The Effects of Digitalization on Employment and Entrepreneurship

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Abstract

We investigate the impacts of the new wave of digitalization and artificial intelligence (AI) on individual transitions in the US labor market. Based on large representative panel data–the matched monthly Current Population Survey–we provide evidence that significant effects of AI are already observable at the individual level. In particular, a larger risk of digitalization of an individual's current occupation is associated with a higher likelihood of switching occupations or becoming non-employed. We find that entry into unincorporated entrepreneurship is most likely at a medium level of digitalization risk, whereas there is no significant association between digitalization risk and entry into incorporated entrepreneurship. We also find significant gender differences in the effects of digitalization on transitions into different types of entrepreneurship.

Keywords: Digitalization, artificial intelligence, entrepreneurship, incorporated, unincorporated, occupational choice, unemployment

JEL classification: J22, J23, L26, O33

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1. Introduction

What is the future of employment in the digital age where artificial intelligence (AI) is increasingly efficient in performing "human" tasks? A recent study by Frey and Osborne (2017) that received substantial academic and media attention concludes that about 47 percent of the US labor force are currently in jobs that are highly likely to be replaced by machines in the next one to two decades. This result has largely been confirmed by other studies for various countries, although the average risk of automation varied a lot across countries (see, e.g., Arntz et al. 2017, Sorgner et al. 2017a). While the mentioned studies provide aggregate estimates of the risk of digitalization by occupations, it is not clear how this risk affects an individual's labor market outcomes. Thus, the aim of this paper is to investigate workers' responses to the risk of automation[1] of their occupation by studying their switching behavior on the labor market. In particular, we analyze whether entrepreneurship provides a viable route for individuals whose current jobs in paid employment are taken over by AI.

We provide the following contributions. First, we analyze whether the occupational risk of automation due to the current wave of digitalization and AI leads to a higher risk of unemployment that is already observable today. The study by Frey and Osborne (2017) relies on expert judgments from the year 2013 concerning the technological possibilities to perform occupation-specific tasks automatically in the near future. Even if technology allowed performing certain tasks very efficiently, this should not necessarily lead to job replacement effects. For instance, existing labor market regulations or lack of necessary infrastructure might prevent immediate deployment of new technologies. Hence, it is not directly evident whether the predicted risk of digitalization of occupations necessarily leads to higher unemployment.

[1] We use the terms "digitalization" and "automation" interchangeably throughout the paper to describe automation due to the new wave of technological developments in artificial intelligence and machine learning.

Second, even if new technologies could replace many jobs that still exist today, entrepreneurship might be a viable alternative to being in paid employment for many individuals. Digital technologies might even enable and facilitate the start-up process (von Briel, Davidsson, and Recker 2018), for instance, by improving access to finance by means of crowdfunding, reducing costs of communication and ICT infrastructure by means of cloud computing, and decreasing initial investments in human labor by means of employing artificial intelligence. A number of studies show that the choice of entrepreneurship over paid employment may be driven by a higher job and life satisfaction that result from being one's own boss, rather than from expectations of a financial profit (Benz and Frey 2008, Fritsch et al. 2018). The possibility that people become entrepreneurs might considerably reduce the expected levels of unemployment due to automation of jobs.

However, the loss of a job due to digitalization may lead to an increase in the levels of necessity entrepreneurship, that is, the decision to become self-employed because of the lack of alternative opportunities in dependent employment (Fairlie and Fossen, 2018). Necessity entrepreneurship can be expected to lead to lower economic and psychological well-being of individuals. Thus, another contribution of the present paper is to investigate how the occupational risk of digitalization affects an individual transition into different types of entrepreneurship. We consider transitions into unincorporated and incorporated entrepreneurship because they may be driven by different motives, such as necessity vs. opportunity motives (Levine and Rubinstein 2016). Last but not least, individuals may escape unemployment in their occupation by switching to a different occupation within paid employment, which would imply additional costs, for instance, related to acquisition of a new qualification.

Our detailed analysis of individual switching behavior on the labor market as a response to the risk of automation of occupations provides a more complete picture of the effects of digitalization on employment by taking account of individual differences in socio-demographic characteristics and human capital variables. Based on comprehensive and representative individual-level monthly rotating panel data from the Current Population Survey (CPS), we analyze which trends on the labor market due to digitalization of occupations can already be observed. Our results reveal that significant effects of automation of occupations due to the current wave of digitalization and AI can already be detected at the level of individual labor market transitions.

In more detail, a higher risk of digitalization of occupations is associated with a higher likelihood of occupational change and switching from paid employment into non-employment in the subsequent year. With regard to entrepreneurship, we find differentiated and non-linear effects. Individuals in occupations with a rather low level of automation risk tend to move to incorporated entrepreneurship, which points to the opportunity-driven motivation for entrepreneurship of persons with skills that cannot be automated. At a medium level of automation risk, individuals are most likely to switch to unincorporated entrepreneurship, which is more likely to be necessity-driven. Thus, entrepreneurship can mitigate the unemployment risk for people at a medium risk of digitalization. However, the propensity to become an entrepreneur is lowest when the occupational risk of automation is very low or very high. Thus, necessity entrepreneurship is not a viable option for people at the highest risk of losing their employment due to the current wave of automation, and these workers become unemployed instead. Especially for women at a high risk of digitalization, entrepreneurship does not currently provide an escape route.

The paper proceeds as follows. Section 2 provides an overview of the literature on the effects of automation on jobs and formulates hypotheses. Section 3 describes the data that we use in the empirical analysis and discusses econometric issues. Section 4 presents the results of the empirical analysis and robustness checks. Section 5 discusses the results and the limitations of the analysis, and section 6 concludes.

2. Theoretical background and hypotheses

Most of the recent studies on the effects of automation on employment were primarily concerned with macro effects of digitalization on (local) labor markets. Frey and Osborne (2017) have estimated that around 47 percent of the US labor force will face a high risk of automation of their jobs. Several follow-up studies for other countries could at least partly confirm that a significant share of jobs will face such a risk. For instance, Bode et al. (2017) provide very similar estimates for selected G20 countries, while their focus is on gender differences in the susceptibility of jobs to automation. Arntz et al. (2016, 2017) arrive at a less pessimistic scenario by emphasizing the within-occupational heterogeneity of tasks. Acemoglu and Restrepo (2017) show that deployment of industrial robots during the time period from 1990 to 2007 reduced the employment to population ratio and wages on the US labor markets.

The evidence of the effects of automation at the level of individuals is scarce. Bode et al. (2018) use the automation probabilities estimated by Frey and Osborne (2017) to analyze the type of individuals who are more likely to be affected by automation of occupations. Using various household surveys for Germany, they show that individuals with certain socioeconomic and psychological characteristics are at a higher risk of digitalization, while characteristics typical of entrepreneurial individuals (e.g., higher levels of human capital, high openness to experiences, creativity) protect workers from automation of their jobs. It also appears that the occupational risk of automation is related to labor market transitions into self-employment and unemployment in Germany (Sorgner 2017).

Indeed, it can be assumed that a high risk of automation of an occupation increases the risk of becoming unemployed, due to a decreasing demand for skills that perform occupation-specific tasks that now can be automatized. At the same time, implementation of new technologies may take a certain time, such that the effects of automation on transitions into unemployment and non-employment might not immediately be observable. In their study, Frey and Osborne (2017) emphasize that occupations might face a very high risk of automation in the next 10-20 years. In addition, protective labor market regulations might help mitigate the displacement of workers. Thus, while it can be expected that automation of occupations will lead to more transitions into unemployment and non-employment, it is not clear whether these effects can already be observed. Hence, we state:

H1: Higher occupational risk of digitalization is already leading to a higher propensity of transitions from paid-employment to non-employment.

Moreover, a higher risk of automation in an occupation might motivate people who have anticipated this risk to change their occupation, for instance, by acquiring a new or an additional qualification.[2] Since this process might be costly, it is not obvious whether a higher risk of automation will necessarily result in a high propensity of occupational change. In addition, previous arguments concerning transition into unemployment (labor market regulations, time needed for implementation of new technologies) also apply for the case of transitions into a new occupation. Thus, we formulate:

H2: Higher occupational risk of digitalization is already leading to a higher propensity of occupational changes.

Transitions from paid employment to entrepreneurship represent a particularly interesting case. A large body of literature has investigated the determinants of entrepreneurial choice, that is, the decision to become self-employed, as opposed to the decision to remain in paid employment. It has been assumed that people select their occupational status (entrepreneurship vs. paid employment) according to the expected utility. They then start an own business venture if the expected utility from entrepreneurship exceeds the expected utility from remaining in paid-employment (Knight 1921; Lucas 1978). It is further assumed that entrepreneurial ability is a crucial factor in determining the expected utility from self-employment. It is not entirely clear what exactly constitutes entrepreneurial ability, although many studies have shown that higher levels of education, work experience, and personality traits such as lower risk aversion make people more likely to become entrepreneurs (see Parker 2009, for an overview).

[2] According to Google Trends, Google searches for the word "digitalization" have increased exponentially after 2012, thus, hinting towards a stronger awareness of workers concerning the digitalization risk of their occupation.

Recent studies highlight a strong heterogeneity of entrepreneurs and call for a more detailed analysis of different types of entrepreneurs. For instance, incorporated and unincorporated entrepreneurs appear to be driven by different motivations, and, as a result, they realize different earnings in self-employment (Levine and Rubinstein 2016). Sorgner et al. (2017b) analyze the recent rise in the levels of entrepreneurs without employees and show that solo-entrepreneurs are on average less likely to earn higher incomes than entrepreneurs with employees. At the same time, the group of solo-entrepreneurs is very heterogeneous, and it also contains superstars that realize very high incomes. In addition, Åstebro and Tåg (2017) show that there is a larger probability that the founder will be coming from non-employment in a sole proprietorship than in an incorporated firm. This might indicate that more able entrepreneurs form incorporated ventures.

Occupation is an important determinant of entrepreneurial choice, and characteristics of occupation-specific environments may facilitate entrepreneurship. For instance, occupations that provide high levels of entrepreneurship-relevant human capital and role models of entrepreneurship may exhibit higher entry rates into entrepreneurship, but also if occupation-specific risk of unemployment is high (Sorgner and Fritsch 2017). This appears relevant for persons employed in occupations with high risk of digitalization, who may consider becoming entrepreneurs as a way to avoid potential future unemployment. Such start-ups may be characterized by rather low levels of growth aspiration and, thus, are more likely to be unincorporated. In turn, incorporated entrepreneurship may arise out of recognition of a profitable entrepreneurial opportunity. Such start-ups are less likely to be necessity-driven, and they usually require high levels of entrepreneurship-relevant human capital. Entrepreneurship-relevant human capital includes, for instance, managerial abilities (Lucas 1978), creativity that is necessary to recognize new opportunities (Ward 2004), but also strong social skills that are essential to build a network of customers and suppliers, acquire financial capital, and lead a team of employees

(Baron and Tang 2009). These skills currently represent bottlenecks to automation (see Table A1 in Appendix A). Therefore, we hypothesize:

H3a: Higher occupational risk of digitalization leads to a higher propensity of transition from paid employment into unincorporated entrepreneurship.

H3b: Higher occupational risk of digitalization leads to a lower propensity of transition from paid employment into incorporated entrepreneurship.

3. Data and empirical strategy

3.1. Data

Current Population Survey

For the purpose of current analysis, we employ the 2010-2017 waves of the monthly Current Population Survey (CPS). The CPS is a representative survey of households in the United States. The U.S. Bureau of Labor Statistics uses the CPS to estimate the widely reported national unemployment rate. Households are interviewed in four consecutive months, then pause for eight months, and then are surveyed again in four more consecutive months. We use the IPUMS-CPS provided by Flood et al. (2017), who match these consecutive individual observations to construct rotating panel data. The first three months of each four-months survey spell can be linked to the subsequent month, so 75% of all observations can be connected to the following month.

The panel data structure allows us to observe labor market transitions from one month to the next based on questions on the current employment status in two consecutive months. It is further possible to distinguish between incorporated and unincorporated entrepreneurs. We use a wide set of control variables, such as socio-demographics (age, gender, marital status, children, race), formal educational degree (four categories), residence in a metropolitan area, and region (at the level of US states), and we include year and month dummies to control for the business cycle and seasonal effects. The full sample contains 2,179,142 person-year observations.

Digitalization risk of occupations

Our measure of occupational susceptibility to digitalization comes from a recent study by Frey and Osborne (2017).[3] The authors estimate automation probabilities for 702 occupations for the next 10-20 years based on expert judgments and statistical indicators on selected characteristics of occupations from O*Net.[4] They first asked an expert group of machine learning or robotics researchers to hand-select occupations that they are most confident about being fully automatable, or not at all, in the foreseeable future of about 20 years. The experts identified 37 occupations with extremely high and 34 with extremely low susceptibility to automation. Frey and Osborne combined these expert judgments with data on nine selected O*Net indicators of occupational tasks that arguably represent automation bottlenecks[5] to construct a training dataset. This training dataset indicates how the probability of digitalization of the 71 occupations varies with the O*Net scores of the bottleneck variables. Based on this training data, they then predicted digitalization probabilities for all 702 occupations from the known O*Net bottleneck indicators.

We match the automation probabilities by Frey and Osborne with CPS, which employs the same occupational classification (6-digit codes of the System of Occupational Classification, SOC).

3.2. Empirical strategy

We estimate discrete choice models of the probabilities of labor market transitions. We start with the sample of paid employees in the first month of a two-

[3] In work currently in progress, for comparison we also use the methods to estimate digitalization risks of occupations suggested by Felten et al. (2018) and Brynjolfsson et al. (2018).
[4] O*Net is a database of quantitative indicators about a variety of attributes for 903 occupations in the US, compiled by the US Department of Labor. Based on expert opinions or worker surveys, these indicators cover various job-oriented attributes (occupational requirements, workforce characteristics, occupation-specific information) and worker-oriented attributes (worker characteristics, worker requirements and experience requirements). By combining subjective and objective information, Frey and Osborne aim at overcoming the shortcomings of purely subjective or purely objective rankings. Subjective rankings such as the one by Autor et al. (2003) are not replicable and may involve misjudgments while objective rankings such as the one by Jensen and Kletzer (2010) (for offshorability) may generate implausible or even unreliable results.
[5] The bottleneck indicators are listed in Table A1 in Appendix. They measure, for each occupation, the level (sophistication) of those work requirements that Frey and Osborne consider to be particularly difficult to computerize in the near future.

months pair, *t*, and estimate the probabilities of individual transitions between month *t* and the next month, *t*+1. We consider the following five choices: The respondent remains in the same occupation in paid employment (reference category), remains in paid employment but changes occupation (as measured by changes in the SOC code), enters unincorporated entrepreneurship, enters incorporated entrepreneurship, or moves to non-employment (including unemployment)[6]. We estimate multinomial logit models to account for the categorical nature of our dependent variable. All explanatory variables are measured in month *t* and thus before a potential transition occurs, which rules out reverse causality. We include linear and squared terms of the automation probability of the respondent's occupation to account for potential nonlinear effects on the transition probabilities.

4. Results

4.1. Descriptive statistics

Table 1 shows the descriptive statistics for the full sample and by the type of labor market transition. The average risk of digitalization in the full sample of paid employed individuals is 50.1%, which varies a lot depending on the type of transition in the subsequent period. The highest average risk of digitalization is observed for individuals becoming non-employed in the next month (63.3%), followed by those who switch their occupation within paid employment (55.1%) and those who enter into unincorporated entrepreneurship (54.8%). The lowest average risk of automation is observed for individuals switching into incorporated self-employment in the next month (43.4%). There are also differences with regard to socio-demographic characteristics between individuals making transitions to different employment states. For instance, respondents who switch into incorporated self-employment are more likely to be males, of older age, coming more often from a metropolitan area, and have a higher educational

[6] When we distinguish between registered unemployment and non-participation in our analysis, we do not find significant differences in the effects of automation risk on transitions into these two states. Therefore, we consider them as one category in the results reported here.

degree on average, as compared to the other groups, including non-switchers. Entry into non-employment is more likely for younger individuals, with on average lower levels of education.

We also observe gender-specific differences in individual characteristics, which are reported in Tables A2 and A3 in Appendix A. Female respondents face on average higher risk of automation (53.1%) than male respondents (48.6%). Moreover, women who enter incorporated entrepreneurship face on average higher risk of automation (46.3%), as compared to males (42.1%). This is different for entries into unincorporated entrepreneurship, where female switchers have on average lower risk of automation of their occupations (52.3%) than males (56.7%).

Table 1: Descriptive statistics, full sample

	Full sample		No change		Entry into unincorporated entrepreneurship		Entry into incorporated entrepreneurship		Entry into non-employment		Occupation change within paid employment	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Digitalization probability	0.508	0.374	0.501	0.375	0.548	0.352	0.434	0.372	0.633	0.337	0.551	0.369
Male	0.515	0.500	0.516	0.500	0.578	0.494	0.689	0.463	0.452	0.498	0.536	0.499
Age	41.8	12.1	42.0	12.0	43.3	11.6	45.3	10.7	37.3	12.5	40.4	12.2
Metropolitan area	0.817	0.386	0.815	0.388	0.806	0.395	0.860	0.347	0.817	0.386	0.849	0.358
No. of children in the househ.	0.903	1.147	0.908	1.146	0.936	1.202	1.046	1.268	0.860	1.196	0.854	1.142
Married	0.578	0.494	0.585	0.493	0.588	0.492	0.736	0.441	0.436	0.496	0.534	0.499
Less than high school	0.068	0.252	0.065	0.246	0.140	0.347	0.043	0.203	0.138	0.345	0.083	0.276
High school degree	0.281	0.449	0.279	0.448	0.304	0.460	0.237	0.425	0.328	0.470	0.293	0.455
Some college	0.312	0.463	0.313	0.464	0.270	0.444	0.264	0.441	0.332	0.471	0.301	0.459
University degree	0.339	0.473	0.344	0.475	0.286	0.452	0.456	0.498	0.202	0.402	0.323	0.468
White	0.821	0.383	0.826	0.379	0.831	0.375	0.841	0.366	0.755	0.430	0.777	0.416
Black	0.093	0.291	0.090	0.286	0.074	0.262	0.071	0.258	0.143	0.350	0.123	0.328
Asian	0.055	0.229	0.055	0.227	0.061	0.239	0.070	0.255	0.056	0.231	0.067	0.250
Other race	0.030	0.171	0.029	0.169	0.034	0.181	0.018	0.134	0.046	0.209	0.033	0.178
Person-year observations	2,179,142		1,979,243		5,641		2,240		58,771		133,247	

Note: Means and standard deviations by type of labor market transition between two consecutive months.
Data source: Matched monthly Current Population Survey, 2010-2017.

4.2. Results of the multivariate analysis

The results of the multinomial logit estimation are presented in Table 2 (multinomial logit coefficients). The dependent variable indicates changes in the labor market status in the subsequent month; the reference category is “no change”. The standard errors are robust to clustering at the level of occupations. For the ease of interpretation, Figures 1-4 in Appendix B show the estimated probabilities of month-to-month labor market transitions as a function of the risk of automation due to the current wave of digitalization and AI (evaluated at the mean values of the other explanatory variables).

We find that individuals whose occupations are at a higher risk of digitalization are significantly more likely to switch from paid employment to non-employment (Figure 1) or to change their occupation (Figure 2).[9] The monthly probability of a transition into non-employment is about 2.3-2.4 percent at higher levels of occupational automation risk, but only 1.3 percent at the lowest level. The probability of an occupational change within wage and salary employment from an occupation with the highest automation risk is about 6.8 percent, as compared to 5 percent for a low-risk occupation.[10] This confirms our Hypotheses 1 and 2.

With respect to entrepreneurship, the results are more nuanced. Transitions into unincorporated self-employment are most likely from occupations with a medium risk of automation (about 0.3 percent), and it is lowest from occupations with very high or very low risk of automation (Figure 3). The inverse U-shape relationship is statistically significant, as indicated by the significant squared term of the digitalization probability (Table 2). The results for entry into incorporated self-employment suggest that the probability of entry into

[9] Although the coefficients of the linear and squared terms of the digitalization risk are individually insignificant in column (4) of Table 2, they are jointly significant at the 1% level, as indicated at the bottom of the table.

[10] The probabilities are relatively high, because we consider a change in a 6-digit occupational code as an occupational change. The results remain significant when we only consider changes at a 2-digit level of occupational classification.

incorporated self-employment is the highest for low levels of automation risk (less than 0.1 percent), but this association is not statistically significant (Figure 4).

Table 2: Effects of the occupational risk of digitalization on labor market transitions, full sample

	(1) Entry into unincorporated entrepreneur-ship	(2) Entry into incorporated entrepreneur-ship	(3) Entry into non-employment	(4) Occupation change within paid employment
Digitalization probability	1.666**	-0.178	1.541***	0.267
	(0.8205)	(0.6854)	(0.4052)	(0.3107)
Digital. prob. squared	-1.430*	0.104	-0.949**	0.0423
	(0.7659)	(0.7043)	(0.3714)	(0.3030)
Male	0.215	0.695***	-0.253***	0.0937***
	(0.1489)	(0.0678)	(0.0605)	(0.0327)
Age	0.0530***	0.102***	-0.115***	-0.0236***
	(0.0146)	(0.0191)	(0.0080)	(0.0047)
Age squared	-0.000504***	-0.000938***	0.00108***	0.000174***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Metropolitan area	-0.160***	0.169**	-0.0554***	0.115***
	(0.0426)	(0.0684)	(0.0146)	(0.0122)
No. of children in househ.	-0.00546	0.0265	0.0339***	-0.0244***
	(0.0139)	(0.0218)	(0.0058)	(0.0045)
Marital status: married	-0.0460	0.401***	-0.219***	-0.0450***
	(0.0369)	(0.0639)	(0.0295)	(0.0119)
High school degree	-0.548***	0.302**	-0.525***	-0.142***
	(0.0563)	(0.1411)	(0.0290)	(0.0372)
Some college	-0.724***	0.350**	-0.648***	-0.219***
	(0.0856)	(0.1411)	(0.0412)	(0.0470)
University degree	-0.728***	0.627***	-0.985***	-0.197***
	(0.1169)	(0.1567)	(0.0656)	(0.0589)
Black	-0.200**	-0.190**	0.397***	0.289***
	(0.0837)	(0.0893)	(0.0305)	(0.0236)
Asian	-0.0202	0.0986	0.211***	0.180***
	(0.0984)	(0.1050)	(0.0302)	(0.0329)
Other non-white	-0.0262	-0.295*	0.300***	0.0847***
	(0.0744)	(0.1581)	(0.0238)	(0.0177)
Year dummies	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes
Number of observations	2,179,142			
Log-likelihood	-804,297			
Test of joint significance of the linear and squared terms of the digitalization probability:				
χ^2	4.306	0.258	28.51	13.07
p-value	0.116	0.879	<0.001	0.001

Notes: Results of the multinomial logit model estimation for the full sample. Reference category for dependent variable is “no occupational change”. Logit coefficients reported. Standard errors are robust to clustering at the occupation level. */**/***: Significance at the 10%/5%/1% levels. *Data source*: Matched monthly Current Population Survey, 2010-2017.

These differences between incorporated and unincorporated entrepreneurs suggest strong variations in their motivations, which is in line with previous research. These findings provide partial support for Hypothesis H3a that proposed a linear and positive relationship between the risk of automation and the probability of entry into unincorporated entrepreneurship: This is true only up to medium levels of digitalization risk. Hypothesis H3b on the effects on incorporated entrepreneurship finds only weak statistical support. The finding that transitions into unincorporated entrepreneurship are less likely for workers facing very high levels of automation risk suggests that necessity entrepreneurship is not a viable option for these individuals because the tasks they are performing can be taken over by digital machines and AI. Thus, entrepreneurship does not offer a feasible escape route for workers at the highest risk of automation, and they become unemployed or have to switch their (wage and salary) occupation instead.

4.3. Gender-specific differences in the effects of digitalization on labor market transitions

In this section, we perform our main analysis separately for men and women, in order to account for occupational segregation and, as a result, different levels of automation risk that men and women may face (Sorgner et al., 2017a). Moreover, research shows that women are in general less likely to become entrepreneurs than men (Caliendo et al., 2015).

Remarkably, we find strong gender differences concerning transitions into unincorporated entrepreneurship (see Tables 3 and 4 below and Figures 5-11 in Appendix B). While higher risk of automation increases the propensity to enter into unincorporated entrepreneurship for men almost monotonically (Figure 7), confirming Hypothesis 3a, the results for women are different (Figure 11). For women, a higher risk of automation (up to 50%) first increases the probability to enter unincorporated entrepreneurship, but then decreases it substantially for very high levels of automation risk. Thus, the inverse U-shape of this relationship we found for the pooled sample is driven by the female subsample.

Concerning the transitions into non-employment, both men and women are more likely to enter non-employment when the risk of automation of their occupation increases, while this probability is higher for women than for men (Figures 5 and 9). The probability of a transition into another occupation in wage and salary employment increases with the risk of automation of the current job for both, men and women (Figures 6 and 10).

Table 3: Effects of the occupational risk of digitalization on labor market transitions for men

	(1) Entry into unincorporated entrepreneur-ship	(2) Entry into incorporated entrepreneur-ship	(3) Entry into non-employment	(4) Occupation change within paid employment
Digitalization probability	1.292*	-0.205	1.272***	0.174
	(0.7794)	(0.7522)	(0.4070)	(0.3015)
Digital. prob. squared	-0.753	0.156	-0.555	0.160
	(0.7612)	(0.7651)	(0.4062)	(0.3086)
Age	0.0527***	0.0992***	-0.120***	-0.0293***
	(0.0150)	(0.0234)	(0.0103)	(0.0053)
Age squared	-0.000500***	-0.000895***	0.00121***	0.000243***
	(0.0002)	(0.0003)	(0.0001)	(0.0001)
Metropolitan area	-0.164***	0.165**	-0.0611***	0.130***
	(0.0528)	(0.0831)	(0.0198)	(0.0167)
No. of children in househ.	-0.00460	0.0287	-0.0139*	-0.0152***
	(0.0188)	(0.0270)	(0.0079)	(0.0052)
Marital status: married	-0.130***	0.330***	-0.534***	-0.0434***
	(0.0486)	(0.0796)	(0.0195)	(0.0142)
High school degree	-0.546***	0.350**	-0.509***	-0.213***
	(0.0586)	(0.1671)	(0.0355)	(0.0269)
Some college	-0.770***	0.392**	-0.630***	-0.298***
	(0.1009)	(0.1668)	(0.0452)	(0.0376)
University degree	-0.750***	0.653***	-1.028***	-0.258***
	(0.1166)	(0.1843)	(0.0643)	(0.0504)
Black	-0.196*	-0.154	0.526***	0.245***
	(0.1063)	(0.1040)	(0.0328)	(0.0271)
Asian	0.0405	0.0717	0.269***	0.204***
	(0.1197)	(0.1305)	(0.0399)	(0.0482)
Other non-white	-0.0914	-0.131	0.381***	0.0707***
	(0.0937)	(0.1980)	(0.0318)	(0.0253)
Year dummies	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes
Number of observations	1,123,291			
Log-likelihood	-411,669			
Test of joint significance of the linear and squared terms of the digitalization probability:				
χ^2	7.526	0.128	35.50	14.66
p-value	0.023	0.938	<0.001	<0.001

Notes: Results of the multinomial logit model estimation for the men. Reference category for dependent variable is “no occupational change”. Logit coefficients reported. Standard errors are robust to clustering at the occupation level. */**/***: Significance at the 10%/5%/1% levels. *Data source*: Matched monthly Current Population Survey, 2010-2017

Table 4: Effects of the occupational risk of digitalization on labor market transitions for women

	(1) Entry into unincorporated entrepreneur-ship	(2) Entry into incorporated entrepreneur-ship	(3) Entry into non-employment	(4) Occupation change within paid employment
Digitalization probability	2.010	-0.232	1.648***	0.375
	(1.3602)	(0.8720)	(0.5575)	(0.4314)
Digital. prob. squared	-2.124*	0.105	-1.160**	-0.0846
	(1.2058)	(0.8772)	(0.4892)	(0.3964)
Age	0.0518*	0.107***	-0.119***	-0.0162**
	(0.0276)	(0.0335)	(0.0101)	(0.0063)
Age squared	-0.000471	-0.000988**	0.00109***	0.0000857
	(0.0003)	(0.0004)	(0.0001)	(0.0001)
Metropolitan area	-0.144**	0.186*	-0.0437**	0.0990***
	(0.0638)	(0.0956)	(0.0205)	(0.0153)
No. of children in househ.	0.0159	0.0392	0.0954***	-0.0365***
	(0.0213)	(0.0413)	(0.0074)	(0.0082)
Marital status: married	0.0579	0.522***	0.0300	-0.0522***
	(0.0481)	(0.1026)	(0.0213)	(0.0166)
High school degree	-0.502***	0.174	-0.544***	-0.0218
	(0.0975)	(0.2111)	(0.0387)	(0.0596)
Some college	-0.604***	0.252	-0.653***	-0.0946
	(0.1302)	(0.2529)	(0.0538)	(0.0718)
University degree	-0.631***	0.564**	-0.942***	-0.0928
	(0.1881)	(0.2478)	(0.0810)	(0.0825)
Black	-0.203*	-0.254*	0.301***	0.333***
	(0.1133)	(0.1385)	(0.0329)	(0.0292)
Asian	-0.0893	0.152	0.160***	0.153***
	(0.1390)	(0.1553)	(0.0396)	(0.0267)
Other non-white	0.0463	-0.725**	0.238***	0.0961***
	(0.1135)	(0.3060)	(0.0298)	(0.0242)
Year dummies	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes
Number of observations	1,055,851			
Log-likelihood	-391,129			
Test of joint significance of the linear and squared terms of the digitalization probability:				
χ^2	4.946	0.515	12.20	7.535
p-value	0.084	0.773	0.002	0.023

Notes: Results of the multinomial logit model estimation for the women. Reference category for dependent variable is "no occupational change". Logit coefficients reported. Standard errors are robust to clustering at the occupation level. */**/***: Significance at the 10%/5%/1% levels. *Data source*: Matched monthly Current Population Survey, 2010-2017.

5. Discussion

Our study is not without limitations, the most important of which result from data availability. One of the strengths of our data is its rotating panel structure, which allows us to identify labor market transitions that are essential to our analysis. Although these data provide a number of important individual-level characteristics that we use as control variables in our empirical analysis, there is no information about personality traits or individual motives. From previous research, it is known that such "soft" factors are important determinants of an individual's occupational choice including the choice of self-employment (see, e.g., Caliendo et al. 2015). However, we are confident that by controlling for an individual's level of formal education, we have at least partly captured these additional measures of ability that are not observable in our data.

Another issue concerns transitions to a different occupation, which could be due to more flexible labor markets in general, making it relatively easy to switch to similar occupations. Our main analysis employs occupational codes at a 6-digit level of SOC (the most detailed level of occupational classification that is available in the data). One might argue that occupational changes defined at such a narrow level may occur "occasionally", for instance, when an employee changes her employer or due to coding inaccuracies in the panel data. However, in a robustness check, we also define occupational changes at a 2-digit level of SOC, thus, accounting only for transitions between broader occupational fields, and still find similar results.

Moreover, it could be argued that our measure of digitalization risk might not solely capture the extent at which technological advances allow automatizing occupational content but might also correlate with other occupation-specific risks, such as offshoring risk. Although the offshoring risk is decreasing in general, and re-shoring of jobs seems to become a new global trend, it still might be relevant for our analysis. At a closer examination, however, it becomes clear that many occupations with high risk of digitalization, such as bus drivers, fast-food cooks and cashiers cannot be offshored because of the required geographic proximity to the customers. In turn, occupations that cannot entirely be digitalized, such as content moderators,[11] are likely to be offshored. Hence, we are confident that our results are not driven by the risk of an occupation being offshored.

[11] Content moderators sift through online visual and textual content to eventually decide upon appropriateness of that content and flag it correspondingly.

6. Conclusions

There is general concern about the future of work in the digital age, when digital machines and AI will be able to replace human labor on a large scale. Recent literature suggests that one in two workers in the US will be at high risk of digitalization of their occupations in the near future.

The present study sheds more light on the effects of digitalization risk on workers by studying individual-level labor market transitions. This micro-level approach allows us to estimate the effects of digitalization on various labor market risks such as unemployment and opportunities such as entrepreneurship. In contrast to prior literature, which primarily focuses on macro effects of digitalization, we account for a wide set of individual characteristics, such as socio-demographic characteristics, human capital variables, and the region of residence.

The worker replacement effects of digitalization are already evident in more frequent labor market transitions into non-employment from employment in occupations facing very high risk of automation. Occupations with a higher risk of automation also lead to more frequent occupational changes. This suggests that workers are already anticipating changes in the labor markets due to digitalization and AI and react accordingly to prevent potential unemployment in the future. This proactive behavior of workers could mitigate the overall job-replacement effects of digitalization. Future research should investigate which occupations individuals are more likely to choose, for instance, in terms of occupational risk of automation and required levels of qualification. These issues remain beyond the scope of the present study.

Another important finding that has largely been ignored in the discussion about the future of employment is that the risk of digitalization also affects individual transitions into entrepreneurship. We show that transitions into incorporated entrepreneurship, which is linked to productive entrepreneurship in terms of growth orientation and job creation, tend to be more likely from rather "secure" occupations with low levels of automation risk. Transitions into unincorporated entrepreneurship, which is linked to necessity entrepreneurship, are most likely from occupations with medium level of automation risk and they are least likely from occupations with very high or very low risk. Thus, while for workers in occupations with a medium automation risk unincorporated entrepreneurship is used as an escape route, entrepreneurship does not seem to be a viable option for workers, in particular women, in occupations with very high automation risk. This is plausible because self-employment is not sustainable if digital machines and AI will soon be able to perform almost all the tasks that these workers are currently performing. As we show, workers at the highest risk of automation end up in non-employment instead.

In summary, we demonstrate that the new wave of digitalization and AI is already having an impact on labor markets. However, the results of the present study also suggest that AI will not necessarily lead to the skyrocketing unemployment rates that prior literature suggested, because labor markets are already adapting to the new wave of technological change. We show that workers are responding by changing their occupations or by becoming entrepreneurs. However, the latter option is not available to the most vulnerable workers in occupations at the highest risk of automation, especially women. Public policy should help these workers to adapt and acquire new skills necessary to remain productive. On the other end of the spectrum, we also show that digitalization is creating new opportunities for growth-oriented entrepreneurs who make the transition from paid employment to entrepreneurship even without being at a high own risk of occupational automation.

Digitalization is an ongoing process that will develop more rapidly in the coming decades. There are still challenges related to the legal framework that regulates the deployment of new technologies, such as self-driving vehicles, and uncertainties regarding the general acceptance of AI in the society. Therefore, it can be expected that labor market adjustments, which are already occurring, will intensify in the future. This study has shown that entrepreneurship will play an important role in this process.

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Appendix A: Supplementary tables

Table A1: Automation bottlenecks (Frey and Osborne 2017)

Automation bottleneck	O*Net item
Perception and manipulation	(i) Finger dexterity Ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects. (ii) Manual Dexterity Ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects. (iii) Cramped Work Space, Awkward Positions How often does this job require working in cramped work spaces that requires getting into awkward positions?
Creative intelligence	(iv) Originality ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem. (v) Fine Arts Knowledge of the theory and techniques required to compose, produce, and perform works of music, dance, visual arts, drama, and sculpture. (vi) Social Perceptiveness Being aware of others' reactions and understanding why they react as they do.
Social intelligence	(vii) Negotiation Bringing others together and trying to reconcile differences. (viii) Persuasion: Persuading others to change their minds or behavior. (ix) Assisting and Caring for Others Providing personal assistance, medical attention, emotional support, or other personal care to others such as coworkers, customers, or patients.

Sources: Frey and Osborne (2017); adopted from Bode et al. (2018).

Table A2: Descriptive statistics for men

	All men		No change		Entry into unincorporated entrepreneurship		Entry into incorporated entrepreneurship		Entry into non-employment		Occupation change within paid employment	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Digitalization probability	0.486	0.362	0.479	0.362	0.567	0.343	0.421	0.363	0.637	0.321	0.533	0.360
Age	41.7	11.9	41.9	11.9	42.8	11.6	45.3	10.7	36.9	12.7	40.2	12.1
Metropolitan area	0.822	0.383	0.820	0.385	0.810	0.392	0.863	0.344	0.817	0.387	0.853	0.354
No. of children in the househ.	0.894	1.172	0.903	1.173	0.905	1.223	1.056	1.254	0.645	1.097	0.843	1.166
Married	0.606	0.489	0.615	0.487	0.591	0.492	0.744	0.437	0.380	0.485	0.564	0.496
Less than high school	0.076	0.265	0.072	0.258	0.160	0.367	0.044	0.205	0.151	0.358	0.099	0.299
High school degree	0.293	0.455	0.291	0.454	0.325	0.468	0.246	0.431	0.360	0.480	0.304	0.460
Some college	0.289	0.453	0.290	0.454	0.244	0.429	0.253	0.435	0.311	0.463	0.275	0.447
University degree	0.342	0.474	0.347	0.476	0.271	0.445	0.456	0.498	0.179	0.383	0.322	0.467
White	0.835	0.371	0.839	0.367	0.838	0.368	0.844	0.363	0.755	0.430	0.796	0.403
Black	0.080	0.272	0.077	0.267	0.069	0.254	0.067	0.251	0.141	0.348	0.104	0.305
Asian	0.056	0.231	0.055	0.229	0.062	0.241	0.067	0.251	0.056	0.231	0.070	0.254
Other race	0.029	0.166	0.028	0.165	0.031	0.173	0.021	0.143	0.048	0.214	0.031	0.173
Person-year observations	1,123,291		1,020,546		3,258		1,543		26,543		71,401	

Note: Means and standard deviations by type of labor market transition between two consecutive months.
Data source: Matched monthly Current Population Survey, 2010-2017.

Table A3: Descriptive statistics for women

	All women		No change		Entry into unincorporated entrepreneurship		Entry into incorporated entrepreneurship		Entry into non-employment		Occupation change within paid employment	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Digitalization probability	0.531	0.385	0.525	0.386	0.523	0.361	0.463	0.392	0.629	0.349	0.572	0.378
Age	41.9	12.2	42.2	12.1	43.9	11.6	45.4	10.7	37.6	12.4	40.6	12.3
Metropolitan area	0.813	0.390	0.811	0.392	0.800	0.400	0.854	0.354	0.818	0.386	0.845	0.362
No. of children in the househ.	0.913	1.120	0.912	1.116	0.979	1.170	1.023	1.301	1.036	1.244	0.866	1.114
Married	0.547	0.498	0.552	0.497	0.585	0.493	0.719	0.450	0.482	0.500	0.500	0.500
Less than high school	0.060	0.237	0.057	0.232	0.112	0.316	0.040	0.197	0.127	0.333	0.065	0.246
High school degree	0.268	0.443	0.266	0.442	0.276	0.447	0.217	0.412	0.302	0.459	0.280	0.449
Some college	0.337	0.473	0.337	0.473	0.306	0.461	0.287	0.453	0.349	0.477	0.330	0.470
University degree	0.336	0.472	0.340	0.474	0.305	0.461	0.456	0.498	0.222	0.415	0.325	0.468
White	0.807	0.395	0.812	0.391	0.822	0.383	0.832	0.374	0.755	0.430	0.755	0.430
Black	0.107	0.309	0.104	0.305	0.081	0.273	0.080	0.272	0.145	0.353	0.146	0.353
Asian	0.054	0.227	0.054	0.225	0.059	0.236	0.075	0.263	0.056	0.230	0.065	0.246
Other race	0.032	0.176	0.031	0.174	0.038	0.192	0.013	0.113	0.044	0.205	0.035	0.183
Person-year observations	1,055,851		958,697		2,383		697		32,228		61,846	

Note: Means and standard deviations by type of labor market transition between two consecutive months.
Data source: Matched monthly Current Population Survey, 2010-2017.

Appendix B: Figures

Figure 1: Estimated probability of entry into non-employment at different levels of digitalization risk, full sample

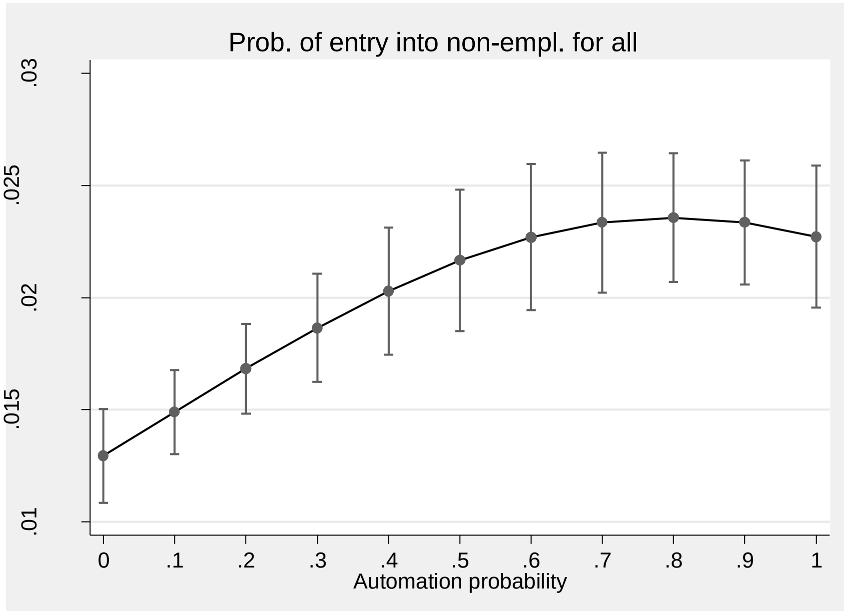

Figure 2: Estimated probability of occupation change within paid employment at different levels of digitalization risk, full sample

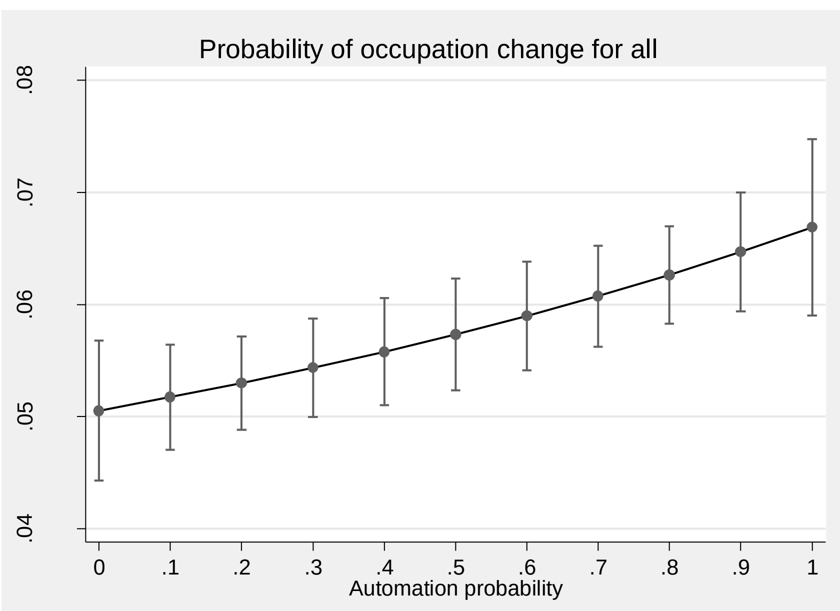

Figure 3: Estimated probability of entry into unincorporated entrepreneurship at different levels of digitalization risk, full sample

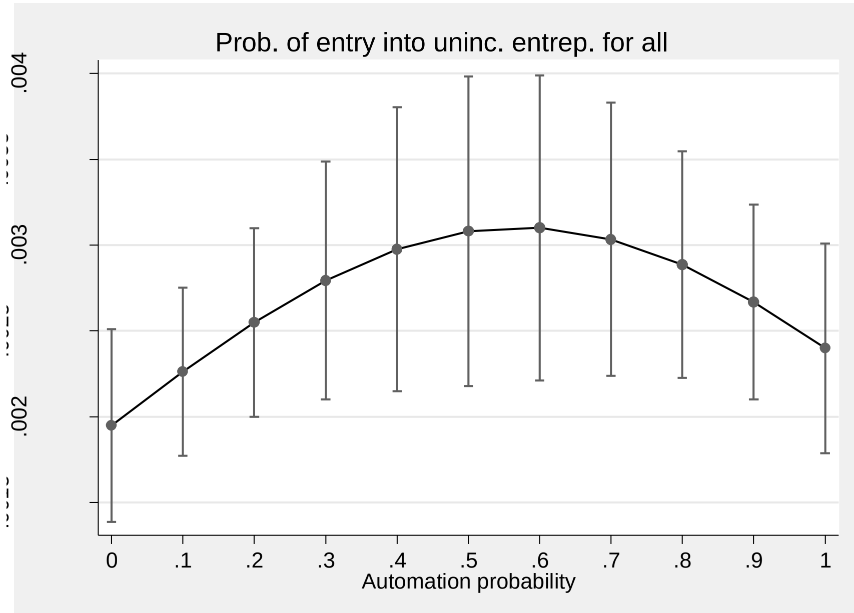

Figure 4: Estimated probability of entry into incorporated entrepreneurship at different levels of digitalization risk, full sample

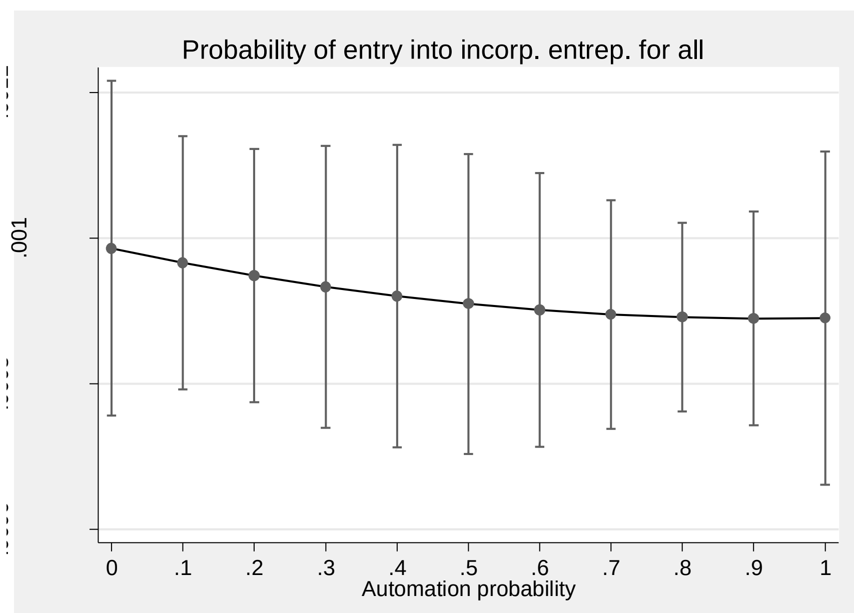

Figure 5: Estimated probability of entry into non-employment at different levels of digitalization risk, men

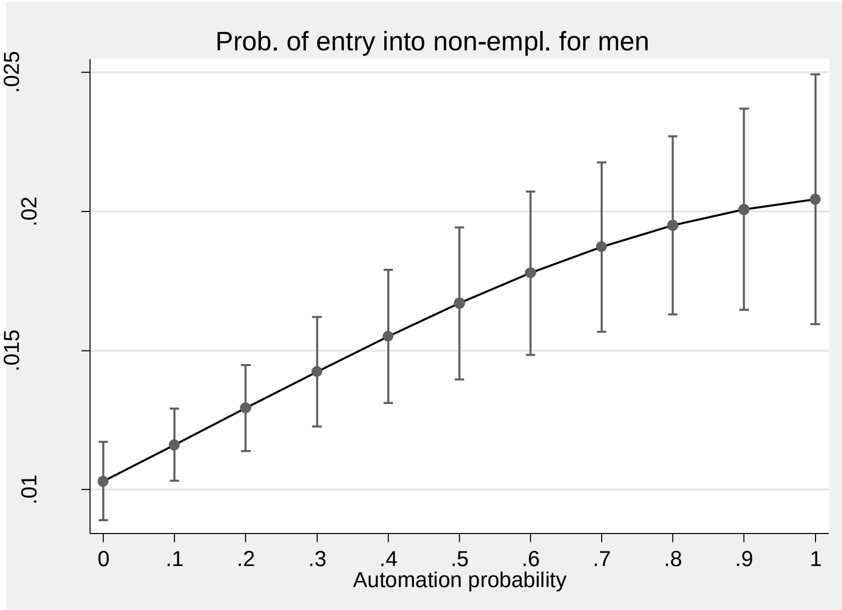

Figure 6: Estimated probability of occupation change within paid employment at different levels of digitalization risk, men

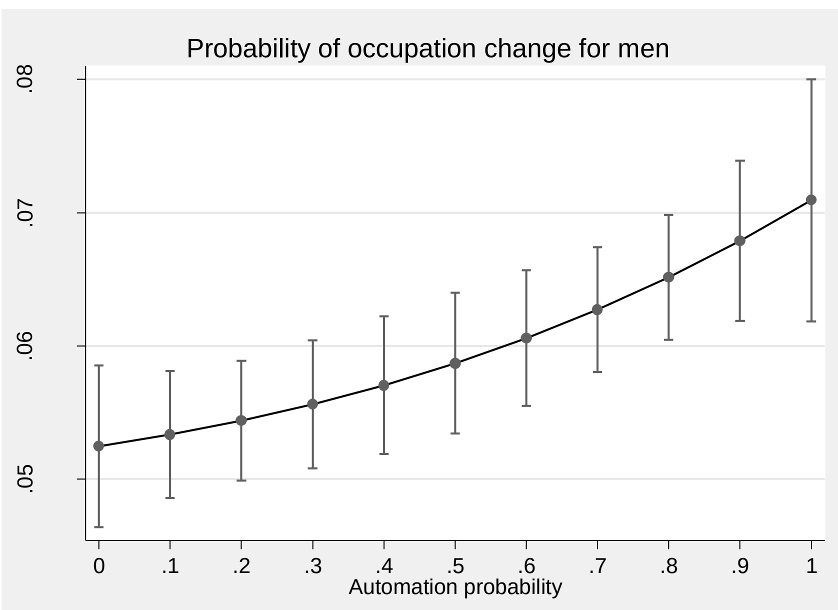

Figure 7: Estimated probability of entry into unincorporated entrepreneurship at different levels of digitalization risk, men

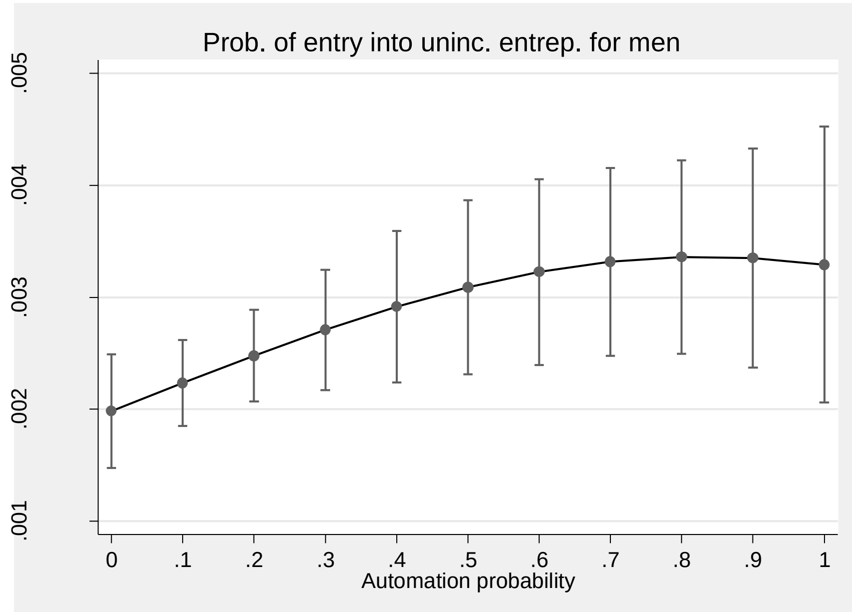

Figure 8: Estimated probability of entry into incorporated entrepreneurship at different levels of digitalization risk, men

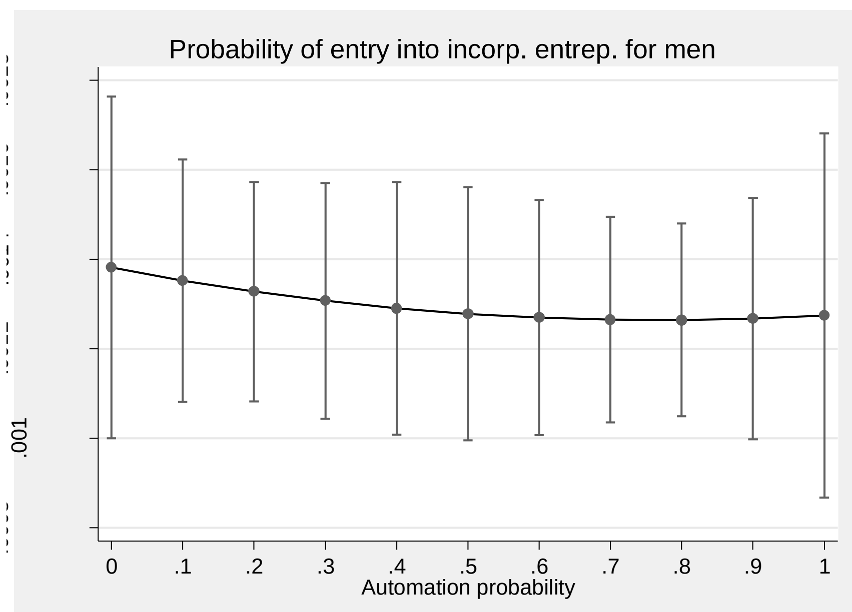

Figure 9: Estimated probability of entry into non-employment at different levels of digitalization risk, women

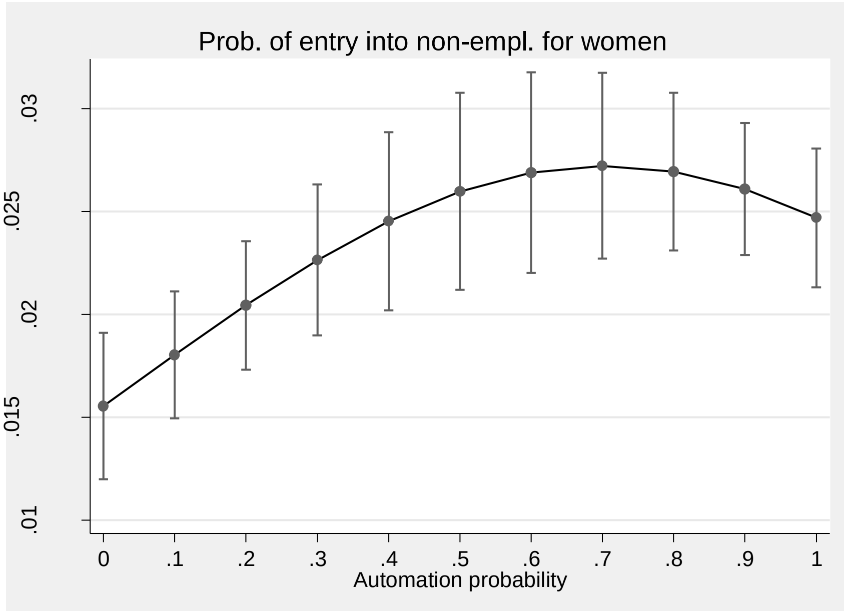

Figure 10: Estimated probability of occupation change within paid employment at different levels of digitalization risk, women

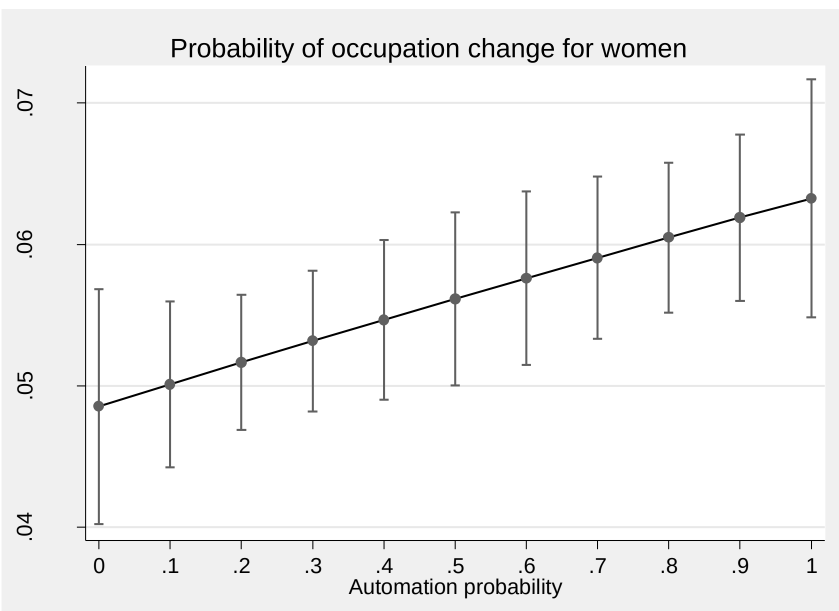

Figure 11: Estimated probability of entry into unincorporated entrepreneurship at different levels of digitalization risk, women

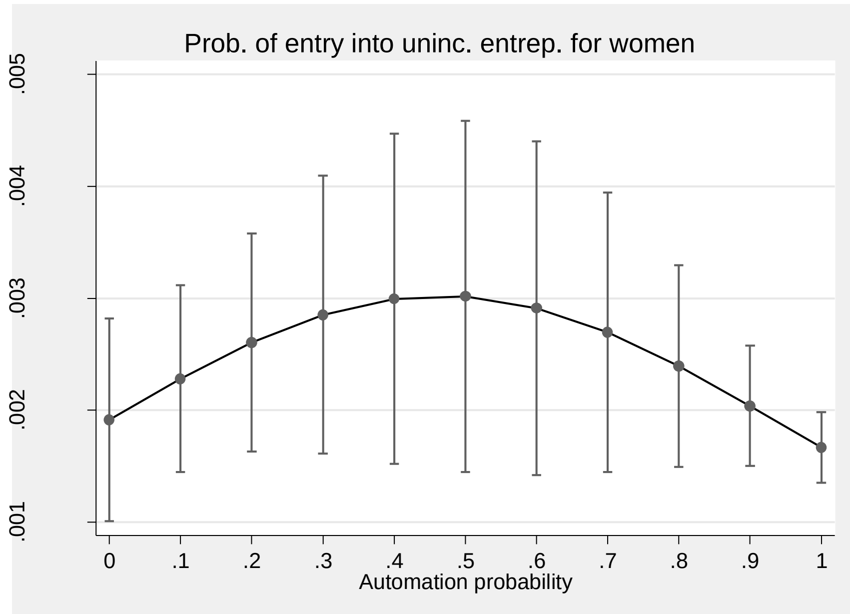

Figure 12: Estimated probability of entry into incorporated entrepreneurship at different levels of digitalization risk, women