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ABSTRACT

New Digital Technologies and Heterogeneous Employment and Wage Dynamics in the United States: Evidence from Individual-Level Data*

We investigate heterogeneous effects of new digital technologies on the individual-level employment- and wage dynamics in the U.S. labor market in the period from 2011-2018. We employ three measures that reflect different aspects of impacts of new digital technologies on occupations. The first measure, as developed by Frey and Osborne (2017), assesses the computerization risk of occupations, the second measure, developed by Felten et al. (2018), provides an estimate of recent advances in artificial intelligence (AI), and the third measure assesses the suitability of occupations for machine learning (Brynjolfsson et al., 2018), which is a subfield of AI. Our empirical analysis is based on large representative panel data, the matched monthly Current Population Survey (CPS) and its Annual Social and Economic Supplement (ASEC). The results suggest that the effects of new digital technologies on employment stability and wage growth are already observable at the individual level. High computerization risk is associated with a high likelihood of switching one's occupation or becoming non-employed, as well as a decrease in wage growth. However, advances in AI are likely to improve an individual's job stability and wage growth. We further document that the effects are heterogeneous. In particular, individuals with high levels of formal education and older workers are most affected by new digital technologies.

JEL Classification: J22, J23, O33

Keywords: digitalization, artificial intelligence, machine learning, employment stability, unemployment, wage dynamics

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1. Introduction

Innovation and technological change are generally seen as drivers of economic growth and development. Nevertheless, there is a growing concern about the effects of new digital technologies on labor markets (e.g., Brynjolfsson and McAfee, 2014). This concern arises because of an increasing ability of new digital technologies to replace human labor in domains that have been considered "human terrain" until recently. Examples for the far-reaching policy implications these developments may have are the debates on the potential need for taxation of robots (Guerreiro et al., 2017; Thuemmel, 2018) or a universal basic income (Hoynes and Rothstein, 2019). While the performance of digital technologies is constantly improving and their costs decline, recent empirical evidence suggests that there has been a disproportionately slow increase in median wages at a rate well below the productivity growth (Goos et al., 2014). Moreover, new digital technologies seem to differentially benefit or harm workers with different types and levels of skills.

The aim of this study is to provide a detailed analysis of heterogeneous effects of new digital technologies such as AI on individual-level employment transitions and wage growth in the U.S. labor market. First, we investigate whether significant effects of the new wave of digitalization on employment stability and wage dynamics are already observable in recent representative U.S. data (2011-2018). The second question that arises is what types of workers are most likely to be affected by new digital technologies. For instance, it is not clear how effects of these technologies are heterogeneous concerning the education, sector, gender, and age of workers. The third question is concerned with the individual strategies of workers to mitigate potentially negative impacts of digitalization on their jobs. Answers to these questions are possible by analyzing individual-level data. As Raj and Seamans (2019) emphasize, existing empirical work primarily uses aggregated data at the industry or country level and examines robotics rather than AI. This paper provides a better understanding of heterogeneous effects of new digital technologies on employment and wage dynamics in the U.S. labor market by using individual-level panel data from the Current Population Survey (CPS) and its Annual Social and Economic (ASEC) supplement.

The contributions of this paper are as follows. First, we analyze how new digital technologies and their specific types, such as artificial intelligence and its subfield, machine learning, impact workers' employment stability by focusing on individual month-to-month labor market transitions. Second, we analyze the impacts of different types of new digital technologies on individual wage growth. Third, we explore the heterogeneity of the effects of new digital technologies by analyzing types of workers that differ in terms of their formal education, age, gender, sector of employment, and other dimensions.

The results of the empirical analysis reveal that significant effects of the new wave of digitalization can already be observed at the individual level. Using the measure of computerization risk developed by Frey and Osborne (2017), we find that an increase in the computerization risk of an individual's occupation by one standard deviation increases the probability of a transition from paid employment to non-employment by 13% of the baseline transition probability for men and by 7% for women. Individuals in occupations with high computerization risk are also more likely to switch to a new occupation. Furthermore, a higher computerization risk decreases annual wage growth significantly. For men, the negative effect of a one standard-deviation increase in the computerization risk is equivalent to the loss of a quarter of the positive effect of a college degree. These results indicate that computerization risk captures new digital technologies that are substitutes for human labor. We further document that individuals can mitigate the negative effect on their wages by switching to another occupation.

In contrast, if an individual faces a one standard-deviation higher score in occupational advances in AI, as estimated by Felten et al. (2018), the probability of becoming non-employed decreases by 13% for men and by 16% for women, and the likelihood of switching to a new occupations also falls. A one standard-deviation increase in the AI impact score increases wages by 11 %-points for men and 14 %-points for women. These results strongly suggest that advances in AI, as captured by this measure, are predominantly complementary to human labor and make workers more productive in their occupations. The beneficial effects of advances in AI are more pronounced for individuals with higher levels of formal education and more experience. Concerning computerization risk, more educated individuals are more likely to be able to adjust by switching to another occupation than workers with lower levels of education.

The paper proceeds as follows. Section 2 provides an overview of the literature on the effects of technological changes on labor markets and formulates hypotheses. Section 3 describes the data used in the analysis and discusses our empirical approach. Section 4 presents the estimation results and robustness checks. Section 5 discusses the results and the limitations and concludes the analysis.

2. Background and hypotheses

The task-based approach, introduced by Autor et al. (2003), has been widely used to explain the effects of technological advances on labor markets. This approach is based on the premise that jobs consist of routine and non-routine tasks that can be both manual and cognitive. In the past decades, computers and robots could substitute humans in job tasks that can easily be codified, such as routine manual tasks (e.g., repetitive movements in structured environments) and routine cognitive tasks (e.g., arithmetic calculations). In turn, non-routine cognitive tasks (e.g., abstract and interpersonal tasks) and non-routine manual tasks (e.g., manual dexterity) that are usually performed in unstructured environments were difficult to automate. Thus, machines could not replace human workers in these areas, but rather supplemented them (Autor et al., 2003; Acemoglu and Autor, 2011; Autor, 2015). Consequently, the demand for workers in jobs that strongly rely on tasks that constituted bottlenecks to automation increased, while the demand for workers in jobs that rely on tasks that could easily be performed by machines declined. In line with this argumentation, Deming (2017) reports that the labor market increasingly rewards social skills, while the share of math-intensive but less social jobs decreased over time. Moreover, De La Rica and Gortazar (2017) show that there is a positive relationship between the use of information and communication technologies (ICT) at work and individual wages, thus, pointing towards a positive wage premium for workers that are complemented by digital technologies. Since many middle-income, middle-skill jobs rely on highly automatable tasks, the task-based approach explains the growing polarization of labor markets, which is evident in increasing shares of low-paid low-skilled and well-paid high-skilled employment as well as stagnation of median wages, as observed in the last decades in many developed countries (Goos et al., 2014; Autor, 2015).

Given increasing availability of large amounts of data and recent advances in digital technologies, including machine learning algorithms and cloud computing, machines have become increasingly able to substitute human workers in jobs that rely on tasks that have until recently been considered human terrain. In particular, machines are more and more capable of performing non-routine cognitive tasks, such as image, video and speech recognition, natural language processing, generating computer programs, and emotions identification, among others. Additionally, advances in robotics have increased the level of dexterity of robots, thus, allowing machines to perform more non-routine manual tasks (Brynjolfsson and McAfee, 2014; Graetz and Michaels, 2018).

In response to these developments, an empirical literature has recently emerged that aims at better understanding the effects of the so called Fourth Industrial Revolution (4IR) technologies on productivity growth, employment and wages. One strand in this literature focuses on one particular 4IR technology, namely industrial robots, and their impacts on labor markets. For instance, 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 U.S. labor market. Graetz and Michaels (2018) analyze the effects of deployment of industrial robots in a number of European countries. They find that robots do not polarize labor markets, as opposed to results of other studies that analyzed earlier ICT, but that robots reduce the share of low-skilled workers. Dauth et al. (2017) do not find evidence that robots cause overall job losses in Germany. While they report that robots have led to a decrease of manufacturing employment in Germany, this loss has been offset by new jobs in the services sector. The paper by Dauth et al. (2017) is also one of the few studies that analyze individual-level data. Remarkably, the authors find that robot-exposed incumbent workers are not more likely to lose their jobs as compared to other workers. This job stability seems to come at the cost of lower wages for medium-skilled workers while high-skilled workers experience increases in wages. Since industrial robots are more likely to be employed for particular applications in a rather small number of industries (for example, automotive industry, electronics, and machinery industry), it is not clear whether these results generalize to other sectors. Also, it is not clear whether the effects of new digital technologies on individual workers are comparable to the effects of industrial robots. Robot-exposed workers may possess a very particular skill set, such as manual routine skills, while new digital technologies may affect a broader range of workers in different sectors.[4]

Another strand in this literature is concerned with the effects of *new* digital technologies on labor markets. One of the most influential studies is provided by Frey and Osborne (2017) for the U.S. labor market. The authors develop a measure of computerization risk of occupations, which captures the predicted risk of replacement of human workers based on expert judgments. This computerization risk can be referred to as destructive digitalization. The authors conclude that 47% of the U.S. labor force are currently in jobs that face a high risk (more than 70 percent) of being computerized in the next 10-20 years (as viewed from the publication year of the working paper in 2013). This study has been replicated for other countries[5] with the result that the average risk of automation varies considerably within occupations, between occupations, and across countries. The variation within occupations is due to strong variation of job-specific tasks (Arntz et al., 2017), and variation across countries is at least partly due to country-specific differences in the occupational structure of local labor markets. Importantly, these studies provide predictions based on expert judgments, but these predictions have not been tested empirically. One of our contributions is to provide empirical evidence based on representative individual-level panel data.

Felten et al. (2018) propose a different measure that captures recent advances in artificial intelligence (AI). This measure is not intended to capture replacement risk of human workers, and prior literature left the open empirical question whether advances in AI are predominantly substitutes or complements to human labor. Providing an empirical test based on individual panel data

[4] Brynjolfsson et al. (2018) argue, for instance, that new digital technologies such as AI constitute a general purpose technology, which is likely to be applied in a broad range of sectors.

[5] For instance, for selected European countries (Berger and Frey, 2016), OECD countries (Arntz et al., 2016), and G20 countries (Sorgner et al., 2017).

is another contribution of our paper. We formulate our hypotheses by presuming that advances in AI are predominantly complements to human labor when they transform occupations (transformative digitalization). As we argue below, this is the most plausible presumption based on prior literature, although far from self-evident. Relatedly, Brynjolfsson et al. (2018) provide a measure of susceptibility of tasks to machine learning, which is a subfield of AI. Importantly, the three measures capture *different* aspects of new digital technologies (see also Fossen and Sorgner, 2019).

In sum, extant literature found that 4IR technologies influenced both the composition of labor and wages substantially (Autor and Salomons, 2017). While previous waves of automation were particularly responsible for polarization of labor markets by favoring workers in low- and high-skilled jobs, it is unclear how the new wave of digital technologies impacts labor markets (Autor, 2015; Brynjolfsson et al., 2018). Moreover, most studies have been conducted at the macro level of national and regional labor markets or at the level of industries. Evidence at the individual level, particularly on the potentially heterogeneous effects of new digital technologies, is largely missing.

It is a crucial question to ask in how far new digital technologies influence individual workers in terms of their employment stability and wage growth. The evidence about the effects of digitalization at the level of individuals is rather scarce. It appears that the occupational computerization risk, as developed by Frey and Osborne (2017), is related to lower employment stability by triggering individual labor market transitions into self-employment and unemployment (see Sorgner, 2017, using German data; and Fossen and Sorgner, 2019, focusing on entrepreneurship). It can be assumed that computerization risk decreases an individual's employment stability and, thus, increases the probability of an individual to exit his or her current occupation. Moreover, it appears plausible to assume that computerization risk in the sense of destructive digitalization decreases an individual's wage growth, since digital technologies outperform human workers in tasks, in which humans can be substituted by machines. Since occupations differ substantially with regard to their computerization risk, it is likely that workers can partially escape these negative effects of computerization risk on wages by switching occupations. However, occupational change is costly, because it might require additional qualification and makes parts of an individual's specific human capital redundant (e.g., Gibbons, 2018). We summarize these considerations in the following hypotheses:

H1a: A higher computerization risk in the current occupation leads to a higher probability of transition to non-employment.

H1b: A higher computerization risk in the current occupation leads to a higher probability of switching occupation within paid employment.

H1c: A higher computerization risk in the current occupation leads to a decrease in individual wage growth. This decrease will be weaker if an individual switches occupation.

Improvements in artificial intelligence, including machine learning, have prominently occurred in fields that have traditionally represented human terrain. These fields are, for instance, image and speech recognition, natural language processing, translation, reading comprehension, abstract strategic games, generating computer programs, and predictive analytics, among others (Brynjolfsson et al., 2018; Felten et al., 2018). Many of these fields most closely correspond to non-routine cognitive tasks. In these areas, rather than completely replacing human workers, it is more plausible that AI will transform occupations. Human workers will work closely together with AI technologies in transformed occupations because not all tasks within an occupation can be performed by AI. Thus, AI is expected to be predominantly complementary to human labor.

Assuming that advances in AI amplify these complementary effects, it appears likely that they increase an individuals' employment stability and make human workers more productive in their jobs. This should lead to an increase in wage growth and make occupational change rather unlikely. However, for these complementary effects to fully unfold, human workers must be able and willing to adapt to the new AI technologies. Otherwise, workers might be forced to switch jobs, which will likely decrease their wage growth relative to those who are able to adapt and stay in their occupation and therefore continue to employ their occupation-specific human capital. These considerations are summarized in hypotheses below:

H2a: More rapid advances in AI lead to a lower probability of transition to non-employment.

H2b: More rapid advances in AI lead to a lower probability of switching occupation within paid employment.

H2c: More rapid advances in AI lead to an increase in individual wage growth. This increase will be weaker if an individual switches occupation.

We expect that the effects of new digital technologies will vary considerably across individuals with different levels of human capital, i.e., formal education and experience (captured by age). However, it is difficult to make an unambiguous theoretical prediction concerning these effects. On the one hand, highly educated workers can be expected to be more prepared than lower skilled individuals to deal with new digital technologies, including destructive digitalization, because education enhances one's ability to learn new information, and highly educated workers can generally adapt better to new technologies (Bartel and Lichtenberg, 1987). Moreover, highly educated individuals are more likely to employ skills that cannot be replaced by digital technologies (e.g., creative and social intelligence, reasoning skills, and critical thinking skills). On the other hand, however, individuals who have accumulated a large amount of human capital are also likely to possess more task-specific human capital, which may make switching to more distant occupations with a lower computerization risk more costly for them (Gathmann and Schönberg, 2010). This might decrease the number of opportunities for high-skilled individuals to mitigate high computerization risk in their current occupation. The implications for wage growth of high-skilled workers in occupations with high computerization risk are ambiguous as well, since, on the one hand, more distant occupational switches may lead to a stronger decline in wage growth for high-skilled individuals, but, on the other hand, their higher ability to adapt to changes in comparison to low-skilled workers may offset these negative effects.

Concerning advances in AI, one can expect, in line with the previous argumentation, that highly educated workers can more easily adapt to new digital technologies that will complement their skills. They might be able to leverage their human capital through complementary advances in AI and therefore experience stronger employment stability and wage growth as compared to low-skilled workers. However, given that advances in AI most strongly affect non-routine cognitive activities, one might conversely expect that advances in AI may lead to a lower employment stability of highly educated workers whose jobs strongly rely on these tasks. Hence, it is an important empirical question to investigate how the effects of new digital technologies vary for individuals with different levels of human capital.

Moreover, one can expect to find heterogeneous effects of new digital technologies for different population groups who might have different skill endowments. For instance, although women are now more likely to participate in non-routine analytic and interactive tasks (Black and Spitz-Oener, 2010), they might still have different skill endowments than men including higher social skills (Cortes et al., 2018). Hence, new digital technologies might have differential effects on both genders (Sorgner et al., 2017). Effects might also be different for employed versus self-employed individuals; for workers employed in different industries, since there might be sector-specific differences in tasks; and for individuals residing in urban versus rural regions. We investigate these heterogeneous effects of new digital technologies in our empirical analysis.

3. Empirical approach

3.1. Data

3.1.1. Individual panel data from the CPS and ASEC

For the analysis of transitions out of an occupation in paid employment to other states, we use the monthly waves of the Current Population Survey (CPS) from January 2011 to October 2018.[6] The CPS is a representative survey of households in the United States provided by the Census Bureau.[7] The CPS follows a rotating survey design: 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-month survey spell can be linked to the subsequent month, so 75% of all observations can be connected to the following month. Thus, for each individual, we include a maximum of six monthly observations with information on subsequent labor market transitions in our estimation sample. The panel data structure of the matched CPS allows us to observe labor market transitions from one month to the next based on questions on the current employment status and occupation in two consecutive months.

[6] We start in January 2011 because the occupational codes changed between 2010 and 2011, and bridging this structural break would reduce accuracy or precision.
[7] The U.S. Bureau of Labor Statistics relies on the CPS to estimate the widely reported national unemployment rate.

For the wage growth regressions, we use the Annual Social and Economic (ASEC) supplement of the CPS. This supplement to the survey, which is always conducted in March, contains information on various categories of income, in contrast to the interviews in the other months. Again using the IPUMS distribution of the data, we can link March ASEC supplements of two subsequent years for most respondents. In the ASEC, respondents are always asked for their income in various categories in the previous calendar year. The ASEC also provides the predominant employment status, main occupation and usual hours worked per week in the previous calendar year. Since our ASEC panel includes March interviews for two subsequent years for most respondents (interviews in t and t+1), we obtain information on income, employment and occupation for t-1 and t and use this to calculate hourly wage[8] changes between t-1 and t. The main explanatory variables, i.e., the measures of digitalization, are merged to the occupation in the initial year, t-1. Likewise, the respondent's industry, status as an entrepreneur (incorporated or unincorporated) or work in an ICT or STEM related occupation also correspond to the occupation in t-1. Other control variables are not elicited for the previous calendar year, but only for the point in time of the interview, so we use the variable for t in these cases (reflecting the situation in March of year t). We define a switch of occupation as a change in the occupational code of a respondent between two periods. Thus, a switch of occupation does not necessarily imply a change of employer. In a robustness check, we assess the robustness of our results with respect to the definition of switching occupations.

3.1.2. Measures of impacts of digitalization on occupations

We use three measures that capture different aspects of the impact of digitalization on occupations (see also Fossen and Sorgner, 2019). Table A1 in the Appendix provides an overview.

[8] In case of entrepreneurship, we obtain hourly labor income analogously by dividing annual business or farm income by hours worked. In this paper, we use the term wage to refer to hourly labor income for simplicity.

First, the occupational computerization risk estimated by Frey and Osborne (2017) is constructed to capture the risk of replacement of human workers by digital technologies. The authors estimate computerization probabilities for the next 10-20 years (as viewed from the publication year of the working paper in 2013) based on expert judgments and selected characteristics of occupations from the O*NET database of occupations compiled by the US Department of Labor. The authors first asked an expert group of machine learning or robotics researchers to tell which occupations would be fully automatable, or not at all, in the foreseeable future of about 20 years. The experts classified 37 occupations with very high and 34 with very low susceptibility to automation. Frey and Osborne (2017) identified nine occupational skills provided in O*NET that arguably represent automation bottlenecks.[9] Then the authors combined the expert judgments with these skills to construct a training dataset. This training dataset indicates how the probability of digitalization of the 71 occupations varies with the required level of these bottleneck abilities. Based on this training data, the authors then used machine learning techniques to predict computerization probabilities for 702 occupations using the O*NET bottleneck skills.

Second, we use advances in AI by occupations estimated by Felten et al. (2018). The authors do not take a stance on whether AI as captured by their measure serves as a substitute or complement to the occupations it affects. One of our contributions is to decide this question empirically. If we find support for Hypothesis 2 (a-c) using this measure, this strongly suggests that advances in AI as reflected in this measure complement rather than replace human workers in their occupations. Specifically, Felten et al. (2018) estimate past advances in AI (in 2010-15) based on the AI Progress Measurement dataset provided by the Electronic Frontier Foundation (EFF) in combination with O*NET occupational data. In contrast to the other two measures we

[9] These bottleneck skills are: Perception and manipulation (finger dexterity, manual dexterity, and cramped work space or awkward positions), creative intelligence (originality, fine arts, and social perceptiveness), and social intelligence (negotiation, persuasion, and assisting and caring for others).

use, this approach does not rely on experts' predictions of the future. Instead, it estimates progress slopes for 16 categories of AI[10] based on past advances of the technologies as reported by EFF. Then the authors link the advances in the AI categories to 52 distinct abilities that O*NET uses to describe job requirements. O*NET provides the importance and prevalence of each ability for each occupation. This allows the authors to estimate progress slopes in AI performance at the level of occupations.

Third, we use suitability for machine learning (SML), a subfield of AI, as estimated by Brynjolfsson and Mitchell (2017) and Brynjolfsson et al. (2018). The authors first assess the suitability of 2,069 narrowly defined work activities[11] for machine learning via surveys conducted on a crowdsourcing platform. To ensure the quality of the data, only respondents with industry-specific experience and understanding of a specific task were sampled. The measure of SML was then aggregated to the level of tasks and then to the level of occupations. The authors also calculate the standard deviation of the SML scores of the tasks within each occupation (sdSML). Brynjolfsson et al. (2018) argue that occupations that include both, tasks that can be automatized and tasks that cannot, are likely to be reorganized rather than replaced. We use SML and sdSML in an exploratory supplement to our empirical analysis.

We match the three measures of different aspects of the impact of digitalization on occupations with our CPS and ASEC samples using a crosswalk of occupational codes. The three measures are available at the 6-digit code level of the System of Occupational Classification (SOC). About 40% of the occupations are only available on a more general level in the CPS (5-digit instead of 6-digit codes). In these cases, we have to aggregate to the more general level of

[10] Categories of AI are, for example, image recognition, speech recognition, and translation.
[11] Direct work activities are units that constitute tasks, which are broader categories. For instance, the task "interacting with others" consists of direct work activities "assisting and caring for others", "coaching others", "coordinating the work of others", etc.

occupational detail. We do so by using mean values of the digitalization risk measures weighted by the number of employees in the respective occupations in the United States as provided by the Bureau of Labor Statistics. We standardize the digitalization measures by subtracting the mean and dividing by the standard deviation to facilitate interpretation of the effect sizes.

It is important to emphasize that all of these measures of occupational digitalization capture *different* aspects of digitalization, which allows a comprehensive analysis of effects of digitalization on labor markets. In fact, the computerization probabilities are strongly negatively correlated with the advances in AI (see Table A4 in the Appendix). The table also shows correlations of these digitalization measures with tasks that constitute occupations. These task measures were constructed from O*NET following Acemoglu and Autor (2011). The computerization risk is strongly and negatively correlated with non-routine cognitive tasks (analytical and interpersonal) and it is positively correlated with routine and non-routine manual tasks. In contrast, advances in AI are positively correlated with routine and non-routine cognitive tasks and negatively correlated with routine manual tasks. This suggests that occupations requiring abilities that are linked to rapid advances in AI are unlikely to be completely automated. These occupations will likely require a high frequency of interaction between humans and new digital technologies.

To shed further light on the difference between the computerization probability and advances in AI, Table A2 in the Appendix lists the occupations with the highest and lowest scores in both measures. Occupations such as pilots, surgeons, biochemists and architects experience rapid advances in AI, but have low risks of computerization. These occupations are being transformed by AI technologies that are complementary to human labor, so workers are not replaced. In contrast, hand sewers, tax preparers and library technicians are at high risk of being replaced by machines in the near future. These examples demonstrate the importance of analyzing different aspects of digitalization when studying effects on labor markets.

Table A3 provides descriptive statistics for the estimation sample of paid employees from the monthly CPS used to estimate transitions. The table splits the sample by the type of transition observed. The computerization risk is largest among those who leave paid employment and become non-employed, second largest for those who enter into unincorporated entrepreneurship, and third largest for those who switch to a new occupation within paid employment. These correlations hint at the possibility that human workers are replaced by machines in these occupations. In contrast, the advances in AI are lowest among workers who become non-employed, which suggests that advances in AI increase employment stability. Table A5 shows the second estimation sample of workers (paid employees and entrepreneurs) based on the annual ASEC used to estimate wage growth, split by gender and employment type. Hourly wages were \$27 for men and \$20 for women, deflated to 2010 dollars. This large and well-known gender gap is a primary motivation for running our estimations separately for men and women. The average annual growth of real wages is 3.4% in the full sample and even 4.7% among entrepreneurs.

3.2. Methods

Our econometric analysis consists of two parts. First, using the monthly CPS, we estimate the impact of the digitalization measures on transitions out of the current occupation in paid employment. Second, we estimate the effects on wage changes based on the annual ASEC.

3.2.1. Employment transitions

We model transitions in a random utility framework. Using the sample of paid employees in the first month of a two-months pair, t, we estimate the probabilities of individual transitions between month t and the next month, $t+1$. We distinguish between $J = 5$ choices: The respondent remains in the same occupation in paid employment (reference category), moves to non-employment (unemployment or not in the labor force), remains in paid employment but changes occupation (as measured by changes in the occupational code of the CPS), enters unincorporated entrepreneurship, or enters incorporated entrepreneurship. We assume that a paid employee i in period t perceives that he or she would derive the following utility U_k in the state k in the future period t+1:

$$U_k(\boldsymbol{x}_{it}) = \boldsymbol{\alpha}'_k\, \boldsymbol{x}_{it} + \varepsilon_{itk}, \tag{1}$$

where $\boldsymbol{x}_{it}$ is a vector of observed individual characteristics with parameters $\boldsymbol{\alpha}_k$, and ε_{itk} captures unobserved preferences and tastes. The probability of transition from the current employment to state k conditional on x_{it} equals the probability that perceived utility in state k exceeds utility in all other states including the current state. With the standard assumption of type I extreme value i.i.d. error terms ε_{itk}, we obtain a multinomial logit model. The vector $\boldsymbol{x}_{it}$ includes one of our measures of digitalization impact as the key explanatory variable. Since these variables do not vary within occupations, we report standard errors clustered at the occupational level in all regressions.

To investigate the heterogeneity of effects at different levels of education, we interact our digitalization impact measures with dummy variables indicating the highest formal educational attainment: less than high school (base category), high school, some college, and college degree. We use the estimated model to calculate marginal effects of the digitalization impact measures on the transition probabilities at the different education levels and the mean values of the control variables. Furthermore, we include the following control variables in x_{it}: socio-demographics (gender, age and its square, marital status, number of children in the household, four race categories), highest educational attainment (the four categories mentioned above), residence in a metropolitan area, region (50 US state dummy variables), and industry (9 categories, see Table A3 in the Appendix). We also include year and month dummies to control for the business cycle and seasonal effects. All explanatory variables are measured in month t, before a potential transition occurs.

3.2.2. Wage changes

To estimate the effect of the digitalization measures on annual wage changes, we estimate OLS regressions of the form

$$\ln\left(wage_{i,t}\right) - \ln\left(wage_{i,t-1}\right) = \beta_1 digi_{i,t-1} + \beta_2 switch_{i,t} + \beta_3 digi_{i,t-1} \times switch_{i,t} + \boldsymbol{\gamma}' \boldsymbol{v}_{i,t-1} + \boldsymbol{\delta}' \boldsymbol{w}_{i,t} + \mu_{it}. \quad (2)$$

The dependent variable is the relative change in hourly labor income between calendar years t-1 and t (log approximation). The key explanatory variable is a measure of the digitalization impact in the occupation held in calendar year, $digi_{i,t-1}$. We also a dummy variable indicating whether a respondent switched the main occupation between the calendar years t-1 and t, denoted $switch_{i,t}$, and an interaction term between these two variables. The coefficient of the interaction term, β_3, captures how much the impact of the digitalization measure in the previous occupation on the individual's wage growth changes when the individual switched occupation. According to Hypotheses 1c and 2c, we expect β_3 to have the opposite sign of β_1 but to have a smaller absolute value, such that a job switch mitigates the effect of the previous job's digitalization measure on wage growth. The vector of control variables $\boldsymbol{v}_{i,t-1}$ is reported for the calendar year t-1: 10 splines of the initial wage level ($wage_{i,t-1}$), 9 industry dummies, and dummy variables indicating incorporated or unincorporated entrepreneurship. By flexibly controlling for base year wage using the splines, we capture a potential general spread in the income distribution that might be correlated with the digitalization impact. Base year income also accounts for unobserved factors that influence an individual's productivity. The socio-demographic characteristics and educational attainment (see the previous section for details), residence in a metropolitan area, and 8 dummies for the US Census regions[12], summarized in $\boldsymbol{w}_{i,t}$, are reported for March in t. We also include year dummies.

4. Results

4.1. Digitalization and employment stability

We first present the results of the multinomial logit estimations of the effects of the different measures of digitalization on transitions out of the current occupation in paid employment. The subsequent section reports effects on wage growth. Tables 1 and 2 provide the main results on the transitions for men and women, respectively. Three separate estimations are shown using different measures of digitalization impact: The first column uses the computerization probability, the second column uses advances in AI, and the third estimation uses suitability for machine learning (SML) and its within-occupation standard deviation (sdSML), shown in the third and fourth columns. In each model, the dependent variable indicates the choice of labor market status in the subsequent month. The five choice alternatives appear in the table rows. The cells show the marginal effects of an increase in the digitalization impact measure by one standard deviation on the probability of a choice (evaluated at the mean values of the control variables).

We find strong effects of digitalization on the probability of entry into non-employment. When the computerization risk in an individual's occupation increases by one standard deviation, the probability of becoming non-employed from one month to the next increases by 0.3 %-points

[12] When using the annual ASEC we do not include state dummies because of the smaller sample size.

for men and by 0.2 %-points for women. This corresponds to 13% of the monthly probability of entry into non-employment of 2.35% for men (see rightmost column). For women, the relative effect is 7% of their monthly probability of entry into non-employment of 2.94% and thus considerably smaller than for men, but still significant. These results support Hypothesis 1a: Workers are already being replaced by new digital technologies in occupations with a high computerization risk.

In stark contrast, more rapid advances in AI decrease the probability of becoming non-employed for both genders. A one standard-deviation increase in the score measuring advances in AI decreases the monthly probability of switching to non-employment by 0.32 %-points for men and by 0.46 %-points for women, which corresponds to 13% of the baseline transition probability for men and 16% for women. Thus, advances in AI do not replace workers on average. These technologies seem to be rather complementary to human labor and contribute to retaining them in their jobs. This supports Hypothesis 2a. We do not observe significant effects of the suitability for machine learning or its standard deviation over tasks within an occupation on transitions into non-employment for either gender.

The result that computerization risk decreases and advances in AI increase employment stability is further substantiated when we look at the probability of switching to a new occupation within paid employment. An increase in the computerization probability by one standard deviation increases the switching probability by 6.7% for men and by 7.4% for women relative to their baseline probabilities, which lends support to Hypothesis 1b. In contrast, a one standard-deviation increase in advances in AI decreases the switching probability by 10% for men and by 7.6% for women relative to the baseline rates, supporting Hypothesis 2b.

For men, we find a similar negative effect of the variability of the suitability of tasks for machine learning within an occupation on the probability of switching an occupation. This suggests that workers in occupations comprising some tasks that are not suitable for machine learning are less likely to be pushed out of their current jobs. For women, a higher average suitability for machine learning of all tasks in an occupation increases the probability of switching occupation. Both findings are consistent with predictions by Brynjolfsson et al. (2018), who state that machine learning techniques might substitute for human labor, but if not all tasks in an occupation can be automated, the occupations are more likely to be transformed, retaining the human workers.

We also observe that a high computerization risk increases the probability of entry into unincorporated entrepreneurship for men. This further supports the hypothesis of a replacement effect because unincorporated entrepreneurship is often motivated by necessity in order to avoid unemployment (Levine and Rubinstein, 2017). This is similar to results reported by Fossen and Sorgner (2019), who focus on entrepreneurship, but do not distinguish effects by gender. A new result from this present paper with respect to entrepreneurship is that the effect mentioned above is close to zero and insignificant for women. A possible explanation is their lower attachment to the labor market, which may reduce the motivation for necessity entrepreneurship. In contrast, advances in AI decrease the probability of entry into unincorporated entrepreneurship for both genders, which is consistent again with an increased employment stability in the current occupation that benefits from these complementary new technologies.

Next, we test whether effects of digitalization on transitions differ by formal education levels. We do so by interacting the digitalization measures with education dummies. Table 3 presents marginal effects of the digitalization impact measures at the four different education levels for men and Table 4 for women. Starting with advances in AI, we find that the effect of this score on the probability of switching one's occupation within paid employment is decreasing monotonically with education for both genders. For men, the effect is always negative, whereas for women, the effect of the AI impact score on switching occupations is significantly positive for women with less than high school education and significantly negative for women with at least some college education. The effect of AI on the probability of entry into non-employed is significantly negative at all education levels for both genders and becomes monotonically stronger with education for women. The effect is also stronger for men with at least some college education than for other men. These estimation results suggest that advances in AI increase employment stability for highly educated workers. High-skilled individuals seem to work closely with these new technologies in a complementary fashion, whereas workers with lower levels of education are not able to benefit as much from these synergies in terms of employment stability.

Turning to computerization risk, the point estimates of the effects on the probability of switching one's occupation within paid employment increase almost monotonically with education for both genders; in fact, the effects are only significant with a college degree. Thus, individuals with higher levels of education are better able to adapt to computerization risk by switching their occupation than workers with lower education. We also find that the positive effect of the computerization probability on the risk of becoming non-employed decreases with the education level for men. Their education seems to enable them to switch to different occupations (especially when they have a college degree) or to move to unincorporated entrepreneurship instead. However, for women we find the opposite effect: Women with at least some college education are more likely to be pushed into non-employment when their current occupation is at high risk of computerization.

For suitability of machine learning, a subfield of AI, we find fewer significant effects. The strongest result concerns the negative effect of the within-occupation variability of the suitability of tasks for machine learning on the probability of switching to a new occupation for men reported above. This effect becomes monotonically weaker with higher education levels, but always remains significantly negative. Apparently, within-occupation variability of SML especially protects workers with lower levels of education who are working on the tasks within the occupation that cannot be automated.

4.2. Digitalization and wage growth

We next investigate the effects of digitalization on the annual growth rate of individual labor income. Table 5 provides the main regression results for men and women. An increase in computerization risk in the current occupation by one standard deviation decreases wage growth by 10 %-points for men and by 7 %-points for women. These effects are statistically significant at the 1%-level and economically important, comparing to a quarter of the absolute value of the effect of a college degree for men and 17% for women. The coefficient of the interaction term with the dummy variable indicating a switch of occupation between two adjacent years is positive and significant for both genders, indicating that switching occupations mitigates the negative effect of computerization risk in the initial occupation on the change in wages between the two years. For both genders, the negative effect of computerization risk on wage growth is decreased by almost half for those who switch away from their occupation. These findings support Hypothesis 1c. Since human workers are at risk of being replaced by machines, demand for these workers decreases and their wages are depressed. Moving to another occupation that might be less at risk of computerization can alleviate this effect, but wages on average still fall for these workers.

They do not seem to be able to make full use of their job-specific human capital after switching occupations.

We find opposite effects of advances in AI on wage growth, similar to our findings for employment stability discussed before. A one standard-deviation increase in the AI impact score increases wages by 11 %-points for men and even 14 %-points for women. These effects are weaker for those who switch their occupation, as indicated by the negative and significant coefficients of the interaction term. Again, the effects are reduced by about half for switchers. This supports Hypothesis 2c and suggests that advances in AI are predominantly complementary to human workers and increase their productivity and wages. However, this requires workers to adapt to the changes in work activities due to the implementation of new digital technologies. Individuals who are unable or unwilling to keep up with these changes might switch to another occupation, but then they do not fully benefit from the productivity and wage increase they would otherwise have experienced.

We do not find any significant effects of the suitability for machine learning on wage growth. Therefore, we omit results for SML in some of the following tables for brevity. Since there are no substantial differences in the wage effects by gender, we also report pooled results for both genders in the following tables.[13]

Table 6 splits the sample by four groups of highest educational attainment. A clear pattern emerges (see also Figure B1 in Appendix B): The positive effects of advances in AI on wage growth become monotonically stronger for individuals who received more formal education. This effect is always significantly smaller for occupation switchers and most decreased for those with a college degree. Thus, individuals with high education can leverage their human capital and benefit the most from advances in AI if they are able to keep pace with the changes and stay

[13] Results regarding the suitability for machine learning and by gender are available from the authors on request.

in their occupation. Concerning computerization risk, the negative effect on wage growth also becomes monotonically stronger with higher levels of education. The mitigating effect of switching one's occupation is only significant with a college degree. Thus, higher education helps individuals to alleviate sinking wages due to computerization risk by switching occupation.

Next we investigate effect heterogeneity by age to learn more about the role of human capital, since age is correlated with experience. Table 7 shows that both the negative effect of the computerization probability and the positive effect of advances in AI on wage growth become stronger (although not completely monotonically) with age. Correspondingly, the mitigating effects of switching one's occupation are also getting stronger with age. Thus, more experienced workers seem to be able to leverage their human capital and benefit more from advances in AI that are complementary to human labor and increase their productivity. However, older workers are also harmed more by destructive digitalization that can substitute for their labor, as captured by the computerization probability, if they do not switch their occupation. The effect heterogeneity by experience is similar to that by formal education. This points to a more general mediating role of human capital with regard to the effects of new digital technologies on wage changes.

In sum, the findings are consistent with the interpretation that technological changes captured by computerization risk are substitutes to human labor and therefore depress wages, whereas advances in AI are complements, increasing productivity and wages. Switching to another occupation, which might be less affected by the new technologies, attenuates these effects. All these effects are stronger for high-skilled workers relative to other high-skilled workers who are not experiencing these technological changes in their occupations than for low-skilled workers differentially affected by new digital technologies, partially due to the fact that wage changes and dispersion for low-skilled workers are generally less dynamic than for high-skilled workers.

4.3. Further effect heterogeneity and robustness checks

In this section, we explore further heterogeneity in the effects of the different aspects of digitalization on wage growth. We estimate the wage growth regressions separately by sector, type of worker, and residency in urban versus rural areas, followed by another robustness check.

Table 8 shows estimation results for the subsamples of individuals initially in an occupation related to information and communication technologies (ICT, left panel) or science, technology, engineering and mathematics (STEM, right panel).[14] The results are similar to the baseline estimates. This indicates that the results are very robust and confirms that the effects of digitalization estimated using the full sample are not due to spurious correlation of the measures of digitalization with occupations in the ICT or STEM sectors.

Table 9 splits the sample between wage and salary employees and entrepreneurs (with incorporated or unincorporated businesses). The results are mostly robust. For entrepreneurs, two results are different from the main sample: First, the coefficient of the interaction term between computerization risk and the occupation switch dummy becomes insignificant, but keeps its sign. Second, suitability of an occupation for machine learning has a significantly negative effect on the growth rate of entrepreneurs' hourly labor earnings, suggesting that destructive effects of machine learning technologies dominate for entrepreneurs. As the last sample split, we estimate the wage regressions separately for individuals living in a central city and those living outside of a central city (Table 10). We find that the results are robust and do not differ much between urban and rural areas.[15]

In a final robustness check we assess the sensitivity of our results with respect to the coding of the dummy variable indicating a switch of occupations. In the baseline regressions, we con-

[14] We use the list of STEM and STEM-related occupations provided by the U.S. Census Bureau (2010).

[15] In the main regressions, we use residency in a metropolitan area as a control variable, not residency in a central city, because the central city status is much more often unknown than the metropolitan area status.

sider any change in the occupational code between two years as a switch of occupations. Some changes from one occupational code to a similar one might be due to coding inaccuracies in the data. In the regressions shown in Table A6 in the Appendix, only switches from one of the 23 major occupational groups to a different one are coded as an occupational switch. The results again remain similar to the baseline results.

5. Discussion and conclusion

5.1. Discussion of results and policy implications

This paper aims at investigating the effects of new digital technologies, such as advances in AI and machine learning algorithms, on employment and wage dynamics on the U.S. labor market. A main contribution of this paper is that it provides empirical evidence at the level of individuals based on large and representative panel data from the monthly CPS and its annual ASEC supplement for 2011-2018, whereas previous studies were mostly conducted on a more aggregated level of countries, regions, and industries. While a fair amount of papers study the labor market effects of previous waves of automation, including the adoption of ICT and industrial robots, there is a lack of evidence on how *new* digital technologies, which constitute the so called Fourth Industrial Revolution (4IR) technologies, are affecting labor markets. We explicitly focus on new digital technologies by utilizing three measures that capture occupational susceptibility to these technologies. The first measure, as developed by Frey and Osborne (2017), assesses the computerization risk of occupations in the near future (as seen from 2013). The second measure developed by Felten et al. (2018) provides an estimate of recent advances in artificial intelligence (AI), and the third measure assesses the suitability of occupations for machine learning (Brynjolfsson et al., 2018), which is a subfield of AI.

We find that new digital technologies have already started to affect labor markets, but in ways that are quite different from previous waves of automation in several respects. First, new computerization risk seems to affect individuals with high levels of human capital most strongly. When facing a high risk of computerization, high-skilled workers experience a larger decline in wage growth than low-skilled workers (relative to workers with the same level of human capital who do not face a high computerization risk). Highly educated women are also more likely to leave the labor market when their occupation is at risk of computerization. This stands in contrast to earlier digital technologies, which have hollowed out the medium-skilled workforce (Goos et al., 2014), and from the effects of industrial robots that caused a drop in low-skilled employment (Dauth et al., 2017). However, highly educated individuals also appear to be more able than workers with lower levels of education to adapt to computerization risk by changing their occupation within paid employment or becoming an entrepreneur. In both cases, switching one's occupation alleviates the negative effects of computerization risk on wage growth. This proactive behavior of workers could mitigate the overall job-replacement effects of digitalization that have been predicted in earlier studies based on expert judgments (Frey and Osborne, 2017).

Second, we find that advances in AI have been predominantly complementary to human labor, even though they mostly affect non-routine cognitive tasks. This is different from earlier waves of automation, which primarily affected workforce involved in routine manual and routine cognitive activities. We also find that advances in AI have benefited workers with regard to both employment stability (lower odds of transition into non-employment or occupational switching) and wage growth. These effects are strongest for highly-educated and experienced workers, who seem to be able to leverage their human capital by working with new AI technologies. A possible explanation for this result is that both low-skilled and high-skilled jobs involve non-routine cognitive activities, but to a different extent. Advances in AI may make workers in high-skilled jobs, which usually rely more strongly on such activities, more productive in their jobs.

This paper has several implications for education policy. Given that our results suggest that high-skilled individuals will be most affected by new digital technologies, both in terms of their destructive effects and complementary effects of advances in AI, tertiary education programs will have to be adjusted to take into account the recent developments in new digital technologies and the way they affect work processes. It is also likely that continuing education programs will have to be developed for highly qualified individuals whose jobs will be transformed due to AI and who will work with new digital technologies more intensively. At the same time, men without college education have the highest risk of being pushed into non-employment by computerization risk. Entrepreneurship seems to be a viable career option for both low- and high-skilled male workers and female workers with a college degree in occupations affected by computerization risk. Thus, specifically designed entrepreneurship education programs focusing on new digital technologies may be needed to help individuals to pursue promising entrepreneurial opportunities.

5.2. Limitations of the analysis and avenues for future research

Our analysis is not without limitations. In our dataset we do not observe whether and in how far firms adopt new digital technologies. If certain types of firms are early adopters of new digital technologies, then workers in these firms are likely to be more affected. However, we control for industries, regions, and the initial wage level as a proxy for individual productivity, and in robustness checks we also investigate differences between sectors and urban versus rural areas to at least partially account for unobserved differences between firm types, and we do not find any significant differences in this respect. While we advance the literature by using data at the level of individual workers, an important avenue for future research is to include data on individual firms as well in order to learn more about the substitutive or complementary nature of new digital technologies, as also noted by Raj and Seamans (2019). Moreover, we only observe the occupation of an individual, which is a rather aggregated measure of work activities. For future research, it would be desirable to collect data allowing to match the measures of new digital technologies with individual data at the level of tasks or work activities rather than occupations.

The results presented in this paper raise a number of further opportunities for future research. One promising research area concerns individual strategies to mitigate the destructive effects of new digital technologies. Our study provides first results suggesting that workers differ in their flexibility to adapt to these changes in their occupation. Higher formal education seems to provide individual workers with an enhanced adaptive capacity by allowing them to pursue more diverse strategies in response to a high computerization risk of their occupation, such as a change of occupation or the choice of an entrepreneurial career, in comparison to individuals with lower levels of formal education. At the same time, it is unclear whether individuals successfully reduce their computerization risk by switching occupations in the long term. Gathmann and Schönberg (2010) show that although human capital can be transferred across occupations, highly educated individuals and more experienced workers move to more similar occupations while less educated and less experienced individuals may switch to less similar occupations. This occurs because highly educated, more experienced individuals accumulate more task-specific human capital. This could imply that highly educated individuals may not be able to sufficiently mitigate the destructive digitalization of their current occupation by switching to occupations that are similar to their original, highly affected occupations. To investigate this issue, individual-level data with information about job tasks are needed.

A related research question concerns the location and potential migration of workers: In how far are regions different with regard to the exposure of the workforce to new digital technologies, such as advances in AI? Are individuals in occupations that are strongly affected by these technologies more likely to change an occupation in conjecture with moving to a different region?

In sum, this paper documents that new digital technologies are already showing a substantial impact on employment stability and wage growth of individual workers in the U.S. labor market. In contrast to previous waves of automation, highly skilled individuals are most affected in terms of employment stability and wage growth. Substantial efforts on the part of policy makers will be needed to help workers at all skill levels to adapt to these changes successfully.

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Tables

Table 1: Marginal effects of digitalization on transition probabilities *for men* (in %-points)

Digitalization impact on probability of…	Computerization probability	Advances in AI	Suitability for machine learning: Mean SML	Suitability for machine learning: Within-occ. std. dev. (sdSML)	Baseline prob. of choice in %
No change	-0.762***	0.982***	-0.110	0.359**	91.1
	(0.177)	(0.163)	(0.173)	(0.147)	
Entry into non-employment	0.307***	-0.315***	-0.0602	0.00687	2.35
	(0.0450)	(0.0422)	(0.0473)	(0.0408)	
Switch to new wage occupation	0.412***	-0.632***	0.191	-0.353***	6.16
	(0.148)	(0.134)	(0.135)	(0.124)	
Entry into unincorp. entrepreneurship	0.0446***	-0.0444***	-0.0121	-0.00419	0.291
	(0.0129)	(0.0130)	(0.0105)	(0.0116)	
Entry into incorp. entrepreneurship	-0.00114	0.00895	-0.00915*	-0.00836*	0.137
	(0.00679)	(0.00706)	(0.00519)	(0.00492)	
Control variables	Yes	Yes	Yes	Yes	
No. of observations	1,580,634	1,589,075	1,434,407		
Log likelihood	-569,489	-572,420	-516,361		

Notes: Marginal effects from multinomial logit estimations in percentage points based on the sample of *male* paid employees. Three separate estimations are shown using different measures of digitalization impact: The first column with numbers uses the computerization probability, the second column uses Advances in AI, and the third estimation uses SML and sdSML, shown in the third and fourth columns. For each model, the five choice alternatives appear in the rows of the table. The cells show the marginal effects of an increase in the digitalization impact measure by one standard deviation on the probability of the choice indicated in the leftmost column. The control variables are listed in Section 3.2.1. The rightmost column shows the unconditional probabilities of each month-to-month transition. The standard errors are robust to clustering at the level of occupations. Stars (***/**/*) indicate significance at the 1%/5%/10% level. Source: Own calculations based on the monthly CPS 2011-18.

Table 2: Marginal effects of digitalization on transition probabilities *for women* (in %-points)

Digitalization impact on probability of…	Computerization probability	Advances in AI	Suitability for machine learning: Mean SML	Suitability for machine learning: Within-occ. std. dev. (sdSML)	Baseline prob. of choice in %
No change	-0.623***	0.931***	-0.133	0.0349	91.1
	(0.201)	(0.169)	(0.157)	(0.152)	
Entry into non-employment	0.215**	-0.461***	-0.0904	-0.0182	2.94
	(0.0979)	(0.0724)	(0.0760)	(0.0830)	
Switch to new wage occupation	0.419***	-0.432***	0.272**	0.00628	5.67
	(0.147)	(0.153)	(0.124)	(0.111)	
Entry into unincorp. entrepreneurship	-0.00623	-0.0448**	-0.0411***	-0.0170	0.218
	(0.0142)	(0.0227)	(0.0116)	(0.0126)	
Entry into incorp. entrepreneurship	-0.00523*	0.00574	-0.00697**	-0.00601**	0.0658
	(0.00315)	(0.00366)	(0.00271)	(0.00284)	
Control variables	Yes	Yes	Yes	Yes	
No. of observations	1,544,843	1,551,890	1,448,599		
Log likelihood	-557,556	-559,661	-525,069		

Notes: Marginal effects from multinomial logit estimations in percentage points based on the sample of *female* paid employees. Three separate estimations are shown using different measures of digitalization impact: The first column with numbers uses the computerization probability, the second column uses Advances in AI, and the third estimation uses SML and sdSML, shown in the third and fourth columns. For each model, the five choice alternatives appear in the rows of the table. The cells show the marginal effects of an increase in the digitalization impact measure by one standard deviation on the probability of the choice indicated in the leftmost column. The control variables are listed in Section 3.2.1. The rightmost column shows the unconditional probabilities of each month-to-month transition. The standard errors are robust to clustering at the level of occupations. Stars (***/**/*) indicate significance at the 1%/5%/10% level. Source: Own calculations based on the monthly CPS 2011-18.

Table 3: Marginal effects of digitalization on transition probabilities *by education for men* (in %-points)

		Computeriz. probability	Advances in AI	Suitability for ML	
Probability of…	*Digitalization impact with…*			Mean SML	Sd. SML
No change	Less than high school	-0.498	0.521	-0.412	0.855***
		(0.406)	(0.320)	(0.403)	(0.293)
	High school	-0.483**	0.751***	-0.0557	0.442**
		(0.223)	(0.195)	(0.212)	(0.189)
	Some college	-0.591***	1.04***	-0.0823	0.277*
		(0.178)	(0.158)	(0.160)	(0.157)
	College degree	-1.13***	1.38***	-0.113	0.244
		(0.274)	(0.201)	(0.202)	(0.195)
Entry into non-employment	Less than high school	0.367***	-0.298***	-0.0522	-0.0644
		(0.104)	(0.0932)	(0.110)	(0.0817)
	High school	0.371***	-0.292***	-0.131**	-0.0149
		(0.0568)	(0.0620)	(0.0626)	(0.0595)
	Some college	0.322***	-0.385***	-0.0471	0.0122
		(0.0510)	(0.0434)	(0.0520)	(0.0479)
	College degree	0.242***	-0.344***	-0.0150	0.0432
		(0.0584)	(0.0375)	(0.0454)	(0.0455)
Switch of wage occupation	Less than high school	0.0749	-0.200	0.420	-0.774***
		(0.351)	(0.273)	(0.299)	(0.255)
	High school	0.0985	-0.430***	0.203	-0.408***
		(0.190)	(0.148)	(0.160)	(0.157)
	Some college	0.237	-0.623***	0.142	-0.269**
		(0.151)	(0.131)	(0.120)	(0.128)
	College degree	0.813***	-0.982***	0.180	-0.288*
		(0.218)	(0.188)	(0.173)	(0.168)
Entry into unincorporated entrepreneurship	Less than high school	0.0950***	-0.0386	0.0378	-0.0218
		(0.0324)	(0.0340)	(0.0379)	(0.0356)
	High school	0.0246	-0.0404**	-0.0129	-0.0123
		(0.0182)	(0.0160)	(0.0146)	(0.0156)
	Some college	0.0369***	-0.0414***	-0.0108	-0.00591
		(0.0133)	(0.0134)	(0.0100)	(0.0122)
	College degree	0.0578***	-0.0601***	-0.0267**	0.00950
		(0.0158)	(0.0139)	(0.0123)	(0.0116)
Entry into incorporated entrepreneurship	Less than high school	-0.0388**	0.0159	0.00637	0.00466
		(0.0169)	(0.0102)	(0.00959)	(0.00869)
	High school	-0.0116	0.0114	-0.00372	-0.00704
		(0.00971)	(0.00703)	(0.00575)	(0.00591)
	Some college	-0.00482	0.00474	-0.00140	-0.0140*
		(0.00938)	(0.00755)	(0.00777)	(0.00721)
	College degree	0.0142	0.00955	-0.0254***	-0.00898
		(0.00923)	(0.0149)	(0.00973)	(0.00909)
Control variables		Yes	Yes	Yes	
Number of observations		1,580,634	1,589,075	1,434,407	
Log likelihood		-569,341	-572,251	-516,308	

Notes: The table follows the same logic as Table 1 for male workers. The difference is that the models additionally include interaction terms of the digitalization impact measures with education dummy variables. The cells show marginal effects of an increase in the digitalization impact measure by one standard deviation on the probability of the choice in the first column conditional on the education level in the second column. The standard errors are robust to clustering at the level of occupations. Stars (***/**/*) indicate significance at the 1%/5%/10% level. Source: Own calculations based on the monthly CPS 2011-18.

Table 4: Marginal effects of digitalization on transition probabilities *by education for women* (in %-points)

		Computeriz. probability	Advances in AI	Suitability for ML	
Probability of…	*Digitalization impact with…*			Mean SML	Sd. SML
No change	Less than high school	0.153	-0.623**	0.0166	0.0765
		(0.460)	(0.314)	(0.348)	(0.273)
	High school	0.0234	0.205	0.250	0.202
		(0.253)	(0.192)	(0.189)	(0.132)
	Some college	-0.439*	0.798***	-0.0939	0.0670
		(0.254)	(0.229)	(0.201)	(0.180)
	College degree	-1.16***	1.80***	-0.545***	-0.0932
		(0.280)	(0.202)	(0.197)	(0.222)
Entry into non-employment	Less than high school	0.160	-0.387**	-0.281**	-0.170
		(0.322)	(0.170)	(0.139)	(0.108)
	High school	0.205	-0.415***	-0.262***	-0.146
		(0.130)	(0.103)	(0.101)	(0.0929)
	Some college	0.231*	-0.474***	-0.0681	-0.0412
		(0.121)	(0.0956)	(0.0998)	(0.106)
	College degree	0.213**	-0.545***	0.0359	0.110
		(0.0901)	(0.0687)	(0.0661)	(0.0864)
Switch of wage occupation	Less than high school	-0.153	1.03***	0.315	0.138
		(0.228)	(0.340)	(0.307)	(0.233)
	High school	-0.180	0.241	0.0833	-0.0188
		(0.183)	(0.163)	(0.147)	(0.124)
	Some college	0.229	-0.296*	0.212	-0.00497
		(0.170)	(0.176)	(0.132)	(0.116)
	College degree	0.920***	-1.19***	0.536***	-0.00239
		(0.217)	(0.177)	(0.169)	(0.173)
Entry into unincorporated entrepreneurship	Less than high school	-0.148***	-0.0398	-0.0593*	-0.0389
		(0.0449)	(0.0601)	(0.0348)	(0.0340)
	High school	-0.0383*	-0.0400	-0.0678***	-0.0303*
		(0.0225)	(0.0351)	(0.0158)	(0.0180)
	Some college	-0.0142	-0.0303	-0.0409***	-0.0139
		(0.0170)	(0.0227)	(0.0114)	(0.0121)
	College degree	0.0264**	-0.0661***	-0.0145	-0.00990
		(0.0133)	(0.0159)	(0.0138)	(0.0131)
Entry into incorporated entrepreneurship	Less than high school	-0.0107	0.0158*	0.00889	-0.00657
		(0.0132)	(0.00890)	(0.00547)	(0.00442)
	High school	-0.00935**	0.00895**	-0.00332	-0.00677**
		(0.00460)	(0.00414)	(0.00456)	(0.00284)
	Some college	-0.00647	0.00263	-0.00871***	-0.00693
		(0.00412)	(0.00467)	(0.00323)	(0.00425)
	College degree	-0.00205	0.00582	-0.0116**	-0.00413
		(0.00510)	(0.00734)	(0.00453)	(0.00489)
Control variables		Yes	Yes	Yes	
Number of observations		1,544,843	1,551,890	1,448,599	
Log likelihood		-557,233	-559,088	-524,908	

Notes: The table follows the same logic as Table 2 for female workers. The difference is that the models additionally include interaction terms of the digitalization impact measures with education dummy variables. The cells show marginal effects of an increase in the digitalization impact measure by one standard deviation on the probability of the choice in the first column conditional on the education level in the second column. The standard errors are robust to clustering at the level of occupations. Stars (***/**/*) indicate significance at the 1%/5%/10% level. Source: Own calculations based on the monthly CPS 2011-18.

Table 5: Effects of digitalization on wage growth

Sample:	Men			Women		
Digitalization measure:	Computeriz. probability	Advances in AI	Suitability for ML	Computeriz. probability	Advances in AI	Suitability for ML
Digitalization measure	-0.100***	0.107***	-0.00474	-0.0675***	0.138***	-0.0127
	(0.0139)	(0.0112)	(0.0137)	(0.0194)	(0.0140)	(0.0135)
Occupation switch	-0.0460***	-0.0273***	-0.0463***	-0.0356**	-0.0449***	-0.0385**
	(0.0101)	(0.00922)	(0.0127)	(0.0155)	(0.0129)	(0.0189)
Digitalizat. measure * occupation switch	0.0487***	-0.0534***	0.00757	0.0313*	-0.0673***	0.00617
	(0.0119)	(0.00999)	(0.0117)	(0.0166)	(0.0118)	(0.0119)
Entrepreneur, incorp.	-0.158***	-0.157***	-0.152***	-0.224***	-0.215***	-0.198***
	(0.0189)	(0.0176)	(0.0216)	(0.0354)	(0.0373)	(0.0361)
Entrepreneur, uninc.	-0.00713	-0.00242	0.0174	-0.0569*	-0.0642**	-0.0269
	(0.0158)	(0.0136)	(0.0174)	(0.0297)	(0.0295)	(0.0284)
High school deg.	0.141***	0.139***	0.155***	0.145***	0.122***	0.152***
	(0.0122)	(0.0120)	(0.0135)	(0.0196)	(0.0180)	(0.0198)
Some college	0.206***	0.205***	0.236***	0.225***	0.183***	0.239***
	(0.0137)	(0.0124)	(0.0142)	(0.0238)	(0.0207)	(0.0251)
College degree	0.412***	0.425***	0.475***	0.396***	0.342***	0.433***
	(0.0185)	(0.0157)	(0.0182)	(0.0278)	(0.0242)	(0.0260)
Age	0.0366***	0.0366***	0.0382***	0.0345***	0.0350***	0.0354***
	(0.00210)	(0.00211)	(0.00216)	(0.00242)	(0.00217)	(0.00256)
Age sqaured	-0.000394***	-0.000394***	-0.000413***	-0.00037***	-0.00037***	-0.00038***
	(0.0000242)	(0.0000242)	(0.0000251)	(0.0000280)	(0.0000250)	(0.0000294)
Married	0.109***	0.108***	0.114***	0.0250***	0.0224***	0.0248***
	(0.00650)	(0.00645)	(0.00694)	(0.00614)	(0.00583)	(0.00635)
No. of children	0.0111***	0.0108***	0.0121***	-0.00902***	-0.00759**	-0.00926***
	(0.00269)	(0.00270)	(0.00304)	(0.00336)	(0.00328)	(0.00356)
Metropolitan area	0.0649***	0.0691***	0.0633***	0.0894***	0.0936***	0.0858***
	(0.00723)	(0.00739)	(0.00788)	(0.00794)	(0.00776)	(0.00817)
Black	-0.0954***	-0.0881***	-0.104***	-0.0475***	-0.0427***	-0.0513***
	(0.0114)	(0.0122)	(0.0123)	(0.0122)	(0.0116)	(0.0131)
Asian	-0.0269	-0.0231	-0.0338*	-0.00735	-0.00720	-0.0191
	(0.0170)	(0.0176)	(0.0187)	(0.0160)	(0.0139)	(0.0172)
Other race	-0.0360**	-0.0352**	-0.0364**	-0.0313*	-0.0317*	-0.0281
	(0.0160)	(0.0163)	(0.0166)	(0.0175)	(0.0174)	(0.0182)
Base year inc. splines	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dum. (full set)	Yes	Yes	Yes	Yes	Yes	Yes
N	65,826	66,148	59,458	61,063	61,375	57,113
R^2	0.307	0.309	0.301	0.310	0.318	0.308

Notes: OLS regressions. The dependent variable is the growth rate in the hourly wage between two adjacent years in 2010 US$ (logarithmic approximation). The digitalization measures pertain to the first year of a two-year pair and are standardized. The switch dummy variable indicates that an individual switched to a new occupation between the two years. We interact this dummy variable with the digitalization measure. The standard errors are robust to clustering at the level of occupations. Stars (***/**/*) indicate significance at the 1%/5%/10% level. Source: Own calculations based on the annual ASEC 2011-18.

Table 6: Effects of digitalization on wage growth *by education*

Sample:	Less than high school		High school		Some college		College degree	
Digit. measure:	Comput. prob.	Advances in AI	Comput. prob.	Advances in AI	Comput. prob.	Advances in AI	Comput. prob.	Advances in AI
Digit.	-0.0576	0.0840***	-0.0665***	0.0963***	-0.0774***	0.105***	-0.0924***	0.153***
	(0.0365)	(0.0225)	(0.0175)	(0.0112)	(0.0182)	(0.0142)	(0.0211)	(0.0186)
Switch	-0.0215	-0.0356*	-0.0144	-0.0171	-0.0489***	-0.0424***	-0.0387**	-0.0157
	(0.0317)	(0.0211)	(0.0146)	(0.0114)	(0.0143)	(0.0115)	(0.0164)	(0.0152)
Digit. x switch	0.0226	-0.0451**	0.0214	-0.0396***	0.0261	-0.0403***	0.0507***	-0.0888***
	(0.0336)	(0.0218)	(0.0155)	(0.0102)	(0.0174)	(0.0133)	(0.0173)	(0.0171)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7766	7772	33,458	33,562	36,577	36,714	49,088	49,475
R^2	0.328	0.330	0.310	0.313	0.317	0.320	0.301	0.309

Notes: Separate OLS regressions for different highest educational attainment levels (men and women combined). The dependent variable is the growth rate in the hourly wage between two adjacent years in 2010 US$ (logarithmic approximation). The digitalization measures pertain to the first year of a two-year pair and are standardized. The switch dummy variable indicates that an individual switched to a new occupation between the two years. We interact this dummy variable with the digitalization measure. The control variables are the same as in Table 5. The standard errors are robust to clustering at the level of occupations. Stars (***/**/*) indicate significance at the 1%/5%/10% level. Source: Own calculations based on the annual ASEC 2011-18.

Table 7: Effects of digitalization on wage growth *by age*

Age	21-30		30-39		40-59		60-64	
Digit. measure	Comput. probability	Advances in AI	Comput. probability	Advances in AI	Comput. probability	Advances in AI	Comput. probability	Advances in AI
Digit.	-0.0666***	0.104***	-0.0763***	0.121***	-0.0883***	0.119***	-0.0819***	0.134***
	(0.0187)	(0.0127)	(0.0144)	(0.0120)	(0.0153)	(0.0121)	(0.0228)	(0.0188)
Switch	-0.0554***	-0.0539***	-0.0304**	-0.0200*	-0.0385***	-0.0315***	-0.0450**	-0.0398*
	(0.0144)	(0.0131)	(0.0124)	(0.0107)	(0.0111)	(0.0100)	(0.0222)	(0.0207)
Digit. x switch	0.0207	-0.0378***	0.0263**	-0.0578***	0.0493***	-0.0611***	0.0408*	-0.0746***
	(0.0156)	(0.0125)	(0.0133)	(0.0115)	(0.0128)	(0.0112)	(0.0237)	(0.0183)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	18,283	18,386	28,675	28,845	68,666	68,971	11,265	11,321
R^2	0.365	0.369	0.315	0.321	0.292	0.297	0.274	0.280

Notes: Separate OLS regressions for different age groups (men and women combined). The dependent variable is the growth rate in the hourly wage between two adjacent years in 2010 US$ (logarithmic approximation). The digitalization measures pertain to the first year of a two-year pair and are standardized. The switch dummy variable indicates that an individual switched to a new occupation between the two years. We interact this dummy variable with the digitalization measure. The control variables are the same as in Table 5. The standard errors are robust to clustering at the level of occupations. Stars (***/**/*) indicate significance at the 1%/5%/10% level. Source: Own calculations based on the annual ASEC 2011-18.

Table 8: Effects of digitalization on wage growth *in the ICT and STEM related sectors*

	ICT			STEM		
	Computeriz. probability	Advances in AI	Suitability for ML	Computeriz. probability	Advances in AI	Suitability for ML
Digitalization measure	-0.102***	0.0989**	-0.0363	-0.104***	0.0776**	-0.0218
	(0.0289)	(0.0390)	(0.0270)	(0.0195)	(0.0338)	(0.0229)
Occupation switch	-0.0707***	-0.0615***	-0.0815***	-0.113***	-0.103***	-0.159***
	(0.0242)	(0.0235)	(0.0201)	(0.0205)	(0.0302)	(0.0192)
Digitalization measure *x* occupation switch	0.0192	-0.0636*	0.0220	0.0485**	-0.0464	0.0374
	(0.0248)	(0.0382)	(0.0229)	(0.0230)	(0.0326)	(0.0231)
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes
N	5099	5206	4621	17,144	17,316	16,384
R^2	0.294	0.291	0.299	0.294	0.294	0.290

Notes: Separate OLS regressions for respondents initially in an ICT or STEM related occupation (men and women combined). The dependent variable is the percent change in the hourly wage between two adjacent years in 2010 US$ (logarithmic approximation). The digitalization measures pertain to the first year of a two-year pair and are standardized. The switch dummy variable indicates that an individual switched to a new occupation between the two years. We interact this dummy variable with the digitalization measure. The control variables are the same as in Table 5. The standard errors are robust to clustering at the level of occupations. Stars (***/**/*) indicate significance at the 1%/5%/10% level. Source: Own calculations based on the annual ASEC 2011-18.

Table 9: Effects of digitalization on hourly earnings growth *by type of worker*

Sample:	Wage & salary employees			Entrepreneurs		
Digitalization measure:	Computeriz. probability	Advances in AI	Suitability for ML	Comput. probability	Advances in AI	Suitability for ML
Digitalization measure	-0.0825***	0.117***	-0.00815	-0.0861***	0.133***	-0.0415***
	(0.0146)	(0.0106)	(0.0118)	(0.0296)	(0.0263)	(0.0148)
Occupation switch	-0.0438***	-0.0381***	-0.0455***	0.00217	0.0196	-0.00357
	(0.0104)	(0.00862)	(0.0123)	(0.0295)	(0.0299)	(0.0359)
Digitalization measure *x* occupation switch	0.0406***	-0.0565***	0.00914	0.0327	-0.0792***	0.00348
	(0.0121)	(0.00910)	(0.00890)	(0.0327)	(0.0299)	(0.0218)
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes
N	114,999	115,567	105,756	11,890	11,956	10,815
R^2	0.299	0.305	0.295	0.347	0.350	0.346

Notes: Separate OLS regressions for initial wage & salary employees and entrepreneurs (men and women combined). The dependent variable is the percent change in the hourly wage between two adjacent years in 2010 US$ (logarithmic approximation). The digitalization measures pertain to the first year of a two-year pair and are standardized. The switch dummy variable indicates that an individual switched to a new occupation between the two years. We interact this dummy variable with the digitalization measure. The control variables are the same as in Table 5. The standard errors are robust to clustering at the level of occupations. Stars (***/**/*) indicate significance at the 1%/5%/10% level. Source: Own calculations based on the annual ASEC 2011-18.

Table 10: Effects of digitalization on wage growth: *urban versus rural*

Sample:	Central city			Outside central city		
Digitalizat. measure:	Comput. probability	Advances in AI	Suitability for ML	Comput. probability	Advances in AI	Suitability for ML
Digit.	-0.0832***	0.113***	-0.00458	-0.0819***	0.121***	-0.0103
	(0.0162)	(0.0123)	(0.0123)	(0.0157)	(0.0116)	(0.0118)
Switch	-0.0356***	-0.0316***	-0.0404***	-0.0429***	-0.0349***	-0.0437***
	(0.0135)	(0.0122)	(0.0155)	(0.0116)	(0.0103)	(0.0135)
Switch *x*	0.0347**	-0.0474***	0.00237	0.0365***	-0.0564***	0.00453
digi.	(0.0143)	(0.0118)	(0.0120)	(0.0134)	(0.0105)	(0.00966)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	30,268	30,417	27,726	74,380	74,768	68,334
R^2	0.312	0.317	0.311	0.304	0.309	0.300

Notes: Separate OLS regressions for respondents in core cities versus in other areas (men and women combined). The samples are smaller than in the main estimations because of missing values in the central city status. The dependent variable is the percent change in the hourly wage between two adjacent years in 2010 US$ (logarithmic approximation). The digitalization measures pertain to the first year of a two-year pair and are standardized. The switch dummy variable indicates that an individual switched to a new occupation between the two years. We interact this dummy variable with the digitalization measure. The control variables are the same as in Table 5. The standard errors are robust to clustering at the level of occupations. Stars (***/**/*) indicate significance at the 1%/5%/10% level. Source: Own calculations based on the annual ASEC 2011-18.

Appendix A: Supplementary tables

Table A1: Measures of impact of digitalization on occupations

	Computerization probability	Advances in AI	Suitability for machine learning
Short	CP	AAI	SML. Within-occupation variance: sdSML.
Source	Frey and Osborne (2017)	Felten et al. (2018)	Brynjolfsson et al. (2018)
Time reference	Next 10-20 years (viewed from 2013)	Past (2010-15)	Near future (viewed from 2018)
Focus	Computerization	Artificial intelligence (AI)	Machine learning (ML) as a subfield of AI
Measurement	Experts' predictions for 71 occupations to obtain training dataset, then classification of 702 occupations using machine learning techniques.	AI progress measured by the Electronic Frontier Foundation mapped to 52 job requirements from O*NET and then aggregated to occupation level.	Scoring of 2069 direct work activities from O*NET through the crowdsourcing platform CrowdFlower, then aggregated to occupation level.

Notes: Overview of the three measures of digitalization impact used in this analysis (see also Fossen and Sorgner, 2019).

Table A2: Impact of digitalization on selected occupations

SOC code	Occupations	Advances in AI score	Computerization prob.
Occupations with highest computerization probabilities:			
51-9151	Photographic Process Workers & Proc. Machine Operators	3.411	0.99
43-9021	Data Entry Keyers	3.100	0.99
49-9064	Watch Repairers	3.051	0.99
13-2053	Insurance Underwriters	3.015	0.99
51-6051	Sewers, Hand	2.840	0.99
43-5011	Cargo and Freight Agents	2.813	0.99
13-2082	Tax Preparers	2.805	0.99
43-4141	New Accounts Clerks	2.663	0.99
15-2091	Mathematical Technicians	2.622	0.99
25-4031	Library Technicians	2.602	0.99
Occupations with lowest computerization probabilities:			
27-2032	Choreographers	3.490	0.004
11-9081	Lodging Managers	3.832	0.004
29-1031	Dietitians and Nutritionists	3.749	0.004
29-1022	Oral and Maxillofacial Surgeons	5.207	0.004
33-1021	First-Line Supervisors of Fire Fighting & Prevention Workers	5.206	0.004
29-2091	Orthotists and Prosthetists	4.152	0.004
29-1122	Occupational Therapists	3.859	0.004
21-1022	Healthcare Social Workers	3.652	0.004
29-1181	Audiologists	4.245	0.003
21-1023	Mental Health and Substance Abuse Social Workers	3.872	0.003
49-1011	First-Line Supervisors of Mechanics, Installers & Repairers	4.579	0.003
11-9161	Emergency Management Directors	4.377	0.003
29-1125	Recreational Therapists	3.772	0.003
Occupations with highest scores in advances in AI:			
53-2011	Airline Pilots, Copilots, and Flight Engineers	6.537	0.18
19-2012	Physicists	5.907	0.10
29-1067	Surgeons	5.780	0.00
53-2012	Commercial Pilots	5.682	0.55
53-2021	Air Traffic Controllers	5.680	0.11
29-1021	Dentists, General	5.414	0.004
19-1021	Biochemists and Biophysicists	5.265	0.03
29-1022	Oral and Maxillofacial Surgeons	5.207	0.004
33-1021	First-Line Supervisors of Fire Fighting & Prevention Workers	5.206	0.004
19-1022	Microbiologists	5.203	0.01
17-1011	Architects, Except Landscape and Naval	5.195	0.02
Occupations with lowest scores in advances in AI:			
39-4021	Funeral Attendants	1.953	0.37
51-6021	Pressers, Textile, Garment, and Related Materials	1.942	0.81
35-3041	Food Servers, Nonrestaurant	1.939	0.86
35-9011	Dining Room Attendants & Bartender Helpers	1.896	0.91
51-3023	Slaughterers and Meat Packers	1.896	0.60
53-7061	Cleaners of Vehicles and Equipment	1.864	0.37
37-2012	Maids and Housekeeping Cleaners	1.849	0.69
39-5093	Shampooers	1.839	0.79
45-2041	Graders and Sorters, Agricultural Products	1.572	0.41
39-3093	Locker Room, Coatroom & Dressing Room Attendants	1.515	0.43
41-9041	Telemarketers	1.510	0.99
41-9012	Models	1.417	0.98

Notes: The advances in AI are adopted from Felten et al. (2018) and the computerization probabilities from Frey and Osborne (2017).

Table A3: Descriptive statistics for employees by transition type (monthly CPS)

	Full sample	No change	Entry into non-employm.	Switch to new wage occupation	Entry into unincorp. entrepreneurship	Entry into incorporat. entrepreneurship
Digitalization impact:						
Computerization probability	0.488	0.482	0.587	0.532	0.538	0.442
Standard deviation	0.373	0.374	0.355	0.368	0.355	0.372
Advances in AI	3.338	3.351	3.094	3.263	3.231	3.488
Standard deviation	0.676	0.675	0.673	0.660	0.681	0.664
Suitability for ML (SML)	3.480	3.480	3.473	3.483	3.460	3.468
Standard deviation	0.102	0.102	0.107	0.106	0.106	0.101
Within-occ. std. dev. of SML	0.591	0.591	0.591	0.588	0.590	0.587
Standard deviation	0.059	0.058	0.061	0.060	0.057	0.057
Socioeconomic variables:						
Male	0.506	0.506	0.450	0.527	0.577	0.682
Age	41.932	42.146	37.637	40.436	43.418	45.013
Married	0.582	0.589	0.444	0.533	0.590	0.724
No. of children in the househ.	0.907	0.911	0.859	0.853	0.940	1.052
Metropolitan area	0.816	0.813	0.817	0.847	0.807	0.863
Less than high school	0.064	0.061	0.123	0.079	0.134	0.046
High school degree	0.264	0.262	0.309	0.281	0.291	0.229
Some college	0.295	0.295	0.321	0.293	0.264	0.234
College degree	0.377	0.383	0.247	0.347	0.311	0.490
White	0.817	0.822	0.751	0.772	0.821	0.836
Black	0.097	0.094	0.147	0.128	0.085	0.077
Asian	0.055	0.054	0.058	0.067	0.058	0.068
Other race	0.030	0.030	0.045	0.033	0.035	0.019
Industries:						
Mining, manufact. & utilities	0.134	0.134	0.094	0.146	0.075	0.107
Construction	0.058	0.056	0.093	0.067	0.146	0.110
Wholesale & retail trade	0.132	0.132	0.136	0.133	0.109	0.136
Transportation & information	0.065	0.066	0.058	0.062	0.073	0.068
Financial services	0.069	0.069	0.044	0.074	0.058	0.088
Profess. & business services	0.106	0.104	0.119	0.126	0.141	0.147
Educational & health services	0.254	0.257	0.238	0.208	0.178	0.183
Leisure & hospitality	0.080	0.078	0.131	0.088	0.076	0.072
Other services	0.102	0.103	0.088	0.095	0.143	0.092
Person-month observations	3,140,965	2,860,597	82,853	186,304	8001	3210

Notes: The table shows means and standard deviations for the full sample of paid employees and by transition choice between the current and the subsequent month. The digitalization impact measures are shown before standardization. Source: Own calculations based on the monthly CPS 2011-18 (see also Fossen and Sorgner, 2019).

Table A4: Correlation coefficients of digitalization impact measures and occupation tasks

	CP	AAI	SML	sdSML
Digitalization impact measures:				
CP: Computerization probability (Frey & Osborne 2017)	1			
AAI: Advances in AI (Felten et al., 2018)	-0.6277	1		
SML: Suitability for ML (Brynjolfsson et al. 2018)	0.1857	-0.1315	1	
sdSML: Within-occupation standard deviation of SML	-0.1219	0.0415	-0.1097	1
*Occupation tasks (from O*NET):*				
Non-routine cognitive: analytical	-0.6372	0.6839	-0.0020	0.0629
Non-routine cognitive: interpersonal	-0.6965	0.5539	-0.0442	0.0645
Routine cognitive	-0.0267	0.2026	0.3235	-0.1307
Non-routine manual: physical adaptability	0.4163	-0.0269	-0.3512	-0.0088
Routine manual	0.4714	-0.1726	-0.2093	-0.0600

Notes: All correlation coefficients are significantly different from zero at the 1% significance level. Number of person-month observations: 3,140,965. Source: Own calculations based on the monthly CPS 2011-18.

Table A5: Descriptive statistics by gender and employment type (annual ASEC)

	All	Men	Women	Employees	Entrep.
Digitalization impact:					
Computerization probability	0.472	0.482	0.462	0.479	0.408
Standard deviation	0.373	0.358	0.387	0.374	0.351
Advances in AI	3.372	3.491	3.243	3.360	3.483
Standard deviation	0.660	0.655	0.642	0.665	0.598
Suitability for ML (SML)	3.478	3.460	3.496	3.481	3.449
Standard deviation	0.104	0.095	0.109	0.103	0.108
Within-occ. std. dev. of SML	0.591	0.592	0.590	0.591	0.590
Standard deviation	0.058	0.058	0.058	0.058	0.054
Socioeconomic variables:					
Hourly labor income (2010 $)	23.75	27.04	20.21	23.24	28.68
Annual wage growth (%)	0.034	0.032	0.035	0.032	0.047
Wage and salary worker	0.906	0.883	0.931	1	0
Entrepreneur, incorporated	0.039	0.053	0.023	0	0.413
Entrepreneur, unincorporated	0.055	0.063	0.046	0	0.587
Male	0.519	1	0	0.505	0.647
Age	43.8	43.7	43.8	43.3	48.0
Married	0.635	0.660	0.607	0.624	0.735
No. of children in the househ.	0.956	0.959	0.952	0.947	1.041
Metropolitan area	0.825	0.830	0.820	0.826	0.816
Central city	0.289	0.288	0.290	0.290	0.281
Less than high school	0.061	0.074	0.047	0.060	0.068
High school degree	0.263	0.289	0.236	0.264	0.257
Some college	0.288	0.271	0.306	0.291	0.263
College degree	0.388	0.367	0.411	0.385	0.412
White	0.832	0.845	0.819	0.828	0.877
Black	0.086	0.074	0.098	0.089	0.049
Asian	0.054	0.054	0.054	0.054	0.054
Other race	0.028	0.027	0.028	0.028	0.021
Industries:					
Mining, manufact. & utilities	0.128	0.179	0.073	0.136	0.050
Construction	0.070	0.122	0.014	0.058	0.181
Wholesale & retail trade	0.127	0.135	0.118	0.129	0.111
Transportation & information	0.066	0.089	0.040	0.066	0.057
Financial services	0.073	0.064	0.083	0.072	0.085
Profess. & business services	0.117	0.129	0.104	0.105	0.230
Educational & health services	0.248	0.116	0.390	0.261	0.123
Leisure & hospitality	0.069	0.065	0.073	0.069	0.072
Other services	0.103	0.101	0.105	0.104	0.093
Person-month observations	127,523	66,148	61,375	115,567	11,956

Notes: The table shows means and standard deviations for the full sample, by gender and by employment status (paid employee or entrepreneur). The digitalization impact measures are shown before standardization. Source: Own calculations based on the annual ASEC 2011-18.

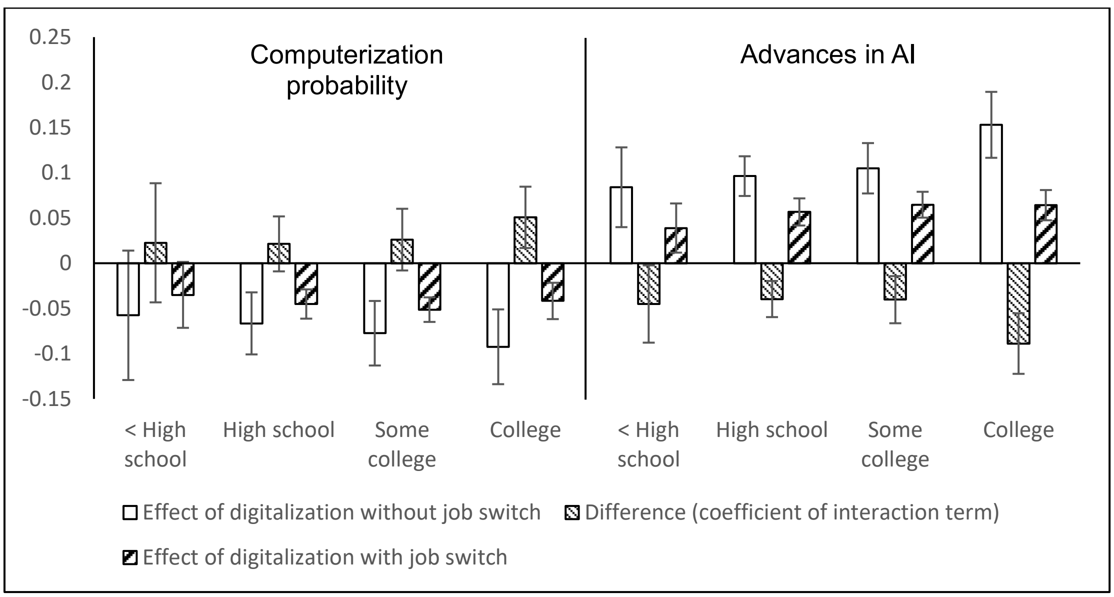
Table A6: Effects of digitalization on wage growth *using only major occupational switches*

Sample:	Men			Women		
Digitalization measure:	Comput. probability	Advances in AI	Suitability for ML	Comput. probability	Advances in AI	Suitability for ML
Digitalization measure	-0.0928***	0.100***	-0.00180	-0.0628***	0.129***	-0.0121
	(0.0120)	(0.00963)	(0.0116)	(0.0154)	(0.0127)	(0.0113)
Major occupation switch	-0.0582***	-0.0383***	-0.0568***	-0.0317**	-0.0451***	-0.0301*
	(0.0102)	(0.00960)	(0.0122)	(0.0137)	(0.0118)	(0.0165)
Digitalization measure x	0.0528***	-0.0604***	0.00273	0.0344**	-0.0733***	0.00490
major occup. switch	(0.0116)	(0.00985)	(0.0108)	(0.0143)	(0.0113)	(0.0108)
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes
N	65,823	66,145	59,455	61,055	61,367	57,106
R^2	0.307	0.309	0.302	0.310	0.318	0.308

Notes: OLS regressions. The dependent variable is the percent change in the hourly wage between two adjacent years in 2010 US$ (logarithmic approximation). The digitalization measures pertain to the first year of a two-year pair and are standardized. The switch dummy variable indicates that an individual switched *from one of the 23 main occupation groups to another* between the two years. We interact this dummy variable with the digitalization measure. The control variables are the same as in Table 5. The standard errors are robust to clustering at the level of occupations. Stars (***/**/*) indicate significance at the 1%/5%/10% level. Source: Own calculations based on the annual ASEC 2011-18.

Appendix B: Figure

Figure B1: Estimated effects of digitalization on wage growth by education



Notes: The figure illustrates the estimated coefficients from Table 6 of the effect of digitalization on wage growth, its interaction term with the dummy variable for job switchers, and the sum of these two coefficients, which indicates the total effect of digitalization for those who switch their occupations. The error bars depict 95% confidence intervals based on standard errors robust to clustering at the level of occupations. Source: Own calculations based on the annual ASEC 2011-18.