 2017

### **Abstract**

This paper investigates the relationship between the risk of automation of jobs and individual-level occupational mobility using a representative German household survey. The results suggest that expected occupational changes such as losing a job, demotion at the current place of employment, or starting a job in a new field are likely to be driven by the high occupation-specific risk of automation. However, switches to self-employment, both with and without employees, are more likely to occur from paid employment in occupations with low risk of automation. Hence, the rising level of entrepreneurial activities is less likely due to jobs becoming obsolete in the course of automation, but rather due to a high number of opportunities that arise in the digital age.

JEL classification: J24, J62, L26

Keywords: automation of jobs, occupational mobility, entrepreneurship,

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## 1. Introduction

Recent technological progress, particularly in the field of ICT that has led to the emergence of Industry 4.0 gave rise to the debate about the future of employment. There is a strong concern that as the technology will develop further, it will become possible that machines will perform tasks at least as efficiently as humans who are currently carrying them out. As a consequence, it is feared that automation will lead to a massive wipe-out of jobs.

Researchers from the University of Oxford recently arrived at the conclusion that given the current state of technology about 47 percent of the US labor force are in jobs that are highly likely to be replaced by machines in the next one to two decades (Frey and Osborne 2017). Numerous follow-up studies mainly confirmed this scenario for other countries, although they report a great variation of automation risk across countries (see, e.g., Arntz, Gregory, and Zierahn 2016 for the analysis of OECD countries, Chang and Huynh 2016 for ASEAN countries, Dengler and Matthes 2015 for the case of Germany; Pajarinen, Rouvinen, and Ekeland 2015 for the analysis of Finland and Norway).

The contribution of this paper is twofold. Firstly, the above mentioned studies provide estimates based on the aggregate employment data, and thus, it remains unclear whether and in how far the predicted risk of automation of jobs<sup>1</sup> is associated with occupational mobility on the level of individuals.

Hence, the present paper aims at shedding more light on this relationship by investigating whether working in an occupation with high risk of automation affects job changes, such as risk of losing a job, demotion at the current place of employment, or starting a job in a new field, among others. Secondly, this paper investigates the impact of automation of jobs on the probability of becoming an entrepreneur. Recent rise of entrepreneurship in many developed countries which is observed in the last two decades raises many questions with regard to the drivers of this development and the quality of the start-ups. Particularly, technological progress that leads to automation of jobs may foster start-ups out of necessity by people whose jobs are likely to be substituted with machines. At the same time, technological progress may

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<sup>1</sup> In this paper the terms computerization, digitization and automation are used interchangeably.

lead to an increase in the level of opportunity-driven growth-oriented start-ups which are likely to emerge in fields that are less susceptible to computerization.

The empirical analysis is based on the German Socio-Economic Panel Data, an annual representative survey of German households containing rich information on an individual's socio-economic background. The results suggest that the risk of automation of jobs increases the risk of occupational changes such as losing a job, demotion at the current place of employment, or starting a job in a new field within the next two years. At the same time, the risk of automation is negatively associated with the probability of becoming an entrepreneur, both with and without employees. Thus, the rising level of entrepreneurship in Germany is more likely to be driven by new technology creating new entrepreneurial opportunities, rather than by destroying jobs.

The remainder of the paper is organized as follows. Section 2 provides an overview of current trends and developments on the labor markets which are due to automation of jobs. It also describes the most recent dynamics of self-employment and relates it to the risk of automation of jobs. Section 3 describes the data and the empirical method. Section 4 presents the results of the empirical analysis, and section 5 concludes.

## **2. Labor market in the digital age: trends and developments**

This chapter reviews trends and developments that currently occur in the labor markets of many developed countries and which are related to the current progress in automation of tasks. In particular, section 2.1 describes the phenomenon of polarization of labor markets. Section 2.2 discusses consequences of automation for the future of employment by considering current trends in the rate of entrepreneurial activities.

### **2.1. Which jobs are at risk of automation?**

In order to understand which jobs are at high risk of automation, it is necessary to analyze what types of tasks can be efficiently performed by computers and in which tasks computers merely supplement human labor. In

Autor, Levy, and Murnane (2003), the authors distinguish between two broad set of tasks according to the extent of their vulnerability to computerization, namely, routine and non-routine tasks. The latter group of non-routine tasks can additionally be divided in manual and abstract tasks. Due to the nature of routine tasks that may be both cognitive (e.g. performing calculations) and physical (e.g. repetitive operations in a stable environment) they can be fully codified and, thus, jobs that mainly comprise routine tasks are highly susceptible to computerization. While machines outperform humans in many of the routine tasks, they did not achieve that high performance level yet when carrying out non-routine tasks, that is, manual and abstract tasks. Manual tasks are those activities that can be easily performed by humans but which require enormous computing power from machines. Examples of such tasks are manual operations in unstable changing environments that require high adaptability and manual dexterity, as well as visual and language recognition. One should note, however, that the current progress in artificial intelligence (AI) is quite impressive and it can be expected that machines will learn to perform those tasks even better in the near future (see Brynjolfsson and McAfee 2014 for different examples). Still, humans currently perform these tasks at a much lower cost, which is the reason for a relatively low risk of computerization of jobs that comprise manual tasks in the near future. Last but not least, abstract tasks require creativity, persuasion and problem-solving abilities, in which computers rather complement high-educated workers.

Given this state of technology, the major trend that is currently observed in various developed countries is that of polarization of labor markets (Autor 2015a, Autor and Dorn 2013, Goos, Manning and Salomons 2014). Job polarization is a phenomenon which refers to growth of employment at opposite ends of the occupational skill distribution. That is, growth of high-paid jobs that require high levels of education and that mostly comprise abstract tasks, on the one hand, and growth of low-paid jobs that comprise manual tasks performed by people with low levels of education, on the other hand.

Recently, in a study of the future of employment in the US Frey and Osborne (2017) arrived at the conclusion that about 47 percent of the US

labor force is currently working in occupations with a particularly high risk of being computerized in the next one to two decades. Those high-risk occupations mainly comprise transportation and logistics occupations, office and administrative support workers, and production occupations. In response to this study the OECD's Directorate for Employment, Labour and Social Affairs commissioned a replication study for OECD countries which has been conducted by Arntz, Gregory, and Zierahn (2016). The authors concluded that the risk of automation might have been overestimated in the previous study by Frey and Osborne (2017). On contrary, they find that, on average across the 21 OECD countries, only about 9 % of jobs are automatable, although there is high variation between countries. The highest risk of automation was found for Germany and Austria (12 %) and the lowest for Korea and Estonia (6 %). The study by Chang and Huynh (2016) of ASEAN countries, however, reports that about 56 percent of employment is at high risk of displacement over the next decade or two. This variation may reflect general differences in industrial structure of economy in those countries. For instance, knowledge-intensive sectors comprise jobs that heavily rely on abstract tasks, while many jobs in manufacturing sectors are routine-based and, thus, susceptible to automation.

While the study by Frey and Osborne (2017) for the US and the follow-up studies for other countries focused on aggregated employment data, it is not clear how the risk of automation and computerization affects occupational changes at the level of individuals, such as transitions from paid employment into unemployment or self-employment. Hence, this paper's aim is to shed more light on this issue by investigating the micro-level data.

## **2.2. Automation of jobs and the rise of entrepreneurship**

Another pronounced development that many developed countries currently experience is that of a fundamental shift from a managed economy towards an entrepreneurial economy. The term 'managed economy' refers to the organization of market economies after the WW2 that was characterized by the prevalence of economies of scale, production routines, high levels of specialization and relatively low levels of uncertainty in manufacturing process. In contrast to the managed economy, the entrepreneurial economy

is predominantly based on pronounced start-up activity, innovation which occurs in entrepreneurial organizations, flexible production and flexible labor markets, and relatively high levels of uncertainty (Audretsch and Thurik, 2000, 2001). Moreover, new business formation - while being largely neglected by policy makers in the managed economies – starts to play an increasingly important role in the entrepreneurial economy with regard to its direct effects such as job creation (Acs 2011) and, most importantly, indirect effects. Concerning the latter, start-ups represent an important challenge for incumbent firms and, thus, force them to perform more efficiently (Fritsch 2011). Last but not least, new entrants may create new markets by introducing radical innovations (Baumol 2004).

This shift towards a more entrepreneurial economy is well reflected in Figure 1 which shows the dynamics of self-employment rates in Germany during the period between 1991 and 2012. The self-employment rate grew steadily from about 8 percent in the beginning of the observation period up to about 11.5 percent in the end of the period under analysis. Noteworthy, this development cannot entirely be attributed to the market transition of the former GDR, although the event of the German reunification contributed significantly to the rise of the overall self-employment rate in Germany. Particularly, the self-employment rate in East Germany converged with the level of self-employment activities in West Germany around the year 2004 and even exceeded it thereafter. Nevertheless, the rise of entrepreneurial activities can also be observed in West German regions.

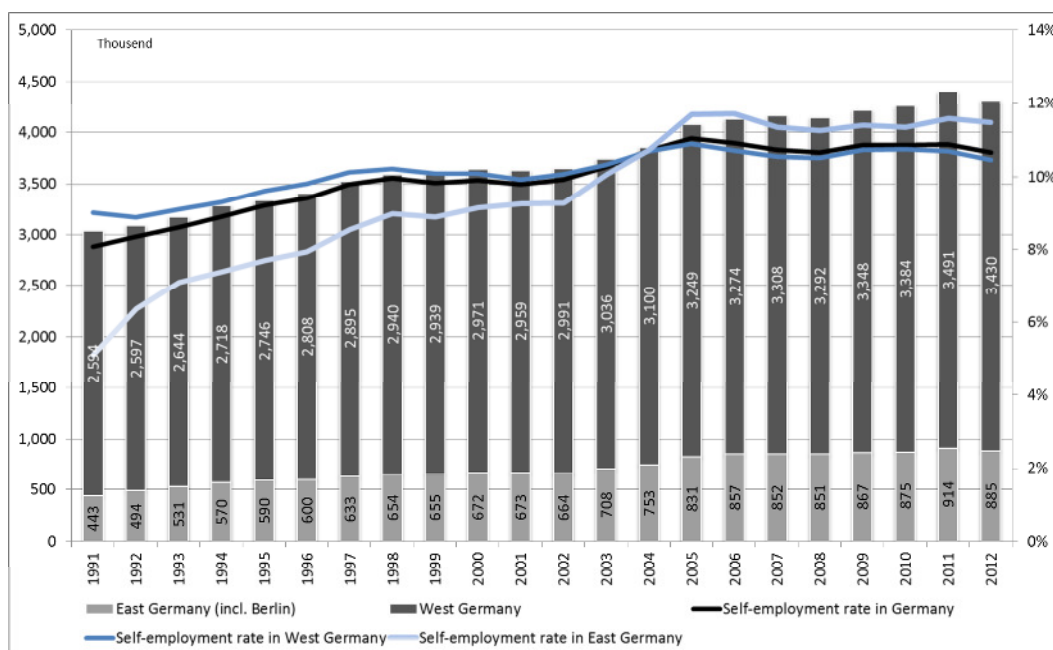


Figure 1: Dynamics of self-employment rates in Germany. Source: own calculations based on the German Micro-Census.

This evidence leads to a question of what are the drivers of this fundamental move towards a more entrepreneurial society. The rising level of entrepreneurial activities may simply reflect various structural changes in a society. For instance, changes in socio-demographic characteristics of the population, such as age structure, increased female labor market participation rate, and an on average higher level of education, may have led to the rise of entrepreneurship (Fritsch, Kritikos, and Sorgner 2015).<sup>2</sup> Moreover, the incentives to become an entrepreneur may have changed as a response to variety of policy measures designed to promote entrepreneurship that have been realized in the last about two decades. For example, in Germany a whole variety of public policy measures have been realized, that promoted, for instance, start-ups by unemployed persons (Caliendo and Kritikos 2010) and by students and highly educated staff at universities and other public research institutes ('EXIST'). Some of those programs aimed at reducing start-up barriers for women related to human

<sup>2</sup> This is because socio-demographic characteristics are important determinants of the decision to become an entrepreneur (Parker 2009).



and financial capital (Welter 2006).<sup>3</sup> Those policy measures may have at least partly shaped a more pro-entrepreneurial attitude in the population and a stronger awareness of entrepreneurship as an alternative career option, thus, also contributing to the rise of entrepreneurship. Last but not least, technological progress, and in particular achievements in ICT that gave rise to the 4<sup>th</sup> industrial revolution, may be responsible for a great number of entrepreneurial opportunities and the shift towards an entrepreneurial economy in many developed countries (Audretsch and Thurik 2000).

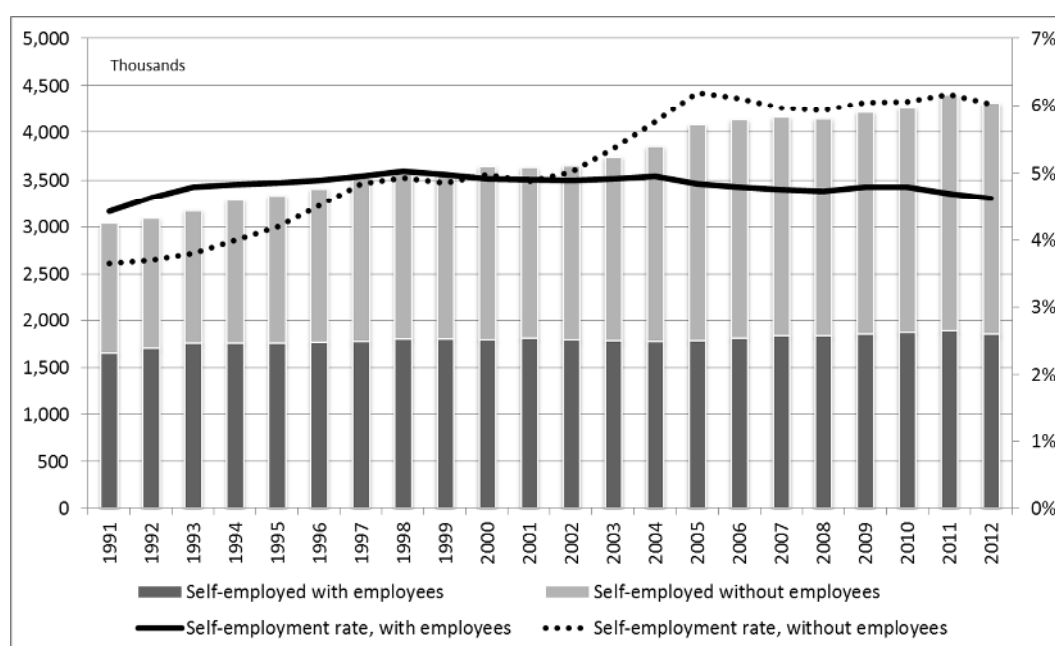


Figure 2: Dynamics of self-employment with and without employees in Germany. Source: own calculations based on the German Micro-Census.

Remarkably, Figure 2 demonstrates that the rise of self-employment rates in Germany was predominantly due to the rise of self-employment without employees (solo self-employment). While the solo self-employment rate increased from about 3.5 percent in 1991 up to 6 percent in 2012, the level of self-employment with employees increased only negligibly. Businesses of solo self-employed have often been regarded as low quality start-ups, as they are not supposed to create much value, for instance, in

<sup>3</sup> Other policy measures included, for instance, deregulation of a number of liberal occupations, introduction of minimum capital requirements for setting up a limited liability company, changes to personal bankruptcy law, and a more restrictive access to social security support.

terms of innovation, employment growth and wealth generation (Shane 2009).

This recent rise in the level of self-employment is quite remarkable and requires investigation, as there is not much evidence about the reasons behind this development and about the quality of such start-ups. Fritsch, Kritikos, and Sorgner (2015) conduct a decomposition analysis of self-employment rates in Germany over time in order to determine the major drivers of their pronounced change. They provide evidence that demographic developments, the shift towards service sector employment and a larger share of population holding a tertiary degree are the major drivers of the increase of the overall level of self-employment. While these factors explain most of the development in self-employment with employees, they could only explain less than a half of a much stronger increase in self-employment without employees. In particular, it remains unclear whether and in how far the rise of solo self-employment was triggered by the technological progress which has led to automation of jobs. It can be assumed that people in jobs with a relatively high risk of automation may be more likely to set up businesses out of necessity, because there is a high risk of their job being replaced by machines. Furthermore, it can be expected that such businesses are less likely to be growth-oriented, as they have been created with a primary aim of employing the business owner (Shane 2009). Thus, automation of human labor may indeed drive the levels of solo self-employment “out of necessity”. On contrary, technological progress may lead to the rise of opportunity-driven growth-oriented entrepreneurship in the fields that are less susceptible to automation and that are characterized by creative and abstract tasks.<sup>4</sup> Hence, another aim of this paper is to investigate the relationship between the risk of automation of jobs and the individual likelihood of becoming an entrepreneur.

### **3. Data and method**

#### *Data source*

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<sup>4</sup> For instance, Shane (2000) provides a review of a variety of profitable entrepreneurial opportunities that emerged in different sectors after introduction of a 3D printing technology.

The empirical analysis is based on the Socio-Economic Panel Data, which is a German annual representative household survey conducted by the German Institute for Economic Research (DIW). It includes information about the detailed socio-economic situation of approximately 22,000 individuals annually living in Germany (Wagner et al. 2007). For the purposes of the present analysis the data for time period from 2005 to 2013 is employed.

### *Dependent variables*

Currently employed individuals are asked in SOEP to assess the probability of occupational changes in the next two years on a 10-point Likert scale from 0 to 100 with a 10-points step. The questions comprise various types of occupational changes related to losing or switching a job, occupational promotion or demotion, expected wage/salary increase, etc. Many of those changes may occur as a consequence of advancing computerization and/or automation of jobs. A precise wording of questions used in the present study is as follows:

“How likely is it that you will experience the following career changes within the next two years? Please estimate the probability on a scale of 0 to 100, with 0 meaning that such a change definitely will not take place, and 100 meaning that such a change definitely will take place.”

- “Will you lose your job?”
- “Will you stop working in your current field and start working in a different one?”
- “Will you be demoted at your current place of employment?”
- “Will you attend courses or seminars to obtain additional training or qualifications?”
- “Will you receive a salary or wage increase beyond the collectively negotiated wage increases?”
- “Will you start working on a self-employed and/or freelance basis?”

Moreover, in our further analysis we study the real transitions from paid employment into unemployment and self-employment, in order to account not only for perceived but also for real risk of automation of jobs. To this end,

two dependent variables are constructed as binary variables that equal to one if a respondent's observed employment status in time period  $t$  is paid employment and his or her employment status two years later is unemployment (self-employment). In addition, for respondents who switched from paid employment to self-employment, we distinguish between those who became solo self-employed and self-employed with employees, in order to partly account for necessity and opportunity motives.<sup>5</sup>

### *Independent variable*

The variable of interest is the occupation-specific automation probability which indicates the level of risk of a particular occupation to be automated or computerized in the next one to two decades. This variable was adapted from the study by Frey and Osborne (2017) who estimate automation/computerization probabilities for 702 occupations according to the US occupational classification system of O\*Net. Together with a group of experts in machine learning and robotics, Frey and Osborne were able to identify a set of occupations that they hand labeled with 1 meaning a 100 percent probability of occupation being computerized in the next one to two decades or 0 if the risk of computerization was regarded as absent.<sup>6</sup> In the next step, they identify technological bottlenecks to computerization, that is, occupation-specific tasks that represent a challenge for machines to substitute them. In particular, they identify three types of such bottlenecks, namely, social intelligence, creativity, and manipulation and perception. While social intelligence and creativity require high abilities and represent abstract tasks, manipulation and perception are mostly manual tasks (such as manual dexterity or tasks that are related to an unstructured work environment) that can be easily performed by humans, but represent a

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<sup>5</sup> It should be noted, however, that not all solo self-employed start their businesses out of necessity. For instance, Sorgner, Fritsch and Kritikos (2014) show that while solo self-employed tend to realize lower incomes than comparable paid employees and employers, there are entrepreneurial "super-stars" among solo self-employed who earn more. The data do not allow to make a more precise distinction between motives for a start-up.

<sup>6</sup> Examples of occupations that they hand labeled by 1 are legal assistants or fast food cooks. Examples of occupations with a 0-risk of computerization are housekeeping cleaners, taxi drivers or economists.

significant challenge for robots and machines.<sup>7</sup> Finally, they train the hand labeled data set in order to find the optimal predicting algorithm, which they then apply to estimate the probabilities of computerization for the remaining occupations, based on the extent to which they are composed of tasks that are bottlenecks to computerization.

Frey and Osborne (2017) provide the estimated probabilities of computerization for 6-digit U.S. System of Occupational Classification (2010 SOC). Hence, they need to be converted to the 4-digit ISCO88 occupations that are available in SOEP in order to match them with other individual-level information. For this purpose, the crosswalk supplied by the US Bureau of Labor Statistics was used.

### *Control variables*

A wide set of control variables is considered which can affect an individual's occupational mobility. In particular, information is available on the number of years that a respondent spent in formal education, tenure with current employer, experienced years of unemployment, socio-demographic characteristics including age, gender, nationality, and children in household. Moreover, SOEP data include short item scales that measure the Big Five dimensions of personality (Costa and McCrae 1992). In particular, the survey comprises 15 items, three for each of the five traits, which has been shown to replicate the results of the more extensive 25-item Big Five inventory accurately (Gerlitz and Schupp 2005). Psychological personality characteristics may affect an individual's willingness to change occupations in general, for instance, if a person has strong preferences for variety in his or her occupational environment (Åstebro and Thompson 2011). Another reason for including personality traits into the model is that they may to a certain extent capture unobserved abilities beyond those measured by the level of formal education that may affect both the choice of a certain occupation and the probability of occupational changes. For definition of

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<sup>7</sup> This phenomenon is also known as Polanyi's paradox which refers to inability to convert tacit knowledge into codifiable and, hence, computerizable rules (Autor 2015b).

variables used in the analysis and measurement issues see Table A1 in Appendix.

### *Method*

The regression method used in the empirical analysis of expected occupational changes accounts for the peculiarities of the dependent variable which is the probability of occupational change to occur within the next two years. Since the dependent variable is bounded between zero and one, the model can be estimated by means of the fractional response model (FRM) proposed by Papke and Wooldridge (1996).

The analysis of transitions from paid employment to unemployment and self-employment is conducted by means of probit regression, which accounts for a binary nature of the dependent variable that takes a value of 1 if an occupational change has occurred and takes a value of 0 if this was not the case.

## **4. Results**

### **4.1 Descriptive results**

According to Table 1, the highest average probability of an occupational change to occur within the next two years reported by currently employed respondents is related to the risk being demoted at the current place of employment (about 46 percent), followed by the probability of acquiring additional qualifications (about 39 percent) and losing a job (about 21 percent). Interestingly, the lowest average probability of occupational change is that with regard to starting working as a self-employed (about 8 percent). Nevertheless, it should be noted that this number is about 8 times higher than the yearly start-up rate in Germany, which is only about 1 percent (Fritsch, Kritikos, and Rusakova 2012). This indicates a rather high willingness among German population to set up a business, a potential that apparently could not be realized to the full extent.<sup>8</sup>

Table 1: Descriptive statistics for dependent variables (probability of occupational changes within the next 2 years)

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<sup>8</sup> The reasons for this may be manifold, such as lack of financial capital, inability to identify a profitable entrepreneurial opportunity, or the decreasing level of over-optimism during the gestation period.

	Mean (%)	Standard deviation
Will you lose your job?	20.79	25.58
Will you stop working in your current field and start working in a different one?	12.17	23.34
Will you be demoted at your current place of employment?	46.28	14.88
Will you attend courses or seminars to obtain additional training or qualifications?	38.64	36.12
Will you receive a salary or wage increase beyond the collectively negotiated wage increases?	15.80	25.64
Will you start working on a self-employed and/or freelance basis?	7.94	20.44

Table 2 presents the probability of occupational changes for respondents who are in occupations that are differently affected by the risk of automation. In particular, we distinguish between three groups of risk of automation: low (less than 30 percent), medium (30 to 70 percent) and high (more than 70 percent). The descriptive evidence in Table 2 suggests that the probability of occupational changes increases with an increasing risk of computerization for the categories losing a job, starting working in a new field, and demotion in a current job. Moreover, a higher risk of computerization of an occupation is associated with an on average lower probability of acquiring additional qualifications. The same pattern is observed for the probability of becoming self-employed. Last but not least, there seems to be a non-linear relationship between the risk of automation and the probability of an increase in wages. However, this relationship may be driven by other factors, such as previous labor market experience or the level of formal education, among others. Hence, this relationship will be investigated in the next section in a multivariate analysis, in which we control for a wide set of socio-demographic characteristics that may drive the result.

Table 2: Probability of occupational changes in the next 2 years by the level of occupation-specific automation risk

	Risk of automation:		
	low (<30%)	medium (30%-70%)	high (>70%)
Will you lose your job?	17.39	22.05	23.03

Will you stop working in your current field and start working in a different one?	8.91	12.10	14.63
Will you be demoted at your current place of employment?	45.88	45.81	47.31
Will you attend courses or seminars to obtain additional training or qualifications?	50.89	37.85	27.90
Will you receive a salary or wage increase beyond the collectively negotiated wage increases?	16.72	17.10	13.73
Will you start working on a self-employed and/or freelance basis?	10.18	7.35	6.57

Additionally, Table A1 in Appendix provides information on descriptive statistics for independent variables. According to this table, an average respondent in the sample is about 42 years old and has enjoyed about 12.2 years of formal education. An average respondent has been in his or her current job for about 11 years and has experienced 0.9 years of unemployment in the past.

## 5.2 Results of multivariate analysis

This section presents the results of the multivariate analysis of the relationship between automation of occupations and the probability of an individual's occupational changes. Section 5.2.1 presents the results for expected risk of occupational changes in the next future, such as losing a job, starting a completely new occupation, or becoming self-employed. Section 5.2.2 investigates whether a higher risk of computerization is associated with real transitions from paid employment into unemployment and self-employment.

### 5.2.1 Risk of computerization and perceived occupational changes

The results of multivariate analysis of the relationship between occupation-specific computerization probability and the self-reported probability of occupational changes within the next two years are reported in Table 3. In order to test for possible non-linear relationship, the occupation-specific probability of computerization enters the model together with its squared



term. The results suggest that there is a statistically significant reversed U-shaped relationship between the risk of computerization and the self-reported probability of losing a current job in paid employment (column I) as well as the likelihood of giving up working in a current occupational field and starting a job in a completely new occupation (column II). This result is quite surprising, because it means that the risk of occupational change rises with the rising risk of automation only until a certain threshold level. People in occupations with a very high automation risk are less likely than people in occupations with a medium risk to expect occupational changes related to losing their job or starting a job in a completely new occupation within the next two years. One possible reason for this finding may be related to existing labor market regulations with regard to employees' protection against dismissal.<sup>9</sup> Alternatively, employees in occupations with high risk of automation may be over-optimistic about the future of their occupations and, thus, underestimate the risk of losing their jobs.

Next, the labor market polarization described in section 2.1 implies that the highest risk of automation applies to middle-skill workers in routine jobs. Moreover, these workers will be prone to downward occupational mobility, when displaced by machines, unless they possess or will acquire skills that are non-susceptible to computerization, such as creativity or social intelligence. Hence, it can be expected that the higher the risk of automation of jobs the higher is the likelihood of being demoted at current place of employment. The results in column IV of Table 3 support this hypothesis: there is a statistically significant (although at a 10% level) effect of occupational automation risk on the probability of demotion at the current place of employment within the next two years.<sup>10</sup>

At the same time, people in occupations with the highest and the lowest risk of automation are significantly more likely than people in jobs with medium risk of automation to expect to gain additional qualifications in the next future (column V). This observation may be indicative of a moderate

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<sup>9</sup> For instance, in Germany a much stricter dismissal protection legislation applies to employees in large firms than in small firms (Bauernschuster 2013). If high-risk routine jobs are more likely to appear in large firms, then people employed in such jobs may still be in a rather secure position, despite of the high risk of automation of jobs.

<sup>10</sup> Model III does not provide evidence of possible non-linear relationship.

risk of downward occupational mobility in the future, as people who urgently require additional skills in order to protect themselves from negative effects of automation are likely to do so.<sup>11</sup> Similarly, gaining additional qualifications may be also of high importance for people in occupations with low risk of automation, in which computers strongly complement human labor. Moreover, a higher risk of automation of occupations is less likely to be associated with the probability of wage increases of individuals in those occupations (column VI).

Last but not least, an interesting result is obtained with regard to the probability of setting up an own business, namely, respondents in occupations with low risk of automation are significantly more likely than people in jobs with high risk of automation to see themselves self-employed in the next future (column VII). This is an important result that points toward opportunity-driven nascent entrepreneurship, since the willingness to set up a business is more pronounced among workers who are in relatively secure jobs in terms of their susceptibility to automation. Moreover, jobs with low risk of automation contain tasks such as creativity, social interactions and abstract thinking which are of high importance for entrepreneurs.

For the effects of control variables, it is observed that people with high and low levels of education are significantly less likely to expect occupational changes, as compared to individuals with medium level of education. People with longer tenure, males as well as those with children have a lower probability of occupational changes. With regard to the effects of personality traits, people with higher levels of conscientiousness, agreeableness and internal locus of control are less likely to expect occupational changes in the next future. The results for other personality traits are mixed. For instance, people with a higher willingness to take risks report a higher probability to start a job in a new field, obtain additional qualifications, expect wage increase, and to become self-employed.<sup>12</sup> On contrary, less risk-averse people report a lower probability of demotion at the current place of employment.

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<sup>11</sup> Unfortunately, the data does not provide information with regard to skills the respondents are going to strengthen by means of attending additional training.

<sup>12</sup> This is in line with previous studies (see, e.g., Caliendo, Fossen and Kritikos 2009).

Table 3: Risk of automation of jobs and probability of occupational changes within the next 2 years

	Self-reported (in $t$ ) probability of occupational changes within the next 2 years:						
	I	II	III	IV	V	VI	VII
	Will you lose your job?	Will you stop working in your current field and start working in a different one?	Will you be demoted at your current place of employment?		Will you attend courses or seminars to obtain additional training or qualifications?	Will you receive a salary or wage increase beyond the collectively negotiated wage increases?	Will you start working on a self-employed and/or freelance basis?
Occupation-specific automation probability in $t$	0.245*** (0.082)	0.462*** (0.109)	0.041 (0.034)	0.019* (0.010)	-0.889*** (0.092)	-0.220** (0.104)	-0.445*** (0.128)
Occupation-specific automation probability in $t$ , squared	-0.211*** (0.082)	-0.288*** (0.107)	-0.024 (0.034)	- (0.000)	0.553*** (0.093)	0.059 (0.105)	0.163 (0.131)
Years of formal education	0.149*** (0.025)	0.171*** (0.032)	0.006 (0.009)	0.006 (0.009)	0.314*** (0.028)	0.100*** (0.031)	0.168*** (0.041)
Years of formal education, squared	-0.006*** (0.001)	-0.006*** (0.001)	0.000 (0.000)	0.000 (0.000)	-0.009*** (0.001)	-0.002* (0.001)	-0.005*** (0.001)
Tenure	-0.032*** (0.002)	-0.036*** (0.003)	0.004*** (0.001)	0.004*** (0.001)	-0.003 (0.002)	-0.014*** (0.003)	-0.034*** (0.003)
Tenure, squared	0.001*** (0.000)	0.001*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	0.000 (0.000)	0.000** (0.000)	0.000*** (0.000)
Experience of unemployment, years	0.028*** (0.004)	0.027*** (0.005)	0.004** (0.002)	0.004** (0.002)	-0.019*** (0.005)	-0.030*** (0.006)	0.001 (0.007)
Age	0.022*** (0.004)	0.034*** (0.006)	0.016*** (0.001)	0.016*** (0.001)	0.024*** (0.004)	0.039*** (0.005)	0.047*** (0.007)
Age, squared	-0.000*** (0.000)	-0.001*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Male	-0.039***	-0.027	-0.032***	-0.032***	0.078***	0.144***	0.178***

	(0.014)	(0.018)	(0.006)	(0.006)	(0.016)	(0.018)	(0.023)
German	0.108***	0.070**	0.007	0.007	0.247***	0.035	0.007
	(0.026)	(0.035)	(0.011)	(0.011)	(0.032)	(0.033)	(0.045)
Children in household	-0.091***	-0.081***	-0.003	-0.003	-0.049***	-0.064***	0.007
	(0.013)	(0.017)	(0.005)	(0.005)	(0.014)	(0.016)	(0.021)
Willingness to take risks	0.001	0.017***	-0.006***	-0.006***	0.020***	0.031***	0.042***
	(0.003)	(0.004)	(0.001)	(0.001)	(0.003)	(0.004)	(0.005)
Conscientiousness	-0.044***	-0.082***	-0.013***	-0.013***	-0.006	-0.004	-0.083***
	(0.007)	(0.009)	(0.003)	(0.003)	(0.008)	(0.009)	(0.012)
Extraversion	-0.021***	-0.002	-0.014***	-0.014***	0.011*	0.024***	-0.013
	(0.006)	(0.007)	(0.002)	(0.002)	(0.007)	(0.007)	(0.010)
Agreeableness	-0.013**	-0.027***	0.001	0.001	-0.008	-0.036***	-0.046***
	(0.007)	(0.008)	(0.003)	(0.003)	(0.007)	(0.008)	(0.011)
Openness	-0.017***	0.043***	-0.006**	-0.006**	0.070***	0.022***	0.113***
	(0.006)	(0.007)	(0.002)	(0.002)	(0.006)	(0.007)	(0.010)
Neuroticism	0.070***	0.069***	0.024***	0.024***	0.004	-0.030***	0.025***
	(0.005)	(0.007)	(0.002)	(0.002)	(0.006)	(0.007)	(0.009)
Internal locus of control	-0.054***	-0.023***	-0.009***	-0.009***	0.008	0.012	-0.003
	(0.007)	(0.009)	(0.003)	(0.003)	(0.008)	(0.009)	(0.012)
External locus of control	0.062***	0.053***	0.012***	0.012***	-0.041***	-0.005	-0.037***
	(0.007)	(0.009)	(0.003)	(0.003)	(0.008)	(0.010)	(0.013)
Year fixed effects	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***
Industry fixed effects	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***
Constant	-1.617***	-2.712***	-0.480***	-0.477***	-3.066***	-2.390***	-3.098***
	-0.203	-0.263	-0.078	-0.078	-0.227	-0.253	-0.346
Number of observations	30,890	30,901	30,677	30,677	30,885	30,717	29,600
Log Likelihood	-12,201	-8,469	-14,314	-14,314	-15,190	-10,293	-6,821

Notes: Dependent variable: self-reported probability of occupational changes within the next two years. Robust standard errors in parentheses.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

### 5.2.2 Transitions into self-employment and unemployment

While previous section presented results for expected occupational changes, in this section the analysis is focused on real occupational transitions from paid employment to unemployment and self-employment within the next two years. The first column of Table 4 suggests that high risk of automation in an occupation is more likely to lead to unemployment in the next two years. This relationship is linear meaning that there is no decrease in the probability of unemployment for those workers who are in jobs with the highest risk of automation.<sup>13</sup> Hence, it is likely that those workers underestimate the risk of losing a job, as it has been shown in the model I of Table 3.

Moreover, there is a statistically significant and negative relationship between the risk of automation and transition from paid employment into self-employment. In order to provide a more differentiated picture of the relationship between the risk of automation and switches to self-employment, we additionally distinguish between self-employment with and without employees. The group of self-employed without employees may contain necessity entrepreneurs, that is, those individuals who were at high risk of losing their jobs, for instance, due to automation. On contrary, the group of self-employed with employees is likely to contain opportunity-driven and growth-oriented entrepreneurs. Hence, one can expect different effects of automation risk on various types of entrepreneurship. However, the results in columns III and IV of Table 4 suggest that both types of entrepreneurs are likely to come from low-risk occupations, although the effect is lower (and only statistically significant at the 10% level) for solo self-employed.

Table 4: Risk of automation of jobs and transitions into self-employment and unemployment

	I	II	III	IV
	Employment status in ( $t+2$ )			
	Unemployed	Self-employed	Self-employed without employees	Self-employed with employees
Occupation-specific automation probability in $t$	0.182*** (0.061)	-0.244*** (0.079)	-0.177* (0.092)	-0.283** (0.111)
Years of formal education	-0.130**	0.12	0.185*	0.016

<sup>13</sup> A test of non-linearity proved to be non-significant in all model specifications of Table 4.

	(0.053)	(0.085)	(0.104)	(0.108)
Years of formal education, squared	0.004*	-0.002	-0.005	0.001
	(0.002)	(0.003)	(0.004)	(0.004)
Tenure	-0.062***	-0.034***	-0.048***	-0.009
	(0.005)	(0.007)	(0.008)	(0.009)
Tenure, squared	0.001***	0.001***	0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Experience of unemployment, years	0.095***	-0.01	-0.002	-0.028
	(0.008)	(0.014)	(0.016)	(0.025)
Age	-0.036***	-0.001	-0.008	0.01
	(0.008)	(0.013)	(0.015)	(0.019)
Age, squared	0.001***	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.034	0.131***	0.087	0.176**
	(0.035)	(0.047)	(0.054)	(0.070)
German	-0.043	-0.107	-0.032	-0.176
	(0.058)	(0.088)	(0.117)	(0.110)
Children in household	-0.058*	0.132***	0.125**	0.107*
	(0.033)	(0.045)	(0.053)	(0.063)
Willingness to take risks	0.006	0.058***	0.050***	0.059***
	(0.007)	(0.010)	(0.011)	(0.015)
Conscientiousness	-0.004	0.014	-0.006	0.042
	(0.019)	(0.027)	(0.031)	(0.038)
Extraversion	-0.019	0.017	-0.001	0.039
	(0.014)	(0.020)	(0.022)	(0.029)
Agreeableness	-0.017	-0.039*	-0.04	-0.032
	(0.016)	(0.023)	(0.025)	(0.034)
Openness	0.014	0.088***	0.107***	0.041
	(0.014)	(0.022)	(0.025)	(0.029)
Neuroticism	0.028**	0.022	0.042**	-0.013
	(0.013)	(0.018)	(0.021)	(0.024)
Internal locus of control	0.012	0.032	0.023	0.036
	(0.016)	(0.022)	(0.025)	(0.033)
External locus of control	0.093***	-0.008	-0.013	0.002
	(0.017)	(0.024)	(0.029)	(0.032)
Year fixed effects	Yes***	Yes***	Yes***	Yes***
Industry fixed effects	Yes***	Yes***	Yes***	Yes***
Constant	-0.23	-4.279***	-4.443***	-3.927***
	(0.418)	(0.686)	(0.811)	(0.850)
Number of observations	47,123	47,048	47,048	46,553
Log Likelihood	-5,219	-2,796	-1,816	-1,323

Notes: Dependent variable: Employment status in ( $t+2$ ). Results of probit regressions. Robust standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

## 5. Conclusions

New and emerging technologies provide a serious challenge to the future of employment. As machines learn to accomplish not only routine tasks but also activities that require abstract skills and abilities to work in an unstructured environment, the concern rises that automation will wipe out a great number of jobs. This paper provided new evidence on the impact of automation of jobs on individual-level occupational mobility. In particular, it shows that the expected probability of occupational changes rises with the occupation-specific risk of automation. This is particularly pronounced for such occupational changes as losing a job, demotion at current place of employment, or starting a new job in a different field. According to respondents' self-reported estimations, these changes are likely to occur within the next two years. This is quite in line with the prediction by Frey and Osborne (2017) who conclude that the current state of technology is such that it will be possible in the next one to two decades to replace about a half of the total US employment by machines.

An important question is then which additional skills should workers in jobs at high risk of automation acquire in order to make themselves less susceptible to negative consequences of automation. The empirical results in this paper provide an indication that workers in high-risk occupations do indeed intend to gain additional qualifications and training in the near future. However, no information was available with regard to the type of training they were more likely to choose. Hence, more research is needed in order to develop educational strategies to make workers less susceptible to automation.

Moreover, given the recent rise of entrepreneurial activities, and in particular self-employment without employees, there is a concern regarding the quality of such businesses. For instance, a high risk of automation may drive self-employed out of necessity. However, the result of this paper is that people in occupations at high risk of automation are significantly less likely than people in low-risk occupations to be both nascent entrepreneurs and to make transitions from paid employment into self-employment. This result holds for both self-employed with and without employees. Hence, new technology is likely to create new entrepreneurial opportunities in occupations that consist of tasks that are less likely to be computerized in the near future.

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## Appendix

Table A1: Descriptive statistics for independent variables

	Definition and measurement	Mean	Standard deviation
Occupation-specific automation probability	The risk of a certain occupation being computerized in the next one to two decades. Adapted from Frey and Osborne (2017)	0.471	0.313
Years of formal education	Number of years spent in formal education	12.219	2.700
Tenure, years	Number of years spent at current place of employment	11.016	10.367
Experience of unemployment, years	Number of years spent in unemployment	0.917	2.307
Age	Respondent's age	41.971	22.368
Male	Dummy variable indicating the gender of a respondent (=1 if male, =0 if female)	0.489	0.500
German	Dummy variable indicating the nationality of a respondent (=1 if German, =0 otherwise)	0.715	0.451
Children in household	Dummy variable indicating if there are children in household (=1 if yes, =0 if no)	0.393	0.488
Willingness to take risks	Likert-type scale from 0 ("fully unwilling to take risks" to 10 ("fully willing to take risks") Precise question: "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?"	4.564	2.329
Conscientiousness	Average score from the scores on 3 items (7-point Likert-type scale) measuring the Big Five dimension "Conscientiousness"	5.827	0.961
Extraversion	Average score from the scores on 3 items (7-point Likert-type scale) measuring the Big Five dimension "Extraversion"	4.818	1.140
Agreeableness	Average score from the scores on 3 items (7-point Likert-type scale) measuring the Big Five dimension "Agreeableness"	5.398	0.978
Openness	Average score from the scores on 3 items (7-point Likert-type scale) measuring the Big Five dimension "Openness to experience"	4.485	1.212
Neuroticism (reversed emotional stability)	Average score from the scores on 3 items (7-point Likert-type scale) measuring the Big Five dimension "Neuroticism"	3.865	1.228
Internal locus of control	Average score on two 7-point Likert scales measuring internal locus of control. Precise questions: "How my life goes depends on me" and "One has to work hard in order to succeed"	5.737	0.954
External locus of control	Average score on six 7-point Likert scales measuring external locus of control. Precise questions: 1) What a person achieves in life is above all a question of fate or luck; 2) Compared to other people, I have not achieved what I deserve; 3) I frequently have the experience that other people have a controlling influence over my life; 4) The opportunities that I have in life are determined by the social conditions; 5) Inborn abilities are more important than any efforts that one can make; 6) I have little control over the things that happen in my life.	3.683	0.940