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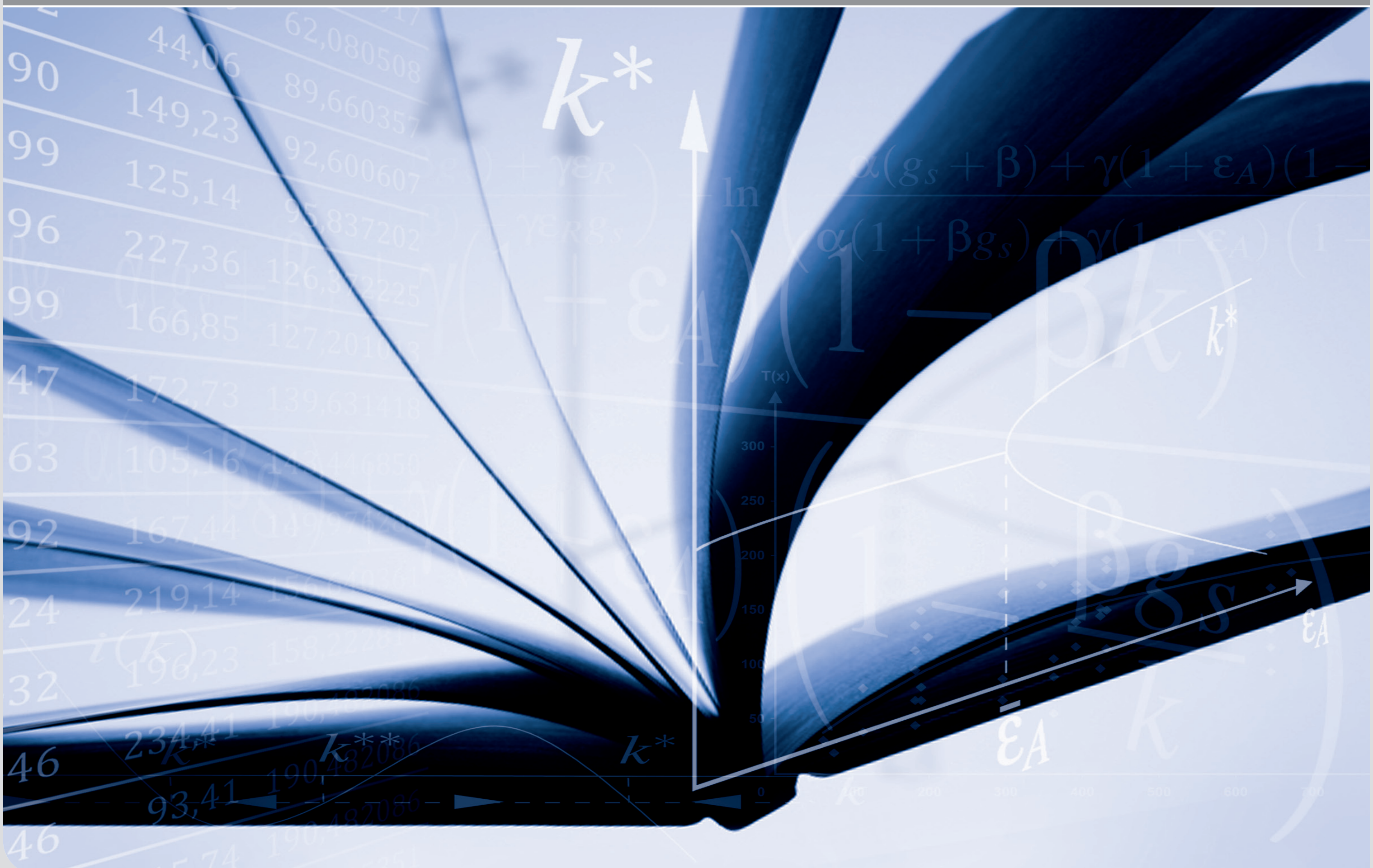

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Worker Personality:
Another Skill Bias beyond Education in the Digital Age

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Abstract

We present empirical evidence suggesting that technological progress in the digital age will be biased not only with respect to skills acquired through education but also with respect to noncognitive skills (personality). We measure the direction of technological change by estimated future digitalization probabilities of occupations, and noncognitive skills by the Big Five personality traits from several German worker surveys. Even though we control extensively for education and experience, we find that workers characterized by strong openness and emotional stability tend to be less susceptible to digitalization. Traditional indicators of human capital thus measure workers' skill endowments only imperfectly.

JEL: C25, J24, O33

Keywords: Worker personality, Noncognitive skills, Digital transformation, Direction of technical change, Germany.

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1. Motivation

This paper checks to what extent workers' personality is systematically related to the future susceptibility of their jobs to digitalization.[1] Personality (noncognitive skills[2]) comprises the inherited or acquired characteristic patterns of values, behaviors and attitudes that constitute part of human capital. We argue that if the digital transformation is skill-biased with respect to not only education but also personality, we should broaden our notion of human capital beyond educational attainment when analyzing the labor market effects of digitalization.

The tension between human and physical capital induced by technological change has been a key topic of economic research since the first industrial revolution. In his seminal paper, Griliches (1969) coined the term (relative) capital-skill complementarity and thus implicitly addressed issues related to the direction of technological change. He hypothesizes that physical capital substitutes better for unskilled, 'raw' labor than for skilled labor. Since then, a variety of studies have discussed the labor market implications of technological change. Recent studies argue that computerization has been skill-biased (e.g., Acemoglu 2002, Mokyr et al. 2015). It has tended to complement tasks that require high-level skills but to substitute for those tasks that require medium- or lower-level skills (Autor et al. 2003, Acemoglu and Autor 2011, Brynjolfsson and McAfee 2011). Empirical studies support this hypothesis (e.g., Autor and Dorn 2013).

Educational attainment has been shown to be a powerful though imperfect proxy of skill levels. Years of schooling or the highest degree completed in school causally affect a variety of labor market outcomes, including individual earnings (Card 1999) and aggregate income (e.g., Gennaioli et al. 2013). Educational attainment does not fully capture the productive potential of personality, though. It captures this potential partially because personality shapes students' success in school (Heckman et al. 2006, Hanushek and Woessmann 2008, Cunha et al. 2010). However, personality additionally affects labor market outcomes like occupational choice or wages directly, i.e., conditional on education (Heckman and Rubinstein 2001, Almlund et al. 2011).

This is the starting point of the paper at hand. We identify possible biases of future technological changes with respect to personality by regressing the susceptibility of jobs to digitalization on the personality of the workers who currently hold these jobs. To account for traditional skill biases, we control for the workers' educations and work experiences. We measure the susceptibility of jobs to digitalization by the "computerization probabilities" estimated by

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1 While somewhat artificial, we will use, for the sake of expositional simplicity, the shortcut "computerization" for technological innovations during the past about three decades, which include computers, the internet and mobile communication, "digitalization" for the upcoming innovations in the fourth industrial revolution, which include machine learning, big data, mobile robotics and cloud computing, and "automatization" as a comprehensive term for both waves of technological progress. We focus on digitalization in this paper but will frequently refer to the related literature on computerization.

2 We use the terms 'personality' and 'noncognitive skills' as synonyms throughout this paper for simplicity.

Frey and Osborne (2013) for occupations, and personality by scores of the Big Five personality traits (Costa and McCrae 1992). The Big Five is a widely used taxonomy that groups the various facets of personality into five broad categories: openness to experience, conscientiousness, extraversion, agreeableness and neuroticism. We use data on the Big Five personality traits from five different German household or workers surveys to check the robustness of our results.[3] While we do not postulate the estimated relationship between digitalization of jobs and workers' skills to be causal, we link digitalization and skills conceptually through workers' optimal job choices. Our identifying assumption is that the workers we observe have chosen their jobs optimally under the current technological regime but have not yet anticipated the future direction of technological change that is reflected by the digitalization probabilities.

The results indicate that not only educational attainment but also personality is systematically related to digitalization. We find, for example, that jobs typically held by workers who are more open to experience or emotionally more stable are less susceptible to being replaced by emerging technologies. We also show that this lower susceptibility is not due to the fact that workers in these jobs are more creative or more entrepreneurial. Given that our estimates are likely biased toward zero, we interpret them as indicating that current technological change is indeed biased with respect to personality. This suggests that putting greater emphasis on the heterogeneity of workers' skills endowments in labor-market models of technological change such as Acemoglu and Autor (2011) and the associated empirical studies may actually yield richer insights into the valuation of workers' skills in the digital age.

The remainder of the paper is organized as follows. The next section gives an overview of the related literature. Section 3 presents the conceptual framework that motivates our empirical analysis while Section 4 introduces the German micro datasets and the digitalization probabilities estimated by Frey and Osborne as well as the estimation method. Section 5 presents and discusses the empirical results, and Section 6 summarizes and discusses some lines for future research.

2. Related literature

Skill-biased technological change (SBTC) due to advances in information and communication technologies (ICT) has arguably destroyed millions of jobs in highly developed countries during the past about three decades, thereby reinforcing polarization of jobs and wages.[4]

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[3] These surveys are the 2009 and 2013 waves of the German Socio-Economic Panel (SOEP), the German National Education Panel Study (NEPS), the Panel Study on Labor Markets and Social Security (*Panelstudie Arbeitsmarkt und Soziale Sicherung*; PASS), and the Linked Personnel Panel (LPP). As a side product, we also identify interesting differences between these surveys that are obviously rooted in either their target populations or their survey designs.

[4] See Autor et al. (2003), Acemoglu and Autor (2011) and Autor (2013, 2015). See also Brynjolfsson and McAfee (2011).

Employment shares of high-skilled and of low-skilled jobs have increased while the middle of the job distribution has hollowed out (e.g., Autor and Dorn 2013, Wright and Gaggl 2015). The upcoming digital revolution is predicted to destroy additional jobs by the million. Frey and Osborne (2013) estimate that almost half of all jobs in the U.S. face a high risk of being automatized during the next about two decades. Bonin et al. (2015) and Brzeski and Burk (2015) obtain qualitatively similar results for Germany.[5] Most studies suggest that low skilled jobs will be affected disproportionately. Brynjolfsson and McAfee (2011) and Pratt (2015) suggest that high-skilled jobs may also be affected to a notable extent, though. Even though the predictions of future job losses by Frey and Osborne (2013) may be too pessimistic (Arntz et al. 2016), many people are deeply concerned about the short- and medium-term frictions the digital revolution induces. Workers who lose their jobs and human capital to the new technologies will have to write off part of their human capital and may need retraining. And education and training curricula will have to be refocused toward those skills that benefit from the new technologies in one way or another.

But what exactly are the skills whose market values are threatened by digital technologies, and what exactly are the skills that benefit? The SBTC approach is still rather sketchy in this respect. Focusing on the demand side of the labor market, it defines workers' skills either in terms of formal education only, assigning work tasks[6] to education levels on a one-dimensional scale (e.g., Autor et al. 2003, Acemoglu et al. 2011), or directly in terms of work tasks, virtually reinterpreting tasks as skills (e.g., Gathmann and Schönberg 2010, Autor and Handel 2013).[7] For example, Autor et al. (2003) hypothesize that medium-educated workers have been more susceptible to computerization than low- or high-educated workers because many of the tasks they have been performing are characterized by repeated standardized workflows that can fairly easily be codified in computer software. By contrast, both low- and high-educated workers have performed tasks that are less susceptible to computerization because these tasks are characterized by either non-routine physical or communication activities, or by advanced intuitive, persuasive and creative problem-solving activities, both of which are still too complex for computers.

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5 Dengler and Matthes (2015) and Arntz et al. (2016) arrive at significantly lower numbers, though. Dengler and Matthes estimate that 15% of the German workers are currently highly susceptible to digitalization, and Arntz et al. estimate that 12% of the German workers face a high risk of being digitalized during the next one or two decades. For other OECD countries, Arntz et al. estimate these shares to range from 6% in Korea to 12% in Austria, with the US being somewhere in-between (9%). These lower estimates may, however, be rather conservative because they are based on rather broad, heterogeneous aggregates of occupations (see Section 4).

6 A work tasks is a fairly homogeneous work activity a worker performs on his job. Jobs typically comprise bundles of tasks, defined by the employer, that any worker holding the job is requested to perform jointly in order to produce output (Autor et al. 2003).

7 Gathmann and Schönberg (2010), for example, subject workers' task-specific productivities to both their general skills, which they label "ability" and approximate by educational attainment, and "task tenure", workers' task-specific knowledge accumulated over time in previous jobs. They thus implicitly assume that workers have, apart from their formal education, no skills at all for performing tasks they never performed before.

In contrast to these demand-side labor economics, supply-side labor economics typically start from the presumption that humans are endowed with a variety of different skills. Adopting insights from psychology and education economics, this “personality economics approach” suggests that workers are endowed with various physical, cognitive[8] and noncognitive skills, which are priced differently in different tasks and jointly determine the workers’ task productivities. From this perspective, tasks require using a whole bundle of heterogeneous skills (with task-specific intensities) rather than a single, composite skill. The task of teaching, for example, requires little physical strength but a good deal of communication skills and a patient, outgoing and caring personality. Accounting also requires little physical strength. But it requires more analytical than communication skills, and more of a dutiful, efficient and introverted personality.[9] The personality economics approach has produced a host of important insights on the relationship between heterogeneous skills and tasks. One of these insights is that workers self-select into those occupations or tasks whose skill requirements match their own skill endowments comparatively closely (Heckman and Sedlacek 1985, Borghans et al. 2008a, Almlund et al. 2011, Holland 1997). This suggests that workers’ comparative advantages for performing specific tasks establish a systematic relationship between tasks and heterogeneous skills. We use this relationship to conceptually link supply-side characteristics of jobs—their susceptibility to digitalization—to demand-side characteristics—workers’ skill endowments—in our empirical approach.

Another insight from the personality economics approach is that heterogeneous skills shape educational choice and educational achievements significantly (Heckman et al. 2006, Cunha et al. 2010). This insight links the personality economics approach to the SBTC approach in that it suggests that the SBTC approach does actually capture heterogeneous skills indirectly when linking tasks to formal education. It does not facilitate decomposing the composite indicator of formal education into the skills needed to perform tasks, though.

Still another insight is that heterogeneous skills affect labor market outcomes, notably occupational choice, not only indirectly, through education, but also directly, conditional on education (Kautz et al. 2014: 14, Gensowski 2014). For Germany, John and Thomsen (2014) show empirically that the Big Five personality traits affect workers’ occupational choices significantly even when their educational attainment is controlled for. Crafts, for example, attract workers with higher conscientiousness but lower extraversion and agreeableness while technical occupations (skilled workers in technical, teaching and related professions) attract work-

[8] See Borghans et al. (2008a), Almlund et al (2011), Brunello and Schlotter (2011), Dohmen (2014) and Thiel and Thomsen (2013) for recent surveys of this literature. Cognitive skills include the abilities to learn, synthesize, store and remember information, to analyze, understand and solve problems, and to communicate with others.

[9] Notice that tasks are actually not well defined. They may be defined very narrowly in order to reduce the variety of skills needed to perform them. But it is hard to imagine that tasks can be defined narrowly enough to require only a single skill, i.e., only physical strength but no mental input, or only dutifulness but no physical action.

ers with lower conscientiousness but higher extraversion and agreeableness. And both management and professional occupations (scientists or academics) attract workers with higher openness to experience and an internal locus of control. But managers are more extraverted and less reciprocal (return favors and resentments less symmetrically). In addition to this, John and Thomsen also show that, depending especially on their noncognitive skills, workers with similar education levels are more productive in some tasks than in others. Education thus reflects heterogeneous skills only imperfectly. This is our motivation for complementing our set of explanatory skill variables by personality.

While our study is, to our knowledge, the first to link workers' heterogeneous skill endowments to future technological progress within an SBTC framework, it is not the first to analyze workers' heterogeneous skill endowments within this framework. Borghans et al. (2011b) show that more extensive use of computers has increased the demand for, and the wages of what they call "people skills". Weinberger (2014) and Deming (2015) show that cognitive and "social skills" complement each other. They also show that this complementarity has increased during the last about four decades, and that employment and wage premia have increased disproportionately in occupations that require high levels of both of these skills.

3. Conceptual background

We explore if there is a systematic relationship between the digitalization probabilities of jobs and the skill endowments of workers who currently hold these jobs. In doing so, we especially focus on the role of personality. While our approach is conceptually rather similar to the SBTC approach (Acemoglu and Autor 2011), it differs from this approach in that it puts greater emphasis on labor supply. We essentially focus on heterogeneous skills rather than heterogeneous tasks as the constituent elements of jobs. While tasks characterize jobs from the perspective of labor demand, skills characterize them from the perspective of labor supply. This distinction is essential for our analysis. We aim at identifying links between technological progress and worker characteristics rather than workplace characteristics.

We start from the premise that both labor demand (jobs) and labor supply (workers) are heterogeneous in terms of skills. Skills include various cognitive and noncognitive skills. Jobs, on the one hand, are heterogeneous in that they require different combinations—and possibly also different levels of sophistication—of the individual skills.[10] The productivity of a specific skill differs across jobs and depends on the state of technology, among others. Workers, on the other hand, are also heterogeneous in that they are endowed with different combinations

[10] In an alternative, more complex framework, one might assume that tasks rather than whole jobs require multiple skills. However, since we lack data on the susceptibility of tasks to digitalization, we have to focus on the susceptibility of jobs to computerization anyway in our empirical investigation.

of skills at different levels of sophistication. To maximize their income, they exploit their comparative advantages by self-selecting into those jobs whose current skill requirements match their own skill endowments most closely, conditional on the actual market prices for the individual skills. At any point in time, the equilibrium prices for the individual skills in an economy thus reflect both the state of technology and the relative abundance of the skills the workers are endowed with.

Technological progress permanently changes this tense relationship. It changes the relative skill requirements of jobs and thus the relative demand by employers for the various skills. This in turn changes the relative prices of the skills and thereby the comparative advantages of workers. As in the SBTC approach, technological progress reduces the relative demand for skills that substitute for the new technologies while it increases that for skills that complement the new technologies.

This is where our empirical investigation sets in. We use the digitalization probabilities of occupations estimated by Frey and Osborne (2013) as an indicator of the direction of technological change. We explore if the expected changes in the relative demand for jobs induced by this digitalization affects skills differently. While the relationship between digitalization and the changes in demand for low-, medium- or highly educated workers has been discussed in the literature (e.g., Brynjolfsson and McAfee 2011, Arntz et al. 2016), very little is known about the relationship between digitalization and the changes of demand for the different facets of personality.

More specifically, we link the estimated future changes in the relative demand for jobs, expected by experts in terms of digitalization probabilities, to the skill endowments of workers who currently hold these jobs. We estimate a model of the general form

$$P_i = \mathbf{G}(\mathbf{S}_i, \mathbf{X}_i), \tag{1}$$

for a cross section of workers, indexed by i $(i = 1, \dots, N)$. P_i denotes the probability that worker i's current job will be computerized within the next one or two decades, which we approximate by the digitalization probability estimated for occupations by Frey and Osborne (2013);[11] $\mathbf{S}_i$ is a vector of worker i's current endowment with heterogeneous skills; and $\mathbf{X}_i$ a vector of control variables which include worker i's other observable characteristics. $\mathbf{G}(\cdot)$ is a known function that satisfies $0 \le \mathbf{G}(\cdot) \le 1$.

Notice that we do not argue that the relationship between skills and digitalization probabilities in (1) is direct or even causal. We just hypothesize that there is an indirect link between future automatization of jobs and the skill endowments of the workers who currently hold these jobs. Nonetheless, identification of the parameters in model (1) rests on two conditions. The first condition is that the digitalization probabilities reflect economically relevant knowledge about

[11] This approximation implies that our dependent variable does not vary across workers within occupations. We will discuss this issue in more detail in Section 4.2.

the changes in labor demand induced by digitalization during the next decade or two. And the second condition is that this expert knowledge has not yet diffused to today's workers and has consequently not yet been anticipated in their choices of their current jobs.

As to the first condition, the estimated digitalization probabilities are subject to considerable uncertainties, indeed. Being based on assessments of what machine learning experts consider technically feasible, they may systematically overstate the digitalization probabilities and the diffusion speed of digital technologies for a variety of reasons (Arntz et al. 2016: 21–23). One reason is that some technically feasible innovations will be economically unprofitable, at least for a longer while than the technicians expect. They may be too expensive, or may not meet customers' preferences. Another reason is legal or ethical obstacles. However, these uncertainties should not disqualify projections into the future like those by Frey and Osborne. Any projection is naturally subject to uncertainty, even more so in turbulent times. Lacking suitable alternative measures, we assume that errors in the estimated digitalization probabilities are not systematically related to workers' skills.

As to the second condition, the information asymmetry between experts and workers, we argue that workers generally face higher information and evaluation costs than machine learning and mobile robotics experts when it comes to predicting the future directions of technological progress, and the consequences of this progress on labor markets. In fact, Brynjolfsson and McAffee (2011) give a variety of recent examples for "science fiction becoming business reality" (p. 48) within just a few years. Technologies and applications publicly considered impossible to realize at some point in time have become ubiquitously available shortly thereafter. Workers' face higher costs of anticipating future directions of technical change not only because they have greater problems in intuitively grasping "Moore's law". This law holds that computing power increases exponentially, doubling every year (or every 18 months). The also face higher costs because it is more difficult for them to anticipate experts' creativity in transferring innovations from one domain to other, apparently unrelated domains. A time lag between the worker surveys and the expert judgements adds to this information asymmetry. The worker surveys we use in our empirical analysis were undertaken around 2010 when the public discussion on topics like the internet of things was just emerging while the evaluation by the experts was done only in 2013 during a workshop at Oxford University (Frey and Osborne 2013.

The set of skills, $\mathbf{S}_i$ in model (1), comprises formal education, proxied by the workers' years of schooling, work experience (worker's age) and noncognitive skills (Big Five personality traits). We also add squares of the years of schooling and age to capture possible nonlinearities. Education links our analysis to the SBTC approach. A hump-shaped relationship between education and the digitalization probability will imply that medium education levels will be more susceptible to digitalization than low or high levels. By contrast, a positive relationship will indicate that the new digital technologies will substitute more for lower education while a negative relationship will indicate that they will substitute more for higher education. The noncognitive skills add elements of the personality economics approach to our analysis. The Big Five personality traits are openness to experience, conscientiousness, extraversion, agreeableness and neuroticism.[12] Table 1 gives a brief description of these traits and the associated facets. These noncognitive skills will add significantly to explaining the digitalization

Table 1: Big Five Personality Traits

Dimension ➔ Short description	Facet (correlated trait adjective)
Openness (vs. Closedness) to Experience ➔ Tendency to be open to new aesthetic, cultural or intellectual experience	Ideas (curious) Fantasy (imaginative) Aesthetics (artistic) Actions (wide interest) Feelings (excitable) Values (unconventional)
Conscientiousness (vs. Lack of Direction) ➔ Tendency to be organized, responsible and hardworking	Competence (efficient) Order (organized) Dutifulness (not careless) Achievement striving (thorough, ambitious) Self-discipline (not lazy) Deliberation (not impulsive)
Extraversion (vs. Introversion) ➔ Orientation of one's interests and energies toward the outer world of people and things rather than the inner world of subjective experience; characterized by positive affect and sociability	Gregariousness (sociable) Assertiveness (forceful) Activity (energetic) Excitement-seeking (adventurous) Positive emotions (enthusiastic) Warmth (outgoing)
Agreeableness (vs. Antagonism) ➔ Tendency to act in a cooperative, unselfish manner	Trust (forgiving) Straightforwardness (not demanding) Altruism (warm) Compliance (not stubborn) Modesty (not showing off) Tender-mindedness (sympathetic)
Neuroticism (vs. Emotional Stability) ➔ Neuroticism: Chronical level of emotional instability and proneness to psychological distress ➔ Emotional Stability: Predictability and consistency in emotional reactions, with absence of rapid mood changes	Anxiety (tense) Angry hostility (irritable) Depression (not contented) Self-consciousness (shy) Impulsiveness (moody) Vulnerability (not self-confident)

Sources: Mueller and Plug (2006: 5), Almlund et al. (2011: 44–45).

[12] Alternative measures of noncognitive skills used in labor or education economics are the Rotter measure of internal (versus external) locus of control (own ability to influence outcomes) or measures of self-esteem. Almlund et al. 2011: 53) associate these measures with the Big Five factor of Neuroticism.

probability only if education proxies them only imperfectly. We will interpret this as an indication that the explanatory power of the SBTC approach may be enhanced by putting greater emphasis on the heterogeneity of workers' skills.

The control variables, $\mathbf{X}_i$ in model (1), comprise

– two individual-level control variables: a gender dummy (male = 1) and a nationality dummy (non-German = 1);
– industry fixed effects at the two-digit NACE Rev. 2 level that account for similarities in digitalization probabilities across jobs within industries as well as for the specificities of the sample datasets in terms of their industrial composition;[13]
– 16 State (Bundesland) fixed effects, which account for systematic regional differences in digitalization probabilities.[14]

There are at least three reasons why the parameters of the Big Five personality traits will likely underestimate (in absolute terms) the true relationship between personality and digitalization in our regressions. First, being itself influenced by personality, education will absorb a good deal of the relationship between personality and digitalization. Second, being based on self-assessments in surveys, the measures of Big Five personality traits are subject to considerable measurement errors (Hanushek and Woessmann 2008, Borghans et al. 2011a). During the surveys, the respondents may be exposed to specific situational contexts and motivations that influence their self-assessments. For example, they may be more inclined to exaggerate their noncognitive skills toward what their employers expect of them, if the corresponding questions are preceded by questions about their employers, than if they are preceded by questions about, say, their family background, hobbies or sports activities.[15] And third, broad measures of personality such as the Big Five suffer from aggregation biases, which will also bias our estimated parameters toward zero (Hogan 2005). Each of the five traits represents a variety of different facets, and these facets are likely required at different intensities in different jobs. A high degree of conscientiousness, for example, may be associated with high digitalization probabilities in jobs that require a high degree of work organization and self-disci-

[13] The industry fixed effects ensure that variations of digitalization probabilities across jobs that are rooted in the specificities of industries are not attributed to workers' skills. To the extent that these industry specificities also affect the skill requirements of jobs, we may underestimate the true relationship between digitalization probabilities and skills.

[14] Our flexibility in controlling for regional differences is restricted by the NEPS dataset, which reports only the respondents' state of residence (Bundesland). To ensure comparability across all datasets, we include state fixed effects in our regressions for all datasets. Test regressions with fixed effects for more disaggregated regions or different degrees of urbanization indicate that our main results are not driven by variations of digitalization probabilities across regions.

[15] In fact, workers' responses on the Big Five items are skewed more toward scores considered preferable from a professional perspective in the Linked Personnel Panel (LPP), which surveys both employers and employees with a focus on human resources management and firm performance (see Section 4.3 below). A strategy to account for measurement errors at least to some extent would be treating personality as a latent variable to be estimated from the Big Five test scores within a structural equation model (see, e.g., Heckman et al. 2006). We leave this estimation strategy for future research.

pline. A similarly high degree of conscientiousness may, however, be associated with a lower digitalization probability in other jobs that require careful and thorough problem analysis. Due to this heterogeneity, proper disaggregation of personality traits into more specific facets typically yields larger and more significant results (Borghans et al. 2008b: 1008–1009, Thiel and Thomsen 2013: 192). In summary, if the parameters of the Big Five measures do actually turn out to be significantly different from zero in the present study, this will be a rather strong indication of a systematic relationship between digitalization probability and noncognitive skills.

4. Data and regression methods

1. Digitalization probabilities

Frey and Osborne (2013) estimate digitalization probabilities—in their terminology "computerization probabilities"—for 702 occupations from essentially two sources of information, (subjective) expert judgements and (objective) statistical indicators on selected characteristics of occupations from O*Net.[16] They first asked an expert group of machine learning or robotics researchers to hand-select occupations that they are most confident about being fully automatable in the foreseeable future of 10-20 years. The experts identified 37 occupations with extremely high and 34 with extremely low susceptibility to digitalization. Frey and Osborne combined these expert judgements with data on nine selected O*Net indicators that arguably represent digitalization bottlenecks[17] to construct a training dataset. This dataset indicates how the probability of digitalization of the 71 occupations varies with the O*Net scores of the bottleneck variables. Based on this training data, they then predicted digitalization probabilities for all 702 occupations from the known O*Net bottleneck indicators.

An important question for the empirical design of the present study is to what extent the bottleneck indicators from O*Net really measure employers' job requirements rather than workers' characteristics. If they measured worker characteristics, our empirical study would yield tautological inferences. We would essentially regress worker characteristics on worker characteristics. In fact, the descriptions given by O*Net for the bottlenecks of *finger* and *manual*

[16] O*Net is a database of quantitative indicators about a variety of attributes for 903 occupations in the US, compiled by the US Department of Labor. Based on expert opinions or worker surveys, these indicators cover various job-oriented attributes (occupational requirements, workforce characteristics, occupation-specific information) and worker-oriented attributes (worker characteristics, worker requirements and experience requirements; see National Center for O*NET Development undated). By combining subjective and objective information, Frey and Osborne aim at overcoming the shortcomings of purely subjective or purely objective rankings. Subjective rankings such as the one by Autor et al. (2003) are not replicable and may involve misjudgments while objective rankings such as the one by Jensen and Kletzer (2010) (for offshorability) may generate implausible or even unreliable results.

[17] The bottleneck indicators, which are depicted in Table A1 in the Appendix, measure, for each occupation, the level (sophistication) of those work requirements that Frey and Osborne consider to be particularly difficult to computerize in the near future.

dexterity as well as *originality* and *fine arts* may suggest that O*Net focuses on measuring worker characteristics. These descriptions refer explicitly to "abilities" or knowledge" (see Table A1 in the Appendix). In addition to this, *finger dexterity*, *manual dexterity* and *originality* are explicitly categorized as worker characteristics in the O*Net content model.[18] However, the questionnaires from which these indicators are developed ask unambiguously for job requirements. The question on *originality*, for example, reads: "What level of originality is needed to perform your current job?" Similarly, the question on *fine arts* reads: "What level of fine arts is needed to perform your current job?" We cannot be sure that the responding experts or workers had only workplace but not worker characteristics in their minds when answering these questions. Nonetheless, there are good reasons to assume that the indicators—and consequently the digitalization probabilities estimated from them—do reflect labor demand- rather than supply-side characteristics of occupations.

While Frey and Osborne estimate digitalization probabilities for 6-digit U.S. System of Occupational Classification (2010 SOC), we have to convert them to several other classification systems to match them to German survey data. We use a two-step conversion procedure. In the first step, we convert the 702 2010 SOC occupations to 422 4-digit ISCO08 occupations (ISCO: International Standard Classification of Occupations), using the crosswalk supplied by the US Bureau of Labor Statistics.[19] In the second step, we convert the 422 4-digit ISCO08 occupations to the classifications used by the five micro datasets.

- For the SOEP 2013 sample, which uses ISCO08, no additional conversion is needed. Our SOEP 2013 sample comprises workers from 354 of the 422 ISCO08 occupations.
- For the SOEP 2009 sample, we convert the 422 ISCO08 occupations to 274 4-digit ISCO88 occupations that are observed in the SOEP 2009 sample.
- For the NEPS, PASS and LPP samples, we convert the 422 ISCO08 occupations to 1,263 5-digit KldB 2010 occupations,[20] of which 592 are observed in NEPS, 499 in PASS and 468 in LPP.

Any conversion of classifications entails a loss of information, if it requires aggregating across occupations from the source classification. To give an impression about possible information losses in the present case, Figure 1 plots the distributions of occupations across deciles of the digitalization probability before and after the conversions. The left, hatched bar gives the distribution of the 702 original SOC2010 occupations, as used by Frey and Osborne

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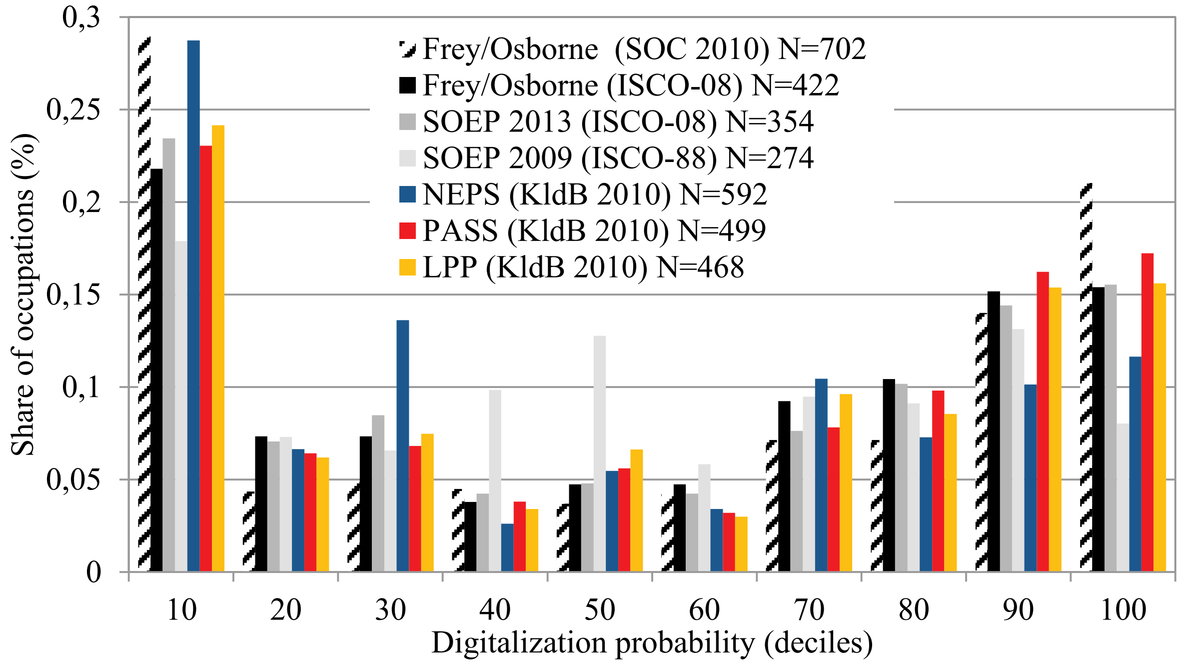
[18] See https://www.onetcenter.org/content.html. The O*Net questionnaires are available for download at **Fehler! Hyperlink-Referenz ungültig.**.

[19] The crosswalk is available at http://www.bls.gov/soc/soccrosswalks.htm. We applying national employment by occupation in the US in May 2010 as weights for aggregating 2010 SOC to ISCO-08 occupations. The employment data are available from the US Bureau of Labor Statistics (http://www.bls.gov/oes/tables.htm).

[20] KldB: German "Klassifikation der Berufe". We use the crosswalk supplied by the German Federal Employment Agency (available at https://statistik.arbeitsagentur.de/Navigation/Statistik/Grundlagen/Klassifikation-der-Berufe/KldB2010/Arbeitshilfen/Umsteigeschluessel/Umsteigeschluessel-Nav.html).

Figure 1: Distributions of occupations across deciles of digitalization probabilities for various occupational classifications and datasets



Sources: Frey and Osborne 2013, U.S. Bureau of Labor Statistics, German Federal Employment Agency, SOEP, NEPS, PASS, LPP, own calculations.

(2013). It shows a strong concentration of occupations at low and high digitalization probabilities. The next, black bar gives the result of the first conversion step, i.e., the distribution of the 422 ISCO-08 occupations. While this conversion entails some regression toward the mean especially from the lowest and highest deciles of the digitalization probability, the ISCO-08 classification largely retains the thick tails of the original distribution. Most notably, the share of occupations with digitalization probabilities above 70%, the threshold used by Frey and Osborne, remains virtually unchanged. It is 50.2% of the ISCO-08 occupations, compared to 49.3% of the original SOC2010 occupations. The remaining five bars give the distributions for the five survey datasets we use. These distributions deviate from the distribution for the ISCO-08 classification (2nd, black bar) partly because of aggregation losses and partly because occupations are not represented in the respective sample. With two exceptions, the distributions do not deviate notably from that of the ISCO-08 classification. The first exception is the SOEP 2009 sample (4th, light grey bar) that uses the older ISCO88 classification. We observe considerable regression toward the mean, especially to the 4th and 5th deciles. These apparent aggregation losses do, however, affect neither the distribution of workers across digitalization probabilities (see Section 4.3 below) nor our regression results notably. The second exception is NEPS (5th, blue bar), which shows markedly higher concentrations of KldB 2010 occupations at lower digitalization probabilities, especially in the 1st and 3rd deciles, mirrored by markedly lower concentrations at high digitalization probabilities, especially in the 9th and

10th decile. This mismatch is likely rooted in the specificities of the NEPS sample. As will be discussed in more detail later in this subsection, the NEPS sample features higher shares of older and more educated workers than the other samples. However, these specificities do not show up in strongly deviating regression results either.

The fact that the aggregation of Frey and Osborne's digitalization probabilities into fewer, broader occupation classes may be associated with significant regression towards the mean keeps us from using alternative data on digitalization probabilities by occupations estimated for Germany by Dengler and Matthes (2015) or Arntz et al. (2016). Covering less than 100 occupation aggregates, this data is way too highly aggregated for the purpose of our study.

2. German micro datasets

We estimate the relationship between workers' personalities and the susceptibility of jobs to digitalization in the future for data from five different German surveys that report Big Five personality traits: Two waves of the German socioeconomic panel (SOEP) in 2009 and 2013,[21] the 2012/13 wave of the National Educational Panel Study (NEPS), the 2011 wave of the Panel Study on Labor Markets and Social Security (Panelstudie Arbeitsmarkt und Soziale Sicherung, PASS), and the 2012 wave of the Linked Personnel Panel (LPP). The main features of the survey datasets are summarized in Table 2.

The **SOEP**, the most well-known and widely used household survey in Germany, is an annual representative survey conducted by the German Institute for Economic Research (DIW), Berlin, since 1984. It includes information about the detailed socio-economic situation of

Table 2: Main features of the survey datasets

Dataset	Surveying institution	Wave, year	Interview method	# Big Five questions	Likert levels	No of obs. used
SOEP 2009	German Inst. for Economic Research (DIW)	26, 2009	CAPI	15	7	10.278
SOEP 2013	German Inst. for Economic Research (DIW)	30, 2013	CAPI	15	7	9.909
NEPS	Leibniz Inst. for Educational Trajectories (LIfBi)	5, 2012/13	Survey	11	5	4.265
PASS	German Inst. for Employment Research (IAB)	5, 2011	CATI/ CAPI	21	5	8.629
LPP	German Inst. for Employment Research (IAB), U Cologne, Centre for European Economic Research (ZEW)	1, 2012	CATI	16	5	5.367

Notes: CATI: Computer assisted telephone interviews, CAPI: Computer assisted personal interviews.

[21] The Big Five were also surveyed in the 2005 wave of the SOEP. Since we do not expect the results for this wave to differ notably from those for the 2009 wave, we exclude this data from our analysis. Like the data from the 2009 wave, the data from the 2005 wave are only available at the older ISCO-88 classification.

approximately 22,000 individuals living in Germany (Wagner et al. 2007). The 26th (2009) and 30th (2013) waves report the respondents' personality traits in terms of a short item scale of the Big Five. The survey comprises 15 items, three for each of the five traits, which is rather short but has been shown to replicate the results of the more extensive 25-item Big Five inventory fairly accurately (Gerlitz and Schupp 2005). After dropping persons who were not active in the labor market or unemployed at the time of the surveys, our 2009 (2013) SOEP sample includes 10,278 (9,909) individuals who actively participated in the labor market (TNS Infratest Sozialforschung 2012, 2014). We will focus mainly on the 2013 wave, which entails less information losses due to conversions of the occupational classification (see Section 3.1 above), and use the 2009 wave mainly to illustrate the effect of an additional conversion of occupations on the regression results.

The National Educational Panel Study (**NEPS**), conducted by the Leibniz Institute for Educational Trajectories (LIfBi), has been collecting longitudinal data on the development of competencies, educational processes, educational decisions, and returns to education in formal, non-formal, and informal contexts throughout the life span since 2007/08. Of the six starting cohorts of this survey,[22] we use only the sixth cohort, which covers about 10,500 adult persons born between 1944 and 1986 who were active in the labor market in the starting year, 2007/08. The fifth wave of the survey of this cohort, conducted in 2012/13, includes a short Big Five inventory of 11 items (NEPS 2013). We restrict the sample to the 4,265 individuals who were still either self-employed or employed subject to social security at the time of the interviews. Their occupations also refer to the time of the interviews.

The Panel Study on Labor Markets and Social Security (Panelstudie Arbeitsmarkt und Soziale Sicherung, **PASS**), conducted annually by the German Institute for Labor Research (IAB) since 2006, is a longitudinal household survey that focuses on households with low socio-economic status (Promberger 2007, Trappmann et al. 2010, 2013). PASS comprises two subsamples of about 5,000 household each. One subsample is drawn from the population of all households where at least one member received unemployment assistance or other social security benefits according to the German "Sozialgesetzbuch II" (SGB II), the other from the population of all households in Germany. Households with low socio-economic status are oversampled in the second subsample as well (Trappmann et al. 2010: 611). In addition to information on the households as a whole, the survey collects information about around 15,000 individual household members. The 5th wave in 2011 includes a 21-items Big Five

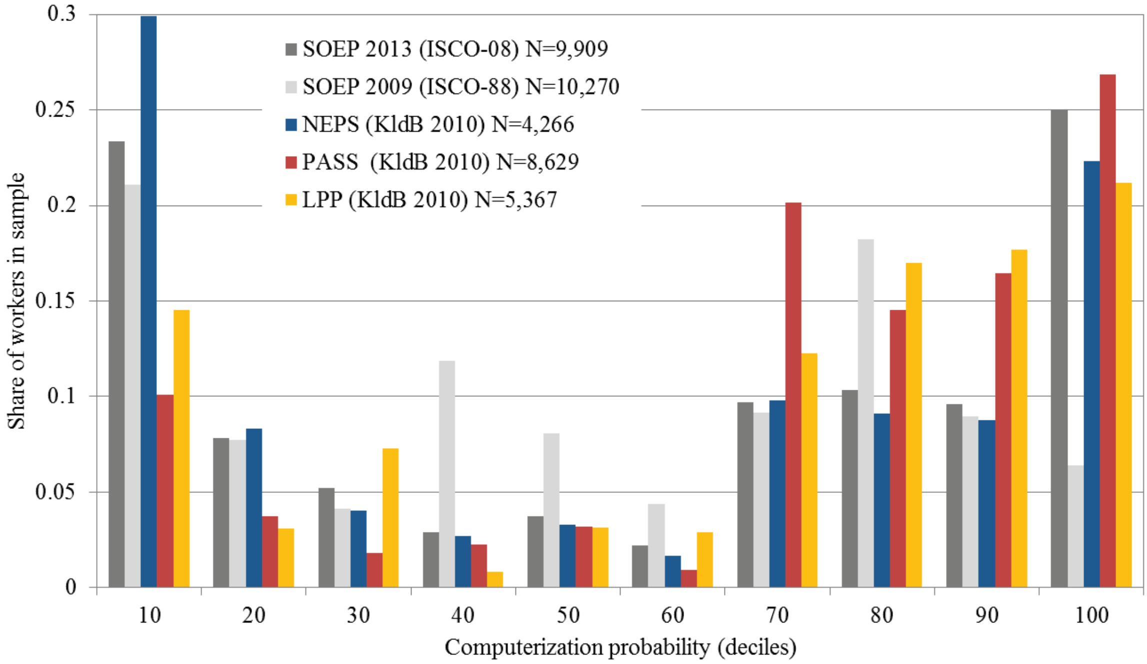
[22] The six starting cohorts, defined in 2007/08 and surveyed annually since then, are (i) newborns, (ii) Kindergarten kids, (iii) 5th grade pupils, (iv) 9th grade pupils, (v) 1st year students, and (vi) adults. Users of data from the sixth cohort are requested to cite Blossfeld et al. (2011) and reprint the following sentences (see https://www.neps-data.de/en-us/datacenter/dataanddocumentation/startingcohortadults/dataandcitation.aspx): "This paper uses data from the National Educational Panel Study (NEPS): Starting Cohort Adults, doi:10.5157/NEPS:SC6:5.1.0. From 2008 to 2013, NEPS data was collected as part of the Framework Program for the Promotion of Empirical Educational Research funded by the German Federal Ministry of Education and Research (BMBF). As of 2014, NEPS is carried out by the Leibniz Institute for Educational Trajectories (LIfBi) at the University of Bamberg in cooperation with a nationwide network."

inventory. After dropping persons who were not active in the labor market or unemployed at the time of the survey, our PASS sample includes 8,629 individuals who were gainfully employed and subject to the public social security system.

Finally, the Linked Personnel Panel (**LPP**), conducted annually by the German Institute for Employment Research (IAB), the University of Cologne and the Centre for European Economic Research (ZEW), is a longitudinal annual employer-employee survey of 1,219 establishments and about 7,508 of their employees (Bellmann et al. 2015). Its focus is on the relationship between human resources management (working conditions, corporate culture and management practices) and firm performance. The employer sample is drawn from the population of all German private-sector manufacturing and services establishments. Smaller establishments with less than 50 employees are excluded from this employer survey, however. In addition to this, manufacturing establishments are overrepresented, accounting for more than 60% of all surveyed establishments (748 / 1,219). The employee sample is drawn from 300,881 persons who were employed by 869 of the surveyed 1,219 establishments in 2011 and were subject to public social insurance or were marginally employed. Employees from smaller establishments in the employer sample are overrepresented. The survey includes at least three employees from each of the 869 establishments. The 1st wave of the employee survey in 2012 includes a 16-items Big Five inventory. After dropping observations with missing values, our LPP sample includes 5,367 individuals who were gainfully employed and subject to the public social insurance system.

The comparative analysis of these five survey datasets does not only help in assessing the robustness of our results to possible errors in the measurement of the Big Five. It also helps us in identifying systematic differences between the worker samples and survey designs that may affect the estimation results. Figure 2 gives an impression of the distributions across digitalization probabilities of the workers surveyed by the five datasets. The Figure shows, on the one hand, that observations are concentrated in the tails of the distribution of the digitalization probability. This polarization is inherited from Frey and Osborne whose estimates suggest that only 19% of the U.S. jobs in 2010 have been facing digitalization probabilities between 30% and 70% (Frey and Osborne 2013: Figure III). On the other hand, the figure shows considerable differences across the samples. The two SOEP samples (left bars, dark and light grey) include a lower fraction of workers in jobs with arguably high digitalization probabilities (>80%) while the fraction of workers in jobs with medium digitalization probabilities (40 – 60%) tend to be higher. By contrast, PASS and LPP (right, red and orange bars) tend to focus disproportionately on workers in jobs with higher digitalization probabilities while the fraction of workers with low digitalization probabilities is lower. For the PASS survey, this focus likely results from the concentration of the survey on problem groups in the labor market. For the LPP survey, it may be a consequence of the fact that workers from manufacturing establishments are overrepresented, in which case the industry fixed effects should take care of this specificity in our regressions.

Figure 2: Distribution of workers across deciles of digitalization probabilities for German micro datasets that report Big Five personality traits

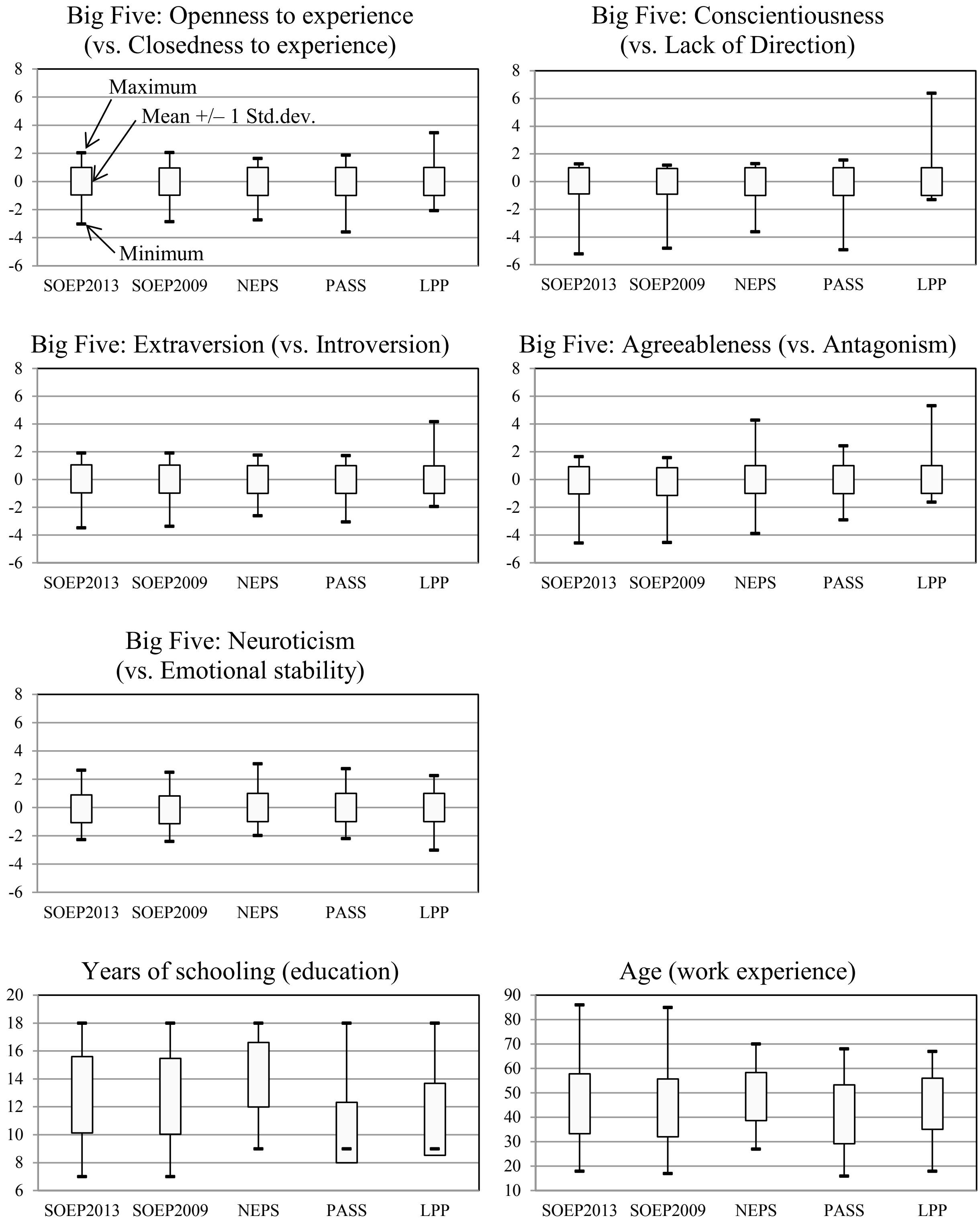


Sources: See Table A2.

In each of the five datasets, we condense the information on individuals' personalities into five variables, one for each Big Five dimension (openness to experience, conscientiousness, extraversion, agreeableness and neuroticism). We calculate the unweighted means of the scores of the items corresponding to each dimension and then (0,1)-standardize these means to make them invariant to arbitrary differences in the levels or variances of the scores across the dimensions. Descriptive statistics for the resulting Big Five indicators as well as for the traditional skill variables, years of schooling (education) and age (work experience), are depicted in Figure 3.[23] The vertical lines depict the ranges of the variables from minimum to maximum, and the boxes the ranges of one standard deviation around the means. Figure 3 indicates that the LPP sample differs from the other samples in several respects. First, while all of the Big Five measures tend to be skewed toward lower levels of openness, conscientiousness, extraversion, agreeableness and emotional stability (higher levels of neuroticism) in all other samples, according to the minima and maxima, they are skewed toward higher levels in LPP. This may result from the combination of the specific focus of the LPP and the design of the survey. The extensive battery of questions about the employer and work conditions that

[23] Tables A2 and A3 in the Appendix report the descriptive statistics for, and correlations among all explanatory variables for all five datasets. Since a few observations had to be dropped from the samples after the standardization of the Big Five scores, some means and standard deviations deviate slightly from zero or one, respectively. This does not affect our regression results notably, however.

Figure 3: Descriptive statistics for skill variables in German micro datasets that report Big Five personality traits



Sources: See Table A2.

precedes the Big Five questions in the LPP worker questionnaire may have motivated more respondents to exaggerate their skills.[24] In addition to this, LPP features a higher concentration of lower educated workers (11.1 years of schooling on average). Table A2 additionally reveals that male workers are strongly overrepresented (74%) while non-German workers are slightly underrepresented (4.2%). LPP also differs in several correlations of the Big Five with education, age and gender (see Table A3). It does, for example, not show any positive correlation of openness to experience with education, or of conscientiousness with age. Likewise, men tend to be more rather than less conscientious, extraverted and neurotic than women in LPP. In conjunction with the fact that the LPP sample is drawn from a rather specific set of larger and mostly manufacturing establishments, all these differences indicate that the regression results for LPP, which turn out to differ considerably from those for other samples, should be interpreted with greater care.

The PASS sample also differs from other samples in several respects. Like in LPP, workers are lower educated on average (10.1 years of schooling), which is to be expected from PASS's focus on households with lower social status. PASS additionally includes a greater fraction of younger workers (average age: 48.5 years) and females (57.1%; see Table A3). Nonetheless, the descriptive statistics for the Big Five in the PASS sample do not differ notably from those in the SOEP or NEPS samples. Essentially the same holds for the NEPS sample, which comprises, on average, more higher educated (14.3 years of schooling) and more older workers (48.5 years) than the other samples.

3. Regression method

To account for the fact that our dependent variable is a probability that is bounded between zero and one by definition, we employ the fractional response model (FRM) proposed by Papke and Wooldridge (1996). We model the expected digitalization probability as a function of workers' characteristics such that

$$E(P_i|S_i, X_i) = \mathbf{\Phi}(\mathbf{S}_\mathrm{i}\boldsymbol{\alpha} + \mathbf{X}_\mathrm{i}\boldsymbol{\beta}), \qquad (2)$$

where we assume $\mathbf{\Phi}(\cdot)$ to be the standard normal cumulative density function, $\mathbf{S}_i$ and $\mathbf{X}_i$ are the vectors of skills and of control variables, as in equation (1), and $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are the associated parameter vectors.[25]

The main advantages of the FRM over alternative regression methods for fractional dependent variables discussed in the literature are that it accounts for the boundedness of the dependent variable while allowing the dependent variable to take values of zero or one with positive

[24] See Borghans et al. (2011a) for an extensive discussion of the role of incentives and personality for the outcomes of surveys. The LPP worker questionnaire is available for download at http://fdz.iab.de/en/Integrated_Establishment_and_Individual_ Data/lpp/Working_Tools.aspx.

[25] We use the Stata *glm* command with *family(binomial)* and *link(probit)* to estimate (3). *fracreg*, available in Stata 14, yields identical results.

probability. While we do not observe values of exactly zero or one of the dependent variable in our samples, the observed values get fairly close. They range from 0.0038 and 0.99.[26] OLS may produce biased estimates because it does not account for the boundedness of the dependent variable. Logistic transformation of the dependent variable, i.e., $ln(y/(1-y))$, may reduce this bias but complicates interpretation of the estimated parameters (Papke and Wooldridge 1996). In addition to this, it still excludes zeros and ones. The same holds for the Betafit regression, which assumes the model to follow a Beta distribution. Betafit is flexible in modeling the conditional mean of the dependent variable (Ramalho et al. 2011; Wagner 2001) but is not robust to violations of the distributional assumption (Papke and Wooldridge 1996). The Tobit model, finally, also accounts for boundedness of continuous variables but treats them as being censored at zero and one. It thus falsely assumes realizations of the dependent variable beyond these bounds to be possible but unobserved.

Even though we are interested in the susceptibility of jobs to digitalization, we observe only the susceptibility of occupations to digitalization. We thus measure the digitalization probability of jobs with an error. Several studies suggest that the task compositions of jobs do differ considerably within occupations (Autor and Handel 2013, Fedorets et al. 2015). We account for this possible error by detailed industry fixed effects, which will capture systematic variations of digitalization probabilities across industries, and by region fixed effects, which will capture systematic variations across the German states that may result from spatial sorting of occupations, for example. Identification of the parameter thus comes from the variation of digitalization probabilities across occupations within industries and states. We cluster the residuals at the level of occupations to additionally account for differences in the variance of the measurement error in the digitalization probabilities across occupations. The remaining measurement errors within occupations, industries and regions are assumed to be random and uncorrelated with workers' skills or other personal characteristics.

5. Results

1. Baseline model

Table 3 reports the results of the fractional response regressions of our baseline model (1) for the five datasets.[27] These results indicate that there is in fact a systematic link between the susceptibility of jobs to digitalization in the future and some facets of workers' personality

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[26] The probabilities estimated by Frey and Osborne for the 702 SOC 2010 occupations range from 0.0028 to 0.99.

[27] For comparison, Table A4 in the Appendix reports the results of the corresponding OLS regressions, which ignore the boundedness of the dependent variable. OLS yields qualitatively fairly similar results but systematically underestimates the relationship between the digitalization probability and personality, education and experience for all datasets except LPP. For LPP, OLS yields higher rather than lower parameter estimates.

Table 3: Personality and the digitalization probabilities of future jobs in Germany: Baseline model

Dataset	SOEP 2013	SOEP 2009	NEPS	PASS	LPP
	(1)	(2)	(3)	(4)	(5)
Noncognitive skills					
Openness	–0.078***	–0.056***	–0.042***	–0.016	0.009**
	(0.014)	(0.011)	(0.015)	(0.014)	(0.004)
Conscientiousness	–0.004	–0.006	0.006	–0.006	–0.006
	(0.009)	(0.008)	(0.016)	(0.014)	(0.004)
Extraversion	–0.008	0.013	–0.037**	–0.008	–0.005
	(0.012)	(0.009)	(0.015)	(0.016)	(0.005)
Agreeableness	0.017	0.021***	0.009	0.001	–0.003
	(0.011)	(0.007)	(0.015)	(0.012)	(0.004)
Neuroticism	0.024**	0.023***	0.042***	–0.002	–0.006
	(0.011)	(0.009)	(0.014)	(0.014)	(0.004)
Education					
Years of schooling	0.079	0.005	0.274***	0.101	–0.072**
	(0.081)	(0.077)	(0.099)	(0.080)	(0.031)
Years of schooling, squar.	–0.008***	–0.005	–0.015***	–0.007**	0.001
	(0.003)	(0.003)	(0.004)	(0.003)	(0.001)
Work Experience					
Age	–0.010*	0.004	–0.016	–0.008	–0.007*
	(0.006)	(0.005)	(0.013)	(0.007)	(0.004)
Age, squared	0.000*	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Individual controls					
Male	–0.346***	–0.193***	–0.359***	–0.071	–0.147***
	(0.078)	(0.056)	(0.110)	(0.058)	(0.027)
Foreigner	0.099**	0.018	0.003	0.040	0.076***
	(0.041)	(0.037)	(0.064)	(0.049)	(0.023)
Constant	1.162**	1.129**	0.215	0.444	1.611***
	(0.536)	(0.499)	(0.755)	(0.585)	(0.254)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Bundesland fixed effects	Yes	Yes	Yes	Yes	Yes
# Individuals	9,909	10,270	4,266	8,629	5,367
# Occupations	354	274	592	499	468
Log-likelihood	–4,508	–4,688	–1,946	–3,771	–709
AIC	9,185	9,547	4,117	7,747	1,600

Notes: Dependent variable: Digitalization probability by ISCO08 (SOEP 2013), ISCO88 (SOEP 2009) or KldB 2010 (NEPS, PASS, LPP) occupation. Robust standard errors in parentheses, clustered by 4-digit ISCO08 (SOEP 2013), 4-digit ISCO88 (SOEP 2009) or 5-digit KldB (NEPS, PASS, LPP) occupations. *** p<0.01, ** p<0.05, * p<0.1.

that exceeds the effects of personality crystallized in education and experience and that is not driven by gender-, industry- or region-specific factors. For three of the five datasets, the 2013 and 2009 SOEP waves and NEPS, we find significant and plausible relationships between several personality traits and digitalization. For the other two datasets, we find either no systematic relationship at all (PASS) or an implausible positive relationship between openness and digitalization (LPP). The reasons for the differences in the results between SOEP and NEPS on the one hand and PASS and LPP on the other are difficult to explore. One reason may be differences in the sample compositions. Both PASS and NEPS focus on specific groups of workers, those with low socio-economic status (PASS), or those employed by larger and manufacturing establishments. For LPP, the larger measurement errors of the Big Five scores evident from Figure 3 may additionally obscure the results. For PASS, such larger measurement errors do not show up in the descriptive statistics. Still, low socio-economic status may come along with lower motivation to answer the questions thoroughly (Borghans et al. 2011a).

The results for the SOEP and NEPS samples suggest that jobs held by workers who are more *open to experience* tend to be less susceptible to digitalization. This result is plausible since more curious, imaginative, excitable and unconventional workers (see Table 1) can be expected to feature comparative advantages for jobs that require flexible and innovative responses to non-standard problems, i.e., jobs that have been more difficult to computerize in the past (Autor et al. 2003) and will likely be more difficult to digitalize in the future. The results also indicate that jobs held by less *neurotic* (i.e., emotionally more stable) workers tend to be less susceptible to digitalization. A higher degree of neuroticism is typically associated with anxiety, depression, impulsiveness or lack of self-confidence or self-consciousness. Workers with such a personality may be more productive in jobs that offer stable, predictable and frictionless work environments. These work environments arguably lend themselves more easily to automatization. Conversely, emotionally more stable, calmer or more stress-resistant workers may be better suited for performing non-standardized problem-solving tasks that have been more difficult to computerize in the past, and will likely be more difficult to digitalize also in the future.

Additionally, there is some evidence from one dataset, NEPS, suggesting that jobs held by more *extraverted* workers tend to be less susceptible to digitalization. Extraversion is closely related to social skills, which have arguably gained in importance and valuation during recent decades (e.g., Borghans et al. 2014, Weinberger 2014, Deming 2015). The lower susceptibility of social skills to digitalization has frequently been attributed to the growing importance of teamwork and of personal and social services, which require collaboration and communication skills or a caring nature. There is also some evidence from the SOEP 2009 dataset suggesting that jobs held by less *agreeable* workers tend to be less susceptible to digitalization. This result is plausible insofar as higher agreeableness may be associated with a more trustful, dutiful, conformist or undemanding personality. Jobs that require these kind of workers may lend themselves more easily to digitalization. However, higher agreeableness is also associated with more altruism or tender-mindedness, facets that facilitate non-competitive personal interactions, for example in social or health services. These jobs were considered more difficult to computerize in the past. Maybe they will be somewhat less difficult to replace in the future, e.g., by service robots.

There is no evidence from any of the five datasets for a systematic relationship of *conscientiousness* with the susceptibility of jobs to digitalization. This is even though conscientiousness has frequently been found to be the most predictive among the Big Five for a wide range of outcomes, including job performance and wages (Kautz et al. 2014: 20–21). More conscientious workers tend to work harder and be more achievement striving, dutiful, efficient, focused and organized. However, its importance does not vary much with job complexity (Kautz et al. 2014: 21), and thus likely also not with the susceptibility of jobs to digitalization.

As to the traditional measures of human capital, schooling, we find a highly significant though frequently nonlinear association with the probability of digitalization. Years of schooling and its square are jointly highly significant with p-values far below 1% in the regressions for all five datasets, according to χ^2 tests. The standard deviations of the individual parameters are just inflated by multicollinearity. In line with the SBTC approach, all datasets except SOEP 2009 and LPP suggest an inversely U-shaped relationship between digitalization probability and education. The implied education level where the digitalization probability is highest is rather low, though, ranging from 5 years (0.079/(2*0.008)) in SOEP 2013 to 9 years in NEPS. With a mandatory school attendance of 9 years in Germany, the digitalization probability is consequently estimated to decrease continuously with increasing education in the range of relevant education levels. The results for SOEP 2009 also suggest that the digitalization probability decreases more or less continuously with increasing education while those for LPP suggest—against the odds—that the probability increases with increasing education.

The relation of work experience, measured by the worker's age and its square, with digitalization probabilities is also estimated to be inversely U-shaped in all datasets except SOEP 2009. This relation is not significant for several datasets, including SOEP 2009, NEPS and PASS, however.

Turning to the control variables, we find that males are less susceptible to digitalization, ceteris paribus. This is generally in line with Black and Spitz-Oener (2010) who observe a more significant decline of routine tasks, the prime candidates for computerization in the past, for women than for men in Germany during the 1980s and 1990s. Frey and Osborne's estimates obviously suggest that this gender bias will continue into the future.

We also tested, by means of interaction terms, if there are complementarities between personality on the one hand and education, experience or gender on the other.[28] Interestingly, we find significant interactions mostly for PASS and LPP, the datasets that do not reveal significant linear relationships between digitalization and the Big Five. Many of the results for the interactions are implausible or indecisive, however. For example, the results for PASS suggest that higher neuroticism is associated with higher digitalization probabilities for males but with lower digitalization probabilities for females while those for LPP suggest exactly the opposite. We take this as an additional indication for the lower reliability of the PASS and LPP results. According to SOEP 2013, there is only a gradual difference between males and females. With increasing neuroticism, the susceptibility to digitalization increases just somewhat less for males than for females.

1. Robustness

This section checks if the significant relationship between personality and digitalization we observe in our baseline model is just driven by specific groups of workers that are particularly difficult to replace by digital technologies. We check this for two groups, entrepreneurs and creative workers, that have received particular attention in the recent literature. Specifically, we test if the relationship between personality and digitalization vanishes after we control for entrepreneurship or creativity in our regressions.

Interestingly, Big Five personality traits show a significant relationship with the digitalization probability only for those of our five datasets that include self-employed, SOEP and NEPS. Our results may thus be driven by the negative relationship between entrepreneurial personality and digitalization probability. Entrepreneurial activities are difficult to digitalize for at least three reasons. First, entrepreneurship has traditionally been regarded as a form of creativity, and entrepreneurs as creative destructors who destroy existing, routinized firms by introducing innovations (Schumpeter, 1934). Even if the majority of entrepreneurs are not innovative in the Schumpeterian sense, all of them are involved in a process of creating new organizations, a task which is unlikely to be digitalized. Second, entrepreneurs are generalists in that they typically perform a broader variety of tasks (Lazear 2004). Hence, they are likely to diversify the risks of their jobs to be digitalized. And third, they usually perform non-routine analytical tasks—e.g., those that require managerial, communicative, and persuasive abilities—that have arguably been difficult to computerize (Autor et al. 2003) and will likely not be easy to digitalize in the foreseeable future.

[28] Tables A5 – A7 in the Appendix report the detailed regression results for the baseline model extended by interaction terms between each of the Big Five traits and years of schooling (A5), age (A6) and the male dummy (A7). As the χ^2 tests reported in the last row of each table indicate, the interactions with schooling are jointly insignificant for all five datasets while the interactions with age are jointly significant in NEPS and PASS, and those with the male dummy in PASS and LPP.

At the same time, there is a host of studies that show personality to be an important determinant for the decision to be an entrepreneur. Entrepreneurs score particularly high on openness to experience, extraversion and conscientiousness and they score low on agreeableness and neuroticism (Sorgner 2012, 2015, Caliendo et al. 2014).[29]

To check if the results of our baseline model are driven by the negative relationship between entrepreneurial personality and digitalization, we add a dummy variable "entrepreneur" that is one if the individual is self-employed and zero else. If it is just entrepreneurial personality that drives our results for the Big Five, the entrepreneur dummy should absorb enough variation of the digitalization probability to render the parameters of the Big Five insignificant.

Columns 2, 4 and 6 of Table 4 report the regression results for this extended model for the two SOEP and the NEPS datasets. For comparison, columns 1, 3 and 5 report the corresponding results for the baseline model from Table 3. While the entrepreneur dummy is negative and highly significant for all datasets, which corroborates the presumption that entrepreneurial activities will less likely be taken over by new technologies during the next about two decades, our results for the Big Five remain virtually unchanged. The point estimates for most parameters drop slightly in absolute terms but we reject the hypothesis that our results for the Big Five are driven by entrepreneurial personality.

Like entrepreneurial activity, creativity, i.e., "the ability to come up with ideas that are new, surprising, and valuable" (Boden 2004, p. 1), is rather difficult to automatize on the one hand and correlated with personality on the other. While smart computers with access to big data may easily come up with new and surprising ideas, they are still not able to evaluate the economic potential of these ideas (Frey and Osborne 2013: 26). Recall that "creative intelligence" is one of the job requirements that Frey and Osborne identify as digitalization bottlenecks and use for estimating the digitalization probabilities. In addition to this, Bakhshi et al. (2015) demonstrate that creative occupations are less likely to be automatized than non-creative occupations. The correlation of creativity with personality is well-documented in the literature. An extensive literature in psychology (see, e.g., Rubenson and Runco 1992, Sternberg 2006, Funke 2009) as well as a host of studies in economics and economic geography (see, e.g., Florida 2004, Bode and Perez Villar Forthcoming) suggests that workers' creativity is rooted not only in their intelligence and their social or work environment but also in their personality. Little is known about how precisely the individual facets of personality affect workers' creativity, though (Sternberg 2006).

We follow Florida in measuring creativity at the level of occupations (Florida 2004). We define a dummy variable "Creative class occupation" that is one for all workers in occupa-

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[29] In addition to this, there is a positive relationship between workers' self-selection into creative professions and entrepreneurship (Fritsch and Sorgner 2014).

Table 4: Personality, entrepreneurship and the digitalization probabilities of future jobs in Germany

	SOEP 2013		SOEP 2009		NEPS	
	Baseline	Incl. Entre-preneurship	Baseline	Incl. Entre-preneurship	Baseline	Incl. Entre-preneurship
	(1)	(2)	(3)	(4)	(5)	(6)
Entrepreneur	—	–0.387***	—	–0.442***	—	–0.241***
		(0.093)		(0.092)		(0.086)
Noncognitive skills						
Openness	–0.078***	–0.070***	–0.056***	–0.047***	–0.042***	–0.035**
	(0.014)	(0.013)	(0.011)	(0.011)	(0.015)	(0.015)
Conscientiousness	–0.004	0.000	–0.006	–0.003	0.006	0.004
	(0.009)	(0.009)	(0.008)	(0.008)	(0.016)	(0.016)
Extraversion	–0.008	–0.003	0.013	0.018**	–0.037**	–0.034**
	(0.012)	(0.012)	(0.009)	(0.009)	(0.015)	(0.015)
Agreeableness	0.017	0.013	0.021***	0.019***	0.009	0.008
	(0.011)	(0.011)	(0.007)	(0.007)	(0.015)	(0.015)
Neuroticism	0.024**	0.021**	0.023***	0.022**	0.042***	0.039***
	(0.011)	(0.011)	(0.009)	(0.009)	(0.014)	(0.014)
Education						
Years of schooling	0.079	0.084	0.005	0.018	0.274***	0.265***
	(0.081)	(0.081)	(0.077)	(0.076)	(0.099)	(0.100)
Years of schooling, squ.	–0.008***	–0.008***	–0.005	–0.005*	–0.015***	–0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Work Experience						
Age	–0.010*	–0.011*	0.004	0.002	–0.016	–0.017
	(0.006)	(0.006)	(0.005)	(0.005)	(0.013)	(0.013)
Age, squared	0.000*	0.000**	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Individual controls						
Male	–0.346***	–0.324***	–0.193***	–0.163***	–0.359***	–0.347***
	(0.078)	(0.075)	(0.056)	(0.053)	(0.110)	(0.108)
Foreigner	0.099**	0.104**	0.018	0.020	0.003	0.008
	(0.041)	(0.041)	(0.037)	(0.037)	(0.064)	(0.063)
Constant	1.162**	1.194**	1.129**	1.045**	0.215	0.404
	(0.536)	(0.542)	(0.499)	(0.498)	(0.755)	(0.760)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bundesland fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
# Individuals	9,909	9,909	10,270	10,270	4,266	4,266
# Occupations	354	354	274	274	592	592
Log-likelihood	–4,508	–4,477	–4,688	–4,645	–1,946	–1,940
AIC	9,185	9,123	9,547	9,461	4,117	4,104

Notes: Fractional response regressions, dependent variable: Digitalization probability by ISCO08 (SOEP 2013) or ISCO88 (SOEP 2009) or KldB 2010 (NEPS 2009) occupation. Robust standard errors in parentheses, clustered by 4-digit ISCO08 (SOEP 2013), 4-digit ISCO88 (SOEP 2009) or 5-digit KldB (NEPS 2009) occupations. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Personality, creativity and the digitalization probabilities of future jobs in Germany

	SOEP 2013		SOEP 2009		NEPS	
	Baseline	Incl. Creativity	Baseline	Incl. Creativity	Baseline	Incl. Creativity
	(1)	(2)	(3)	(4)	(5)	(6)
Creative class occupation	—	–0.764***	—	–0.717***	—	–1.063***
		(0.188)		(0.163)		(0.174)
Noncognitive skills						
Openness	–0.078***	–0.059***	–0.056***	–0.037***	–0.042***	–0.023
	(0.014)	(0.015)	(0.011)	(0.010)	(0.015)	(0.015)
Conscientiousness	–0.004	–0.007	–0.006	–0.006	0.006	0.003
	(0.009)	(0.008)	(0.008)	(0.007)	(0.016)	(0.014)
Extraversion	–0.008	–0.008	0.013	0.010	–0.037**	–0.023
	(0.012)	(0.012)	(0.009)	(0.009)	(0.015)	(0.016)
Agreeableness	0.017	0.009	0.021***	0.013**	0.009	–0.002
	(0.011)	(0.010)	(0.007)	(0.006)	(0.015)	(0.014)
Neuroticism	0.024**	0.016	0.023***	0.016*	0.042***	0.035**
	(0.011)	(0.011)	(0.009)	(0.008)	(0.014)	(0.014)
Education						
Years of schooling	0.079	0.154*	0.005	0.054	0.274***	0.387***
	(0.081)	(0.086)	(0.077)	(0.064)	(0.099)	(0.091)
Years of schooling, squ.	–0.008***	–0.008***	–0.005	–0.005*	–0.015***	–0.016***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.003)
Work Experience						
Age	–0.010*	–0.008	0.004	0.002	–0.016	–0.004
	(0.006)	(0.005)	(0.005)	(0.006)	(0.013)	(0.011)
Age, squared	0.000*	0.000*	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Individual controls						
Male	–0.346***	–0.310***	–0.193***	–0.150***	–0.359***	–0.308***
	(0.078)	(0.072)	(0.056)	(0.049)	(0.110)	(0.085)
Foreigner	0.099**	0.079**	0.018	–0.019	0.003	–0.028
	(0.041)	(0.038)	(0.037)	(0.035)	(0.064)	(0.059)
Constant	1.162**	0.408	1.129**	0.683*	0.215	–1.313**
	(0.536)	(0.554)	(0.499)	0.406)	(0.755)	(0.668)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bundesland fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
# Individuals	9,909	9,909	10,270	10,270	4,266	4,266
# Occupations	354	354	274	274	592	592
Log-likelihood	–4,508	–4,238	–4,688	–4,446	–1,946	–1,714
AIC	9,185	8,646	9,547	9,063	4,117	3,653

Notes: Fractional response regressions, dependent variable: Digitalization probability by ISCO08 (SOEP 2013) or ISCO88 (SOEP 2009) or KldB 2010 (NEPS 2009) occupation. Robust standard errors in parentheses, clustered by 4-digit ISCO08 (SOEP 2013), 4-digit ISCO88 (SOEP 2009) or 5-digit KldB (NEPS 2009) occupations. *** p<0.01, ** p<0.05, * p<0.1.

tions classified as creative occupations by Florida's notion of the creative class.[30] Table 5 reports the regression results for our baseline model extended by the creativity dummy for the two SOEP waves and NEPS. The first row indicates that creative class occupations are associated with significantly lower digitalization probabilities in all three datasets, as expected. Still, the parameters of most of personality traits that are significant in the baseline model are still significant in the extended model. The estimated parameters for openness to experience and neuroticism as well as for extraversion (NEPS) and agreeableness (SOEP 2009) drop slightly in absolute terms, and a few of them turn statistically insignificant due to this drop, but our main result remains unchanged. The systematic relationship between personality and digitalization is not just driven by the fact that jobs of more creative workers are more difficult to digitalize.

6. Conclusions

We present evidence suggesting that the so-called "fourth industrial revolution", characterized by machine learning, big data, mobile robotics and cloud computing, may be skill-biased not only with respect to skills acquired through education, as available theoretical models and empirical evidence abundantly suggest, but also with respect to facets of noncognitive skills (personality). Measuring the future direction of technological change by estimated probabilities of occupations to be automatized during the next about two decades (Frey and Osborne 2013), and noncognitive skills by the Big Five personality traits from several German worker surveys, we find that jobs that currently require more openness to experience or more emotional stability will be less susceptible to automatization in the future. We also find some evidence suggesting that jobs that require more extraversion or less agreeableness may also be less susceptible to automatization. These correlations are significant even though we control extensively for formal education and work experience, the traditional measures of human capital.

As a by-product of our empirical analysis, we find interesting differences between the German worker surveys that report Big Five personality traits. Compared to the responses in the Socioeconomic Panel (SOEP) and the National Educational Panel Study (NEPS), those in the Linked Personnel Panel (LPP), an annual employer-employee survey, are skewed notably towards Big Five scores employers would prefer. And the Panel Study on Labor Markets and Social Security (PASS) may, due to its focus on problem groups in the labor market, be of limited use for general-purpose analyses of labor markets.

Our results corroborate earlier findings suggesting that formal education is a rather imperfect proxy of human capital. Personality is an important factor of success in school, and thereby affects success in subsequent work life indirectly. Over and above this indirect effect, it is also

[30] See Fritsch and Sorgner (2014) and Fritsch and Stützer (2014) for the details of this classification.

an important independent factor of success in work life, however. It affects not only wages and occupational choices directly, as James Heckman and his coauthors have shown. It also affects workers' resilience to future technological changes directly, as we suggest in the present study.

Accounting for this role of personality may well sharpen the hypotheses to be drawn from theoretical models of skill-based technological change such as the Ricardian model in Acemoglu and Autor (2011). To account for personality, these models may put more emphasis on labor supply. Workers are actually endowed with multifaceted skills, and tasks require a variety of different skills as productive inputs. The task of teaching, for example, requires a university degree and additionally a good deal of communication skills and a patient, outgoing and caring personality. The task of doing research also requires a university degree but a rather different personality. It requires more curiosity, determination and self-discipline while deficits in communication skills will not hurt too much. Heterogeneous skill endowments give rise to a richer variety of comparative advantages for performing tasks than education alone does. In addition to this, they open up a richer set of options in response to exogenous technology shocks. Workers may take other jobs that involve different tasks but similar skill compositions. Or they may readjust the skills set they supply to the labor market by focusing on skills they are endowed with but have not needed in earlier jobs.

Accounting for this role of personality may also enhance the explanatory power of empirical studies founded in models of skill-based technological change. Much is left to be done by psychologists and economists to disentangling the relevant skills behind composite skill categories like the Big Five or the so-called "social" skills (Weinberger 2014, Deming 2015), "people" skills (Borghans et al. 2014) or "21st-century" skills (Pellegrino and Hilton 2012). More reliable measurement of these skills is an extremely important and difficult related issue, of course.

Appendix

Table A1: "Digitalization bottlenecks" identified by Frey and Osborne (2013)

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

Sources: Frey and Osborne (2013), National Center for O*NET Development (undated).

Table A2: Descriptive statistics for German micro datasets that report Big Five personality traits

Variable	Dataset	N	Mean	Std.dev.	Min	Max
Openness to experience	SOEP 2013	9,909	0.021	0.978	–3.018	2.041
	SOEP 2009	10,270	–0.007	0.971	–2.857	2.064
	NEPS	4,266	–0.004	0.998	–2.718	1.652
	PASS	8,629	0.003	0.998	–3.587	1.880
	LPP	5,367	–0.002	0.995	–2.054	3.471
Conscientiousness	SOEP 2013	9,909	0.060	0.946	–5.230	1.268
	SOEP 2009	10,270	0.018	0.934	–4.818	1.176
	NEPS	4,266	–0.002	1.001	–3.618	1.299
	PASS	8,629	0.004	1.001	–4.916	1.556
	LPP	5,367	–0.001	0.998	–1.307	6.368
Extraversion	SOEP 2013	9,909	0.053	1.013	–3.467	1.928
	SOEP 2009	10,270	0.024	1.009	–3.353	1.915
	NEPS	4,266	–0.002	1.000	–2.603	1.774
	PASS	8,629	0.005	0.998	–3.045	1.737
	LPP	5,367	–0.003	0.996	–1.931	4.186
Agreeableness	SOEP 2013	9,909	–0.051	0.982	–4.563	1.666
	SOEP 2009	10,270	–0.139	0.995	–4.520	1.593
	NEPS	4,266	0.000	1.001	–3.877	4.297
	PASS	8,629	–0.005	1.001	–2.894	2.435
	LPP	5,367	0.001	0.998	–1.623	5.319
Neuroticism	SOEP 2013	9,909	–0.089	0.979	–2.264	2.648
	SOEP 2009	10,270	–0.166	0.981	–2.392	2.506
	NEPS	4,266	0.001	1.001	–1.964	3.106
	PASS	8,629	0.008	1.004	–2.184	2.754
	LPP	5,367	0.001	0.999	–3.004	2.259
Years of schooling	SOEP 2013	9,909	12.858	2.731	7	18
	SOEP 2009	10,270	12.753	2.724	7	18
	NEPS	4,266	14.292	2.309	9	18
	PASS	8,629	10.151	2.161	9	18
	LPP	5,367	11.103	2.577	9	18
Age	SOEP 2013	9,909	45.563	12.238	18	86
	SOEP 2009	10,270	43.813	11.839	17	85
	NEPS	4,266	48.452	9.847	27	70
	PASS	8,629	41.227	12.021	16	68
	LPP	5,367	45.517	10.483	18	67
Dummy Male	SOEP 2013	9,909	0.490	0.500	0	1
	SOEP 2009	10,270	0.504	0.500	0	1
	NEPS	4,266	0.511	0.500	0	1
	PASS	8,629	0.429	0.495	0	1
	LPP	5,367	0.740	0.438	0	1

to be continued

Table A2 continued

Variable	Dataset	N	Mean	Std.dev.	Min	Max
Dummy Foreign citizen	SOEP 2013	9,909	0.045	0.208	0	1
	SOEP 2009	10,270	0.053	0.223	0	1
	NEPS	4,266	0.072	0.259	0	1
	PASS	8,629	0.061	0.239	0	1
	LPP	5,367	0.042	0.200	0	1
Creative class occupation	SOEP 2013	9,909	0.411	0.492	0	1
	SOEP 2009	10,270	0.376	0.484	0	1
	NEPS	4,266	0.522	0.500	0	1
	PASS	8,629	0.202	0.402	0	1
	LPP	5,367	0.342	0.475	0	1
Entrepreneurship	SOEP 2013	9,909	0.106	0.307	0	1
	SOEP 2009	10,270	0.108	0.310	0	1
	NEPS	4,266	0.147	0.354	0	1
	PASS	8,629	—			
	LPP	5,367	—			

Sources: German Socioeconomic Panel (SOEP) by the German Institute for Economic Research (DIW) Berlin, 2013 / 2009 waves; National Educational Panel Study (NEPS) by the Leibniz Institute for Educational Trajectories (LIfBi), University of Bamberg, 2012/13 wave; Panel Study on Labor Markets and Social Security (Panelstudie Arbeitsmarkt und Soziale Sicherung, PASS) by the German Institute for Labor Research (IAB), 2012 wave; Linked Personnel Panel (LPP) by German Institute for Employment Research (IAB), University of Cologne and Centre for European Economic Research (ZEW), 2012/13 wave.

Table A3: Correlation matrices for the German micro datasets that report Big Five personality traits

	Sample	Openness	Conscien-tiousness	Extra-version	Agree-ableness	Neuroti-cism	Educa-tion	Age	Male	Foreigner	Creative class
Conscientiousness	SOEP(2013)	0.11	1								
	SOEP(2009)	0.12	1								
	NEPS	0.09	1								
	PASS	0.20	1								
	LPP	0.19	1								
Extraversion	SOEP(2013)	0.33	0.17	1							
	SOEP(2009)	0.35	0.16	1							
	NEPS	0.18	0.15	1							
	PASS	0.22	0.23	1							
	LPP	0.37	0.30	1							
Agreeableness	SOEP(2013)	0.14	0.27	0.08	1						
	SOEP(2009)	0.13	0.26	0.07	1						
	NEPS	–0.05	–0.06	–0.01	1						
	PASS	0.04	0.05	0.01	1						
	LPP	0.13	0.29	0.13	1						
Neuroticism	SOEP(2013)	–0.04	–0.09	–0.15	–0.12	1					
	SOEP(2009)	–0.03	–0.09	–0.15	–0.10	1					
	NEPS	–0.06	–0.11	–0.17	–0.03	1					
	PASS	0.06	–0.12	–0.22	–0.04	1					
	LPP	–0.01	–0.09	–0.19	–0.15	1					
Years of education	SOEP(2013)	0.15	–0.10	–0.03	0.02	–0.09	1				
	SOEP(2009)	0.17	–0.07	–0.02	0.01	–0.06	1				
	NEPS	0.14	–0.12	–0.02	–0.01	–0.01	1				
	PASS	0.10	–0.02	0.01	0.02	–0.05	1				
	LPP	–0.01	0.12	–0.01	0.03	0.04	1				
Age	SOEP(2013)	0.02	0.15	–0.06	0.02	–0.01	0.04	1			
	SOEP(2009)	0.01	0.14	–0.08	0.01	–0.01	0.07	1			
	NEPS	0.04	0.13	–0.05	0.03	–0.06	–0.07	1			
	PASS	0.03	0.12	–0.12	0.09	0.01	0.02	1			
	LPP	–0.03	–0.04	0.07	–0.02	0.02	–0.02	1			

to be continued

Table A3 continued

	Sample	Openness	Conscien-tiousness	Extra-version	Agree-ableness	Neuroti-cism	Educa-tion	Age	Male	Foreigner	Creative class
Male	SOEP(2013)	–0.07	–0.09	–0.12	–0.15	–0.21	0.00	0.02	1		
	SOEP(2009)	–0.08	–0.07	–0.12	–0.17	–0.21	0.00	0.03	1		
	NEPS	–0.10	–0.14	–0.13	0.04	–0.22	0.03	0.03	1		
	PASS	–0.10	–0.11	–0.10	–0.07	–0.21	0.06	–0.03	1		
	LPP	–0.01	0.09	0.04	0.08	0.12	–0.02	–0.02	1		
Foreigner	SOEP(2013)	–0.01	0.04	0.03	0.02	0.02	–0.12	–0.03	0.00	1	
	SOEP(2009)	0.00	0.02	0.00	0.02	0.00	–0.13	–0.05	0.01	1	
	NEPS	–0.02	0.02	–0.02	0.07	0.04	–0.04	–0.05	–0.01	1	
	PASS	–0.01	0.02	–0.01	0.09	0.01	–0.04	–0.06	–0.02	1	
	LPP	–0.03	0.01	0.01	0.01	–0.04	0.03	–0.07	–0.01	1	
Creative class occupation	SOEP(2013)	0.14	–0.06	0.00	0.00	–0.08	0.51	0.04	0.03	–0.07	1
	SOEP(2009)	0.15	–0.04	0.00	–0.01	–0.05	0.49	0.06	0.01	–0.08	1
	NEPS	0.12	–0.06	0.03	–0.03	–0.04	0.43	0.03	0.01	–0.04	1
	PASS	0.10	–0.01	0.04	0.04	–0.04	0.39	–0.01	–0.01	–0.07	1
	LPP	–0.02	0.11	0.02	0.03	0.04	0.39	0.09	0.04	–0.05	1
Entrepreneurship	SOEP 2013	0.12	0.05	0.06	–0.01	–0.06	0.12	0.16	0.08	0.00	0.14
	SOEP 2009	0.11	0.03	0.05	–0.01	–0.05	0.15	0.15	0.08	–0.02	0.20
	NEPS	0.14	0.01	0.05	0.00	–0.05	0.10	0.11	0.05	0.01	0.10

Sources: See Table A2.

Table A4: Personality and the digitalization probabilities of future jobs in Germany: OLS regressions for the baseline model

Dataset	SOEP 2013	SOEP 2009	NEPS	PASS	LPP
	(1)	(2)	(3)	(4)	(5)
Noncognitive skills					
Openness	–0.027***	–0.020***	–0.013***	–0.005	0.026**
	(0.005)	(0.004)	(0.005)	(0.005)	(0.012)
Conscientiousness	–0.001	–0.002	0.002	–0.001	–0.016
	(0.003)	(0.003)	(0.005)	(0.004)	(0.010)
Extraversion	–0.003	0.004	–0.012**	–0.003	–0.015
	(0.004)	(0.003)	(0.005)	(0.005)	(0.013)
Agreeableness	0.005	0.007***	0.002	0.000	–0.011
	(0.004)	(0.003)	(0.005)	(0.004)	(0.012)
Neuroticism	0.008**	0.008**	0.013***	–0.000	–0.018
	(0.004)	(0.003)	(0.005)	(0.004)	(0.012)
Education					
Years of schooling	0.004	–0.025	0.063*	0.041	–0.198**
	(0.032)	(0.029)	(0.035)	(0.028)	(0.079)
Years of schooling, squar.	–0.002	–0.001	–0.004***	–0.003**	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Work Experience					
Age	–0.003*	0.001)	–0.005	–0.003	–0.019*
	(0.002)	(0.002	(0.004)	(0.002)	(0.011)
Age, squared	0.000*	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Individual controls					
Male	–0.108***	–0.064***	–0.110***	–0.022	–0.447***
	(0.025)	(0.020)	(0.038)	(0.018)	(0.080)
Foreigner	0.029**	0.002	–0.003	0.013	0.216***
	(0.014)	(0.014)	(0.021)	(0.016)	(0.066)
Constant	1.044***	1.070***	0.753***	0.635***	3.107***
	(0.206)	(0.189)	(0.264)	(0.194)	(0.672)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Bundesland fixed effects	Yes	Yes	Yes	Yes	Yes
# Individuals	9,909	10,270	4,266	8,629	5,367
# Occupations	354	274	592	499	468
R^2	0.409	0.397	0.409	0.324	0.282

Notes: Dependent variable: Digitalization probability by ISCO08 (SOEP 2013), ISCO88 (SOEP 2009) or KldB 2010 (NEPS, PASS, LPP) occupation. Robust standard errors in parentheses, clustered by 4-digit ISCO08 (SOEP 2013), 4-digit ISCO88 (SOEP 2009) or 5-digit KldB (NEPS, PASS, LPP) occupations. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Personality and the digitalization probabilities of future jobs in Germany: Interactions between personality and education

Dataset	SOEP 2013	SOEP 2009	NEPS	PASS	LPP
	(1)	(2)	(3)	(4)	(5)
Noncognitive skills					
Openness	–0.081	0.009	–0.092	–0.078	0.049
	(0.066)	(0.047)	(0.116)	(0.071)	(0.066)
× years of schooling	0.000	–0.005	0.004	0.006	–0.002
	(0.005)	(0.004)	(0.008)	(0.007)	(0.006)
Conscientiousness	0.064	–0.007	0.014	–0.110	0.032
	(0.051)	(0.041)	(0.102)	(0.071)	(0.061)
× years of schooling	–0.005	0.000	–0.000	0.010	–0.004
	(0.004)	(0.003)	(0.007)	(0.007)	(0.006)
Extraversion	–0.062	–0.076*	0.093	0.099	–0.038
	(0.055)	(0.041)	(0.089)	(0.081)	(0.069)
× years of schooling	0.004	0.007**	–0.009	–0.011	0.002
	(0.005)	(0.003)	(0.006)	(0.008)	(0.006)
Agreeableness	–0.019	–0.047	0.054	–0.117*	–0.002
	(0.055)	(0.054)	(0.100)	(0.062)	(0.058)
× years of schooling	0.003	0.006	–0.003	0.012*	–0.001
	(0.005)	(0.004)	(0.007)	(0.006)	(0.005)
Neuroticism	–0.04	0.065	–0.061	0.009	–0.136***
	(0.050)	(0.046)	(0.103)	(0.069)	(0.050)
× years of schooling	0.005	–0.003	0.007	–0.001	0.011**
	(0.004)	(0.004)	(0.008)	(0.007)	(0.005)
Education					
Years of schooling	0.076	0.002	0.284***	0.120	–0.198**
	(0.079)	(0.076)	(0.099)	(0.080)	(0.079)
Years of schooling, squared	–0.008***	–0.004	–0.015***	–0.008***	0.003
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Work Experience					
Age	–0.010*	0.003	–0.016	–0.007	–0.019*
	(0.006)	(0.005)	(0.013)	(0.007)	(0.011)
Age, squared	0.000*	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Individual controls					
Male	–0.345***	–0.192***	–0.357***	–0.071	–0.449***
	(0.078)	(0.056)	(0.111)	(0.058)	(0.080)
Foreigner	0.100**	0.020	0.000	0.042	0.216***
	(0.041)	(0.037)	(0.064)	(0.049)	(0.065)
Constant	1.182**	1.144**	0.147	0.321	3.124***
	(0.527)	(0.492)	(0.755)	(0.581)	(0.672)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Bundesland fixed effects	Yes	Yes	Yes	Yes	Yes
# Individuals	9,909	10,270	4,266	8,629	5,367
# Occupations	354	274	592	499	468
Log-likelihood	–4,507	–4,686	–1,945	–3,767	–2,525
Joint significance interaction terms (LR test)	4.5	11.67**	4.6	7.1	7.5

Notes: Fractional response regressions, dependent variable: Digitalization probability by ISCO08 (SOEP 2013), ISCO88 (SOEP 2009) or KldB 2010 (NEPS, PASS, LPP) occupation. Robust standard errors in parentheses, clustered by 4-digit ISCO08 (SOEP 2013), 4-digit ISCO88 (SOEP 2009) or 5-digit KldB (NEPS, PASS, LPP) occupations. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Personality and the digitalization probabilities of future jobs in Germany: Interactions between personality and age

Dataset	SOEP 2013	SOEP 2009	NEPS	PASS	LPP
	(1)	(2)	(3)	(4)	(5)
Noncognitive skills					
Openness	–0.115***	–0.043	0.002	0.092*	–0.028
	(0.041)	(0.028)	(0.077)	(0.050)	(0.048)
× age	0.001	0.000	–0.001	–0.003**	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Conscientiousness	0.014	0.007	–0.173**	–0.098**	0.042
	(0.035)	(0.026)	(0.073)	(0.045)	(0.047)
× age	0.000	0.000	0.004**	0.002**	–0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Extraversion	0.006	0.025	–0.096	–0.030	–0.022
	(0.035)	(0.031)	(0.062)	(0.045)	(0.049)
× age	0.000	0.000	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Agreeableness	–0.071**	–0.020	0.115*	–0.129**	–0.005
	(0.032)	(0.027)	(0.063)	(0.058)	(0.048)
× age	0.002***	0.001	–0.002*	0.003**	–0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Neuroticism	–0.023	–0.006	0.103*	–0.009	0.015
	(0.032)	(0.022)	(0.062)	(0.045)	(0.044)
× age	0.001	0.001	–0.001	0.000	–0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education					
Years of schooling	0.079	0.005	0.273***	0.100	–0.198**
	(0.081)	(0.077)	(0.100)	(0.079)	(0.079)
Years of schooling, squared	–0.008***	–0.005	–0.015***	–0.007**	0.004
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Work Experience					
Age	–0.010*	0.003	–0.011	–0.005	–0.019*
	(0.006)	(0.005)	(0.013)	(0.007)	(0.011)
Age, squared	0.000*	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Individual controls					
Male	–0.346***	–0.193***	–0.357***	–0.070	–0.447***
	(0.078)	(0.056)	(0.110)	(0.059)	(0.080)
Foreigner	0.097**	0.017	0.005	0.043	0.216***
	(0.041)	(0.037)	(0.063)	(0.049)	(0.066)
Constant	1.153**	1.125**	0.108	0.376	3.118***
	(0.541)	(0.502)	(0.769)	(0.571)	(0.672)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Bundesland fixed effects	Yes***	Yes	Yes	Yes	Yes
# Individuals	9,909	10,270	4,266	8,629	5,367
# Occupations	354	274	592	499	468
Log-likelihood	–4,507	–4,688	–1,944	–3,764	–2,526
Joint significance interaction terms (LR test)	9.93*	4.18	14.8**	10.2*	3.4

Notes: Fractional response regressions, dependent variable: Digitalization probability by ISCO08 (SOEP 2013), ISCO88 (SOEP 2009) or KldB 2010 (NEPS, PASS, LPP) occupation. Robust standard errors in parentheses, clustered by 4-digit ISCO08 (SOEP 2013), 4-digit ISCO88 (SOEP 2009) or 5-digit KldB (NEPS, PASS, LPP) occupations. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Personality and the digitalization probabilities of future jobs in Germany: Interactions between personality and gender

Dataset	SOEP 2013	SOEP 2009	NEPS	PASS	LPP
	(1)	(2)	(3)	(4)	(5)
Noncognitive skills					
Openness	–0.102***	–0.076**	–0.074***	–0.029	0.034
	(0.032)	(0.031)	(0.021)	(0.020)	(0.022)
× male	0.015	0.013	0.063**	0.034	–0.011
	(0.023)	(0.018)	(0.029)	(0.028)	(0.025)
Conscientiousness	0.005	–0.030	–0.013	–0.022	0.035
	(0.031)	(0.031)	(0.026)	(0.019)	(0.022)
× male	–0.006	0.016	0.035	0.036	–0.065**
	(0.020)	(0.021)	(0.034)	(0.025)	(0.026)
Extraversion	0.055*	0.062**	–0.037*	–0.022	–0.007
	(0.031)	(0.030)	(0.022)	(0.023)	(0.024)
× male	–0.043**	–0.033*	0.000	0.031	–0.009
	(0.019)	(0.019)	(0.035)	(0.031)	(0.030)
Agreeableness	0.002	0.025	0.007	–0.004	–0.044*
	(0.031)	(0.023)	(0.019)	(0.017)	(0.025)
× male	0.011	–0.003	0.005	0.008	0.042
	(0.021)	(0.016)	(0.026)	(0.021)	(0.028)
Neuroticism	0.123***	0.010	0.037*	–0.040**	0.038
	(0.036)	(0.023)	(0.020)	(0.019)	(0.023)
× male	–0.065***	0.008	0.011	0.095***	–0.076***
	(0.022)	(0.014)	(0.027)	(0.028)	(0.028)
Education					
Years of schooling	0.082	0.004	0.275***	0.097	–0.195**
	(0.081)	(0.077)	(0.100)	(0.080)	(0.079)
Years of schooling, squared	–0.008***	–0.005	–0.015***	–0.007**	0.003
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Work Experience					
Age	–0.010*	0.003	–0.016	–0.008	–0.019*
	(0.006)	(0.005)	(0.013)	(0.007)	(0.011)
Age, squared	0.000*	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Individual controls					
Male	0.342***	0.196***	–0.358***	–0.065	–0.460***
	(0.079)	(0.056)	(0.110)	(0.059)	(0.079)
Foreigner	0.100**	0.017	0.003	0.050	0.219***
	(0.041)	(0.037)	(0.065)	(0.048)	(0.066)
Constant	0.465	0.742	0.226	0.485	3.111***
	(0.582)	(0.536)	(0.754)	(0.584)	(0.672)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Bundesland fixed effects	Yes	Yes	Yes	Yes	Yes
# Individuals	9,909	10,270	4,266	8,629	5,367
# Occupations	354	274	592	499	468
Log-likelihood	–4,505	–4,687	–1,945	–3,765	–2,524
Joint significance interaction terms (LR test)	15.79***	4.94	6.5	15.6***	14.8**

Notes: Fractional response regressions, dependent variable: Digitalization probability by ISCO08 (SOEP 2013), ISCO88 (SOEP 2009) or KldB 2010 (NEPS, PASS, LPP) occupation. Robust standard errors in parentheses, clustered by 4-digit ISCO08 (SOEP 2013), 4-digit ISCO88 (SOEP 2009) or 5-digit KldB (NEPS, PASS, LPP) occupations. *** p<0.01, ** p<0.05, * p<0.1.

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