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The Relative Importance of Personal Characteristics for the Hiring of Young Workers

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The Relative Importance of Personal Characteristics for the Hiring of Young Workers*

Peter Hoeschler[†] and Uschi Backes-Gellner[‡]

January, 2018

First Draft. Preliminary Results.

Abstract

We investigate the relative importance of different personal characteristics for firms' hiring decisions. Our design allows firms to observe potential workers during a long screening period. At the end of that period firms can decide to make job offers, thereby revealing their preferences about workers' personal characteristics. We connect real-world job offers and workers' personal characteristics, both of which are usually unobserved. To investigate the relative importance of various personal characteristics for the likelihood to receive a job offer, we use a unique panel data set of entry-level workers. We find that grades and non-cognitive skills are important for receiving a job offer, with the Big Five Personality traits being the most important predictor. We find no effects for intelligence or economic preferences.

Keywords: Job Offers, Ability, Non-Cognitive Skills, Preferences, Vocational Education.

JEL Classification: D03, M51, J24.

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1 Introduction

When making job offers, employers reveal their preferences about workers' personal characteristics (skills, abilities, and traits). However, employers face uncertainty as to certain personal characteristics that might be unobservable. Non-cognitive skills, which a growing literature shows to be important in the labor market (e.g., Deming, 2016; Heckman & Kautz, 2012; Heckman, Stixrud, & Urzua, 2006), tend to be particularly difficult for employers to observe. This uncertainty might be even more pronounced for entry-level workers who have no employment history. To reduce this uncertainty, firms might screen entry-level workers' personal characteristics during programs such as internships, traineeships, or apprenticeships. For example, firms engaging in apprenticeship training learn about the ability of their trainees during the intense training period of several years (e.g., Acemoglu & Pischke, 1998). Afterwards, firms can decide to make job offers to these workers, thereby revealing their preferences for certain personal characteristics. We study these revealed preferences by investigating the influence of various personal characteristics on firms' job offers at the end of apprenticeship training.

A growing literature applies various research designs to investigate which personal characteristics employers value. This literature, which also suggests that non-cognitive skills are very important, uses five research designs. First, some studies use stated (discrete) choice experiments to elicit employer preferences over personal characteristics. In these studies, employers receive a set of CVs (or results from assessment centers) of potential applicants and are asked to select the candidates to whom they would offer a job (e.g., Biesma, Pavlova, van Merode, & Groot, 2007; Humburg & van der Velden, 2015). Second, correspondence studies attempt to identify the effect of the characteristics by exploiting real-world firm decisions. In these studies, researchers send out fake CVs with differing signals of personality to firms with job openings and observe the response rates (e.g., Protsch & Solga, 2015).

Third, researchers simply ask employers for their preferences across a fixed set of personal characteristics (e.g., Biesma et al., 2007; Teijeiro, Rungo, & Freire, 2013). Such employer skill surveys are also frequently conducted by government agencies in various countries (e.g., CEDEFOP, 2014). Fourth, laboratory experiments study the effect of perceived personality on the likelihood of receiving a job (Baert & Decuypere, 2014). Fifth, to derive the skill demands of employers, some studies investigate job opening postings (e.g., Deming & Kahn, 2017). This approach is gaining popularity because such postings have become more easily accessible through increasing online job searches.

However, all five approaches are limited, for at least two reasons, in their ability to study employers' preferences. The first reason is related to firms' stated and revealed preferences: No study uses real-world high-stakes firm decisions that are relatively costly for the firms and that therefore should reveal their true preferences. The second reason is related to firms' limited ability to observe important personal characteristics. To fully evaluate the relative importance of all personal characteristics, studies may use designs in which firms also know about the less-observable personal characteristics of individuals. Even though some studies have attempted to tackle this problem (e.g., Baert & Decuypere, 2014), none includes a substantial screening period during which employers can fully learn about the workers' characteristics. In contrast, our research design both includes an extended screening period, thereby accounting for the limited observability of various personal characteristics, and uses job offers that result in real employment.

Using this research design, we investigate the link between personal characteristics and job offers, both of which generally are hard to observe for researcher. We use a unique data set of Swiss apprentices, data that provides us with high-quality and well-established measures of intelligence, non-cognitive skills, and economic preferences—dimensions that many studies regard as unobservable ability. Moreover, we observe explicit job offers after an intense training and screening period. In our analysis we combine this information and compare the relative importance of different personal characteristics for the likelihood of receiving an offer. With our analysis we aim at answering the following questions: Which personal characteristics are important for receiving a job offer at the end of apprenticeship training? Are these personal characteristics the same that make retained apprentices more likely to stay in the firm permanently? Do these offers matter for later labor market outcomes?

We use jobs offers at the end of apprenticeship training because they are likely to reveal firms' true preferences.[1] Towards the pre-specified end of the training, training firms can make job offers

[1]The transitions at the end of apprenticeship has been intensively studied. These studies focus primarily on the analysis of wage differences between firm movers and firm stayers (e.g., Acemoglu & Pischke, 1998; Harhoff & Kane,

and, if they do not, they face no firing costs because the training contracts simply run out. Moreover, in our sample, offers are selective: Only 70 percent of the apprentices receive a job offer at the end of the training period. Of the subsample that received an offer, 94 percent accepted. In addition, the distribution of the absolute values of the offers has a high mean and is very limited in range. Therefore, firms make job offers only to apprentices whom they really want to keep. In sum, these job offers are selective, result in employment at high wages, and thus are clearly not cheap talk.

In our main analysis we assess the power of different personal characteristics in explaining the likelihood of receiving a job offer. Our type of analysis is related to Humphries and Kosse (2017), who investigate the importance of cognitive ability, personality, and economic preferences for high school grade point average; to Burks et al. (2015), who investigate the importance of cognitive ability, personality, and economic preferences for college outcomes; and to Becker, Deckers, Dohmen, Falk, and Kosse (2012), who investigate the importance of economic preferences and personality for education, labor market, and health outcomes. We add to these studies, which focus mainly on educational outcomes, by investigating firms' hiring decisions in detail.

We find that grades and non-cognitive skills are important for the likelihood of receiving a job offer. In contrast, we find no effects for intelligence or economic preferences. To investigate the relative importance of the different personal characteristics, we compare the predictive power of several personal characteristics. Only the models for grades, Grit, and the Big Five have predictive power in explaining offers. The relative predictive power of the Big Five is particularly striking, and they are by far the most important predictors. For the Big Five, we find that the baseline scores at the beginning of the training matter most, while for Grit we find that its development during training is most important.

Our results show that firms base their job offers on hard-to-observe non-cognitive skills. Firms take this phenomenon into account by extensively offering programs that allow them to screen entry-level workers. Firms appear to use these programs to screen primarily for non-cognitive skills. For policy

1997; Mueller & Schweri, 2015; von Wachter & Bender, 2006) and on factors affecting the probability of staying in the training firm (Euwals & Winkelmann, 2004; Franz & Zimmermann, 2002; Mohrenweiser, Wydra-Somaggio, & Zwick, 2017).

makers, our results imply that policies targeted towards the preparation of young people for entering the labor market should also focus on improving non-cognitive skills because employers not only value those skills but also changes in them. Indeed, Hoeschler, Balestra, and Backes-Gellner (2018) show that non-cognitive skills change during adolescence and adulthood. Moreover, policy makers may facilitate training programs that include screening periods in which individuals can communicate their valuable non-cognitive skills to potential employers.

To show the importance of the job offers we investigated, we relate them to later labor market outcomes. First, individuals who receive a job offer at the end of the training period heavily reduce their search activities for other jobs. We observe significant and large differences in the number of job applications sent out and the number of months spent on job search. Second, we test whether the wages two years after training differ for individuals both with and without offers, and find significantly higher full-time wages for those who received an offer. The wage difference between the two groups is equal to 605 Swiss Francs (CHF), or about 13 percent. In sum, we show that job offers are related to further labor market outcomes, and—because we show in our main analysis that the strongest predictors for receiving a job offer are the trainees' non-cognitive skills—provide an indication that employers value non-cognitive skills.

The link between offers—which are related to non-cognitive skills—and wages provides valuable insights into labor market selection processes. Studies that examine wage differences between firm movers and firm stayers usually put great effort into establishing research designs that help reduce the selection issues between the two groups (e.g., Acemoglu & Pischke, 1998; von Wachter & Bender, 2006). For example, while von Wachter and Bender (2006) find substantial wage differences between firm movers and stayers when not accounting for the selection into the two groups, they find no wage differences when estimating the causal effect of moving and staying. By describing this non-random selection process, our study reveals differences in non-cognitive skills between movers and stayers, differences that explain the different results in, for example, von Wachter and Bender (2006).

By showing that firms use non-cognitive skills when deciding to make retention offers, we also contribute to the growing literature on the importance of skills other than pure cognitive ability (e.g., Deming, 2016; Heckman et al., 2006). However, while the wage returns to non-cognitive skills are established in a causal manner (e.g., Heckman et al., 2006), in this paper we make no causal claims. Instead we describe the usually unobserved selection processes into employment. As this is a major selection issue in labor economics, our study provides valuable insights for researchers, firms, and policy makers alike. To investigate this selection process, we use a unique research design that we describe extensively in the next section.

2 Research Design

Our research design has several favorable elements that enable us to tackle our questions. These elements are based on both our panel data, which gives us extensive measures of personal characteristics, and on the unique institutional setting of the Swiss apprenticeship training system. This sections describes both factors.

2.1 Data

We use the Leading House Apprenticeship Panel, a panel data set started in 2009 with individuals who had just begun their apprenticeship training in Zurich, Switzerland.[2] The training is conducted in three major occupations (commercial employee, electrician, and polymechanic) and takes three to four years.[3] While the students receive one to two days per week of classroom learning in a vocational school, they receive most of their training in a host company (Wolter & Ryan, 2011). Given that the host company conducts such a substantial part of the training, it should be able to fully observe the trainee's personal characteristics.

We collected measures at the start of the apprenticeship training (at age 15-16), during the training, and two years after the training (at age 21-22). Figure A1 provides an overview of the time structure of the project. The training last three years for commercial employees and four years for technicians (electricians and polymechanics). For the main analysis, we use information provided in the initial and

[2]For a detailed description of the data and an overview of the entire project, see Oswald and Backes-Gellner (2014).

[3]Vocational education and training is the main route of secondary education in Switzerland, serving 70 percent of young people (Hoffman & Schwartz, 2015). The occupations investigated in our study all rank in the top ten of the apprenticeship training occupations, with commercial employees outnumbering all other occupations by far (SERI, 2014).

the final surveys. The initial survey provides us with rich baseline measures of personal characteristics and additional background variables. The final survey, which took place two years after the respective training ended, includes information on retention offers and further labor market outcomes.

[Insert Figure A1 about here.]

By giving us detailed information on job offers and personal characteristics, our data set is ideal for answering our research questions. First, it allows us to directly observe job offers, which register, firm-level, and large survey data sets rarely include. To this end, our data set provides detailed information on job offers by the training firm at the end of the training. By asking the trainees in great detail about their offers, we are confident that trainees truly report their offers.[4] Second, the data set gives us measures for intelligence, economic preferences (time preferences and risk aversion), and non-cognitive skills (Grit and the Big Five). Given such an extensive bundle of personal characteristics, our data set provides us with the unique opportunity to investigate the importance of all these characteristics for the likelihood of receiving a job offer.

Another advantage of our data is that the surveyed population is very homogeneous with respect to occupation, education, and region. As all individuals received the same level of training, the restriction on range reduces selection issues. The setting we use is also similar to the reality of the hiring process, in which firms select workers for a given position within a given occupation. Moreover, studies investigating individual wage differences usually control for occupation, and therefore investigate differences *within* occupations rather than *between* them (e.g., von Wachter & Bender, 2006). Therefore, in line with Deming and Kahn (2017), we investigate the relative importance of various personal characteristics within narrowly defined occupations.

As with all panel data sets, we have to investigate attrition issues. The initial sample in 2009

[4]Ideally, we would like to match the trainee's information on the offers with additional information provided by the firms. However, as the Leadinghouse Apprenticeship Panel exclusively surveys individuals, not firms, such matching is not feasible.

consists of 265 individuals, 235 of whom provide measures of intelligence, grades, economic preferences, non-cognitive skills, and background variables. In the final wave, six years later, 159 individuals responded to our intense survey efforts (via e-mails, letters, phone calls, and social media), and 135 provided all analyzed measures. We view all our results as conditional on finishing apprenticeship training and staying in the sample. However, the overall attrition, which is 40 percent, is unrelated to intelligence, baseline non-cognitive skills, economic preferences, or various background variables (results available from the authors upon request).

2.2 Measures of Personal Characteristics

To measure personal characteristics, we use well-established measures of intelligence, economic preferences (time preferences and risk aversion), and non-cognitive skills (Grit and the Big Five).[5] As our measures of intelligence, we use two tests: a general intelligence (IQ) test and the Cognitive Reflection Test (CRT). Our IQ test is one of the 11 modules of the Wechsler Adult Intelligence Scale (WAIS-III)—one of the most widely used IQ tests (Kaufman & Lichtenberger, 1998). We use the *digit symbol-coding test*, which asks subjects to match as many digits and symbols according to a given key as possible in a fixed time (for details, see Dohmen, Falk, Huffman, & Sunde, 2010). Our other measure of intelligence, the CRT, developed in Frederick (2005), asks subjects three questions, each having an intuitive answer that is incorrect. Finding the correct answer requires some cognitive reflection. However, once explained, the correct answer is easily understood. Both measures of intelligence are well established and appear to measure different facets of intelligence. Indeed, the correlation between the two measures is basically zero.

Using these measures of intelligence, we show that the apprentices in our data set are average-ability students. The mean IQ score in our sample (table A1) is equal to the 50th-percentile score of a general sample of 16- to 17-year-olds in Austria, Germany, and Switzerland (von Aster, Neubauer, & Horn, 2009). Comparing the mean CRT score in our sample (0.926) to the scores of undergraduate students at selected public U.S. colleges (Frederick, 2005), we find that our score is in the range of the

[5]For a detailed overview of the measures, see also Bessey (2010).

reported scores at the University of Michigan at Ann Arbor (1.18), Bowling Green State University (0.87), the University of Michigan at Dearborn (0.83), and Michigan State University (0.79). Moreover, Brañas-Garza, Kujal, and Lenkei (2015) survey 118 studies using the CRT and calculate for a total population of 44,558 students and non-students a mean of 1.19. Thus the apprentices in our data are clearly within the average-ability range.[6]

For economic preferences, we use well-established paid experiments, using choice tables for measuring patience and the willingness to take risks (Dohmen et al., 2010).[7] Our measure of patience is the switching point X, at which individuals choose X today over 100 CHF in three months (for more details, see Oswald & Backes-Gellner, 2014). Our measure of the willingness to take risks is the certainty equivalent X, at which individuals choose a definite X over a coin toss yielding 5 CHF in expectation (for more details, see Bessey, 2010). Table A1 shows that our subjects are on average risk-loving. However, the modal certainty equivalent is equal to the expectation of the coin toss (5 CHF). As these two measures are uncorrelated, each covers a different aspect of economic preferences.

[Insert Table A1 about here.]

To derive our measures of non-cognitive skills, we use two well-established multiple-question inventories. For Grit, defined as the "perseverance and passion for long-term goals" (Duckworth, Peterson, Matthews, & Kelly, 2007, p. 1087), we use the 8-item Grit scale, a highly efficient questionnaire developed in Duckworth and Quinn (2009). Psychologists view Grit in particular as a universally important non-cognitive skill in many domains, one that has predictive validity over and above the Big Five personality traits (Duckworth et al., 2007; Duckworth & Quinn, 2009).

To measure the Big Five personality traits (conscientiousness, extraversion, agreeableness, open-

[6]This finding is a result of vocational education and training's being the main route of secondary education in Switzerland, serving 70 percent of each cohort (Hoffman & Schwartz, 2015).

[7]Following the empirical findings of Meier and Sprenger (2015) and Andersen, Harrison, Lau, and Rutström (2008), we assume that economic preferences are stable over time.

ness, and emotional stability),[8] we use a well-established 3-item-per-trait scale based on the original Big Five Inventory (BFI) scale and further developed in Gerlitz and Schupp (2005).[9] The Big Five construct is the standard taxonomy for classifying personality traits (John, Naumann, & Soto, 2008). As previously mentioned, some non-cognitive skills change during apprenticeship training (Hoeschler et al., 2018). Therefore, for all measures of non-cognitive skills, we include changes over time (*deltas*), which are the differences between the respective measure before and after the apprenticeship training (table A1). By construction each measure's delta is correlated with its initial value.[10]

In addition, our data set provides us with information on school grades, the easiest signals to observe for trainee characteristics.[11] We use two grades, measured at two times on the standard Swiss grade scale, which ranges from 1 (worst) to 6 (table A1). *Grade Middle School* is the average grade in math, German, and English in the last year of full-time schooling before the apprenticeship training started. *Final Grade APT* is the final grade for the apprenticeship training after training ended. Measuring both education and training content, the final grade is based on grades (a) in vocational school and (b) for hands-on tasks in training centers and the host company. Therefore, this grade measures general, vocational, and occupational skills. Moreover, our measures for intelligence and for non-cognitive skills have similar predictive power for the final grade.[12] Therefore, the final grade constitutes a credible signal for a certain set of personal characteristics, including cognitive ability, non-cognitive skills, and general, vocational, and occupational skills. As expected, the two grades are correlated ($r = 0.256^{***}$).[13]

[8] We calculate emotional stability as the reverse of neuroticism.

[9] For agreeableness, we can only use two items due to data issues.

[10] However, none of our results is affected by this correlation.

[11] For an overview of the relationship between grades, intelligence, and personality, see Borghans, Golsteyn, Heckman, and Humphries (2016). They show that grades, when compared to IQ scores, are a better predictor for various important life outcomes, because grades capture more relevant personality traits.

[12] Following Borghans et al. (2016), who investigate the relationship between grades, intelligence, and personality, we use our measures of intelligence (IQ and CRT) and non-cognitive skills (Grit and the Big Five) to explain the final grade. Therefore, we regress these measures both individually and jointly on the final grade. Individual regressions show that intelligence (*adjusted* $R^2 = 0.067$) and non-cognitive skills (*adjusted* $R^2 = 0.043$) perform about equally in explaining the final grade. A joint model (*adjusted* $R^2 = 0.108$) shows that both intelligence and non-cognitive skills appear to be complementary, and that—in contrast to the results in Borghans et al. (2016)—our models perform relatively poorly in explaining the final grade. Thus the final grade might be highly influenced by other, uncorrelated skills, for example, occupational or vocational skills.

[13] However, all the results we show for jointly estimated models also hold for unconditional models.

2.3 Job Offers

Our main outcome variable is a binary indicator for receiving a job offer after apprenticeship training. While doing their apprenticeship training, trainees are employed by host companies, where they receive a substantial share of their training. Therefore, firms can observe the trainees' productivity and screen for specific skills. In the final year of the training, the firm can decide to offer a trainee a permanent position after the training period ends (for a detailed timeline, see figure A1). The trainee can then decide whether to accept this offer.[14] The training period ends for all apprentices at the same time, generating a spot market-like situation. All apprentices who are not retained by the training firm enter the secondhand market with all other un-retained apprentices (Acemoglu & Pischke, 1998) and theoretically become unemployed if they have not found other employment when training ends.

For job offers to reveal employers' true preferences, at least two requirements have to be fulfilled. First, employers must be unconstrained in their ability to make offers. Only when employers can freely decide to whom to make an offer, offers can reveal true preferences. Second, offers should be no cheap talk. Therefore, making an offer needs to have real consequences for employers, i.e., hiring the former trainee at a competitive wage. In the remainder of this section, we argue that in our case these two requirements are fulfilled.

Swiss firms are free in making job offers to their trainees at the end of the apprenticeship training. Given the low level of labor market regulation in Switzerland, firms are not constrained by institutional boundaries in their ability to make retention offers. Neither laws nor large-scale agreements between unions and firms cover the retention of apprentices. Moreover, firms can make offers to all their apprentices, even those with possibly more compelling outside options, such as other employment, further education, or the military service. However, these options are somewhat endogenous to the offer, with none restraining the firms' ability to make job offers to their apprentices. As long as the process of making an offer is relatively costless, firms can even make an offer to individuals who, they

[14]While each trainee clearly has only one training firm, a training firm could potentially have several trainees. By combining the observable information on firms to form unique cells, we find 81 combinations of firm characteristics, i.e., we observe at least 81 unique firms. Within one potential firm, the apprentices could still be in different departments with unrelated retention strategies. However, as we have no model for the interaction of several trainees in one firm with regard to the firm's retention offers, we assume a single-level model in which each firm employs one trainee.

assume, would never accept it. In sum, firms are neither obligated to make offers to any of their apprentices nor restrained from making offers to all of them.

Another reason that Swiss firms are free in making offers is that they do not face any costs when deciding not to make one. On average, training firms face no training costs from apprenticeship training (Muehlemann, Pfeifer, Walden, Wenzelmann, & Wolter, 2010)[15] and therefore do not need to retain a certain number of trainees to recoup such costs. Neither do firms face firing costs if they do not retain a trainee, as all training contracts just expire at the fixed end of the training. Not having any costs of separation is a major difference between our setting and up-or-out contracts, promotions in general, or other forms of retention that may also provide settings for studying employer preferences. Our setting has the advantage of allowing firms to truly state their preferences without taking into account firing issues. In sum, firms are totally free in making offers.

Investigating the second requirement, we show that offers have a high likelihood of resulting in employment at high wages. In our sample, 70 percent of the apprentices receive a job offer at the end of the training period (table A2). Therefore, offers are selective, and—as not all trainees receive one—we can use them to infer employer preferences. Figure A2 shows the distribution of retention wages. This distribution has a high mean, a clear lower threshold, and only limited variation.[16] Offers have a high mean wage of 4,647 CHF per month (or 55,763 CHF per year), with a low standard deviation of 392.[17] Such a limited variation in wages of young workers with the same level of education is in line with the earnings dispersion literature, which shows that earnings fan out with workers' age (for an overview, see Neal & Rosen, 2000). Indeed, the limited variation in retention wages is the reason for our focus on explaining the likelihood of receiving an offer, not on explaining the amount offered.

[15]Different occupations have different training costs. The technical occupations investigated in this study tend to lead to positive net training costs on average but with a high variance between firms (Strupler & Wolter, 2012). Moreover, the commercial apprenticeship training causes no substantial training costs on average (Strupler & Wolter, 2012). Therefore, we assume that for our full sample positive training costs play no major role. We further examine this issue in section 4.1.

[16]Figure A2 shows a clear cut-off, as there are no offers below a certain threshold (3,500 CHF). Despite no general minimum wage in Switzerland, some sector-specific wage floors exist. In addition, firms appear to agree on an implicit lower bound for the wage offer. The observed distribution implies an equilibrium in which not every trainee simply receives an offer according to his or her marginal productivity but in which only the "best" apprentices receive offers and in which, therefore, offers can act as a credible signal for ability.

[17]The mean wage offer differs by occupation. Electricians have a statistically significant higher mean offer (4,938 CHF) than commercial employees (4,564 CHF) or polymechanics (4,691 CHF). The offered fixed pay per month is measured in intervals of 500 CHF. All reported additional payments are converted to monthly wages and added to the fixed pay. The limited variation might be partly due to the measuring of wages in relatively large intervals.

In the subsample that received an offer, 94 percent accepted (table A2).[18] This high acceptance rate shows that offers almost always result in employment. Moreover, it shows that at this stage firms appear to act as price setters, which can decide to make an offer or not. Afterwards, given they received an offer, almost all apprentices simply accept it. Put differently, firms appear to have some market power over the trainee, i.e., some monopsony power (e.g., Manning, 2011).[19] This market power at the end of training could be based on various sources (for an overview, see Acemoglu & Pischke, 1999), at least two of which are related to the time elapsed since the end of training: low regional mobility[20] and asymmetric employer learning (Schönberg, 2007). Therefore, we also investigate the likelihood of staying in the training firm more permanently, i.e., at least two years after training. In total, 56 percent of the apprentices who accepted the retention offer stayed in their training firm for at least two years (table A2).[21] We estimate all our models for both the likelihood of receiving an offer and that of staying in the training firm for at least two years.

[Insert Table A2 about here.]

In sum, we argue for two reasons that the offers should reveal employers' true preferences. First, firms can freely make offers. Second, the offered retention wage is high on average and varies little among trainees. Moreover, almost all trainees accept these offers, thereby forcing employers to

[18]The remaining 6 percent, who do not accept their offers, are not offered particularly low retention wages.

[19]Another reasons could be rent-sharing in a bilateral monopoly.

[20]Regional mobility in our sample is low but increases over time. Initially, almost all individuals in our sample live in the metropolitan area of Zurich. At the end of the apprenticeship training, 95.6 percent of them still live with their parents. Therefore, at the end of training, regional mobility is very low. Two years after the training, 68.1 percent still live with their parents. Therefore, the early twenties appear to be a period in which individuals start moving out of their parents' places, a finding also observable in Swiss census data (FSO, 2016). Nevertheless, regional mobility remains low.

[21]Our general transition patterns are in line with those of other studies for Switzerland. Mueller and Schweri (2015) find that 51 percent of apprentices stay with their training firm one year after training. Strupler and Wolter (2012) find a retention rate with the training firm of 37 percent during that first year. While a survey among graduates of apprenticeship training shows that 47 percent of graduates continue to work for their training firm (SERI, 2017), it shows differences in the retention rates in training occupations. In addition, the estimated retention rates crucially depend on the timing of the assessment. By definition the retention rate falls as the time between the assessment and the end of the training increases. Given our immediate assessment of the retention rate directly at the end of the training and the specific occupations we investigate, our estimated retention rates might be at the upper end. However, our data shows a general transition pattern of relatively low mobility directly at the end of training, coupled with high mobility within the first years after training. This pattern explains the difference between our study and others.

pay these wages. Therefore, by investigating the likelihood of receiving a job offer, we can observe employers' true preferences for certain personal characteristics.

3 Results

3.1 Relation of Personal Characteristics and Job Offers

To derive our results, we estimate OLS models. First, we run individual regressions for each personal characteristic, including a set of control variables. Second, to compare the relative predictive power of each personal characteristic, we compare the *adjusted* R^2s of models without control variables (for a similar approach, see Borghans et al., 2016). We use OLS in our main analysis, as it provides a well-established measure of relative predictive power (*adjusted* R^2) that accounts for differing numbers of regressors.[22] Given that our personal characteristics consist of differing numbers of variables, such a measure is crucial for our analysis. Nonetheless, we show that all our results are robust to various other model specifications.

By providing the raw correlations between our personal characteristics and the likelihood of receiving an offer, Table A1 shows overall our main result that grades and various non-cognitive skills are important for receiving an offer. Moreover, Table A1 shows in detail that the final grade of the apprenticeship training is positively correlated with job offers. For the non-cognitive skills, the changes in Grit and some of the Big Five variables are significant. Positive changes in Grit, higher initial level of conscientiousness, lower initial levels of openness, and positive changes in emotional stability are all correlated with the likelihood of receiving an offer. However, given that we will primarily estimate joint models with all Big Five traits, the raw correlation of each trait is only of limited information. When investigating these joint models, as we have no theoretical expectation of the effect direction for each trait, we therefore, interpret the Big Five traits as a bundle and—in line with other studies (e.g., Becker et al., 2012)—do not discuss the effect direction of any single trait. Indeed, each effect is

[22]The relationship between the R^2 and the *adjusted* R^2 (for degrees of freedom) is given as: *adjusted* $R^2 = 1 - \frac{(n-1)}{(n-K)}(1 - R^2)$, with n being the number of observations and K being the number of estimated coefficients. If the R^2 is sufficiently close to zero, i.e., when the sample correlation between the explanatory variables and the outcome is basically zero, the *adjusted* R^2 becomes negative.

simply a residual one conditioned on all the other traits. Given no clear procedure for attaching any meaning to these residual effects, we therefore treat all the Big Five initial values as one variable and all the deltas as a second variable. Our main line of argumentation for all personal characteristics is then based on F-tests of joint significance and *adjusted* R^2s.

Moving towards the regression results, we find that the final training grade is a significant predictor for receiving a job offer after training (table A3, column 2). Given that the training firm has three to four years to observe the trainee's abilities, the firm does not need to rely on grades as a signal for ability. In contrast, we find no significant relationship between the likelihood of receiving an offer and intelligence (measured by IQ and CRT).[23] These contradictory findings suggest that training firms value the final grade not because they constitute a measure of pure cognitive ability but because they measure occupational, vocational, and non-cognitive skills. As with our results for intelligence, we find no effects for economic preferences, i.e., for patience or the willingness to take risks (table A3, column 3).

In contrast, we find that various non-cognitive skills have an impact on the likelihood to receive an offer (table A3, columns 4 and 5). For Grit, this likelihood is strongly related to its development during training. This result shows that employers value changes in certain non-cognitive skills.[24] For the Big Five, the likelihood of receiving an offer is strongly related to the baseline personality at the beginning of training. However, all the changes taken as one group are not significant. An explanation for this result could be that training firms might be biased by the initial personality traits and might change their priors only slowly over time. In sum, for the Big Five, the initial levels appear more important, while for Grit the importance lies on the changes over time. However, for both the Big Five and Grit, we find that initial values and deltas are jointly significant, not a surprising finding given the high correlation between the two measures.

[23]When including four dummies, one for each potential outcome of the CRT, thereby allowing the CRT score to affect offers in a more flexible manner, we also find no effect for CRT.

[24]Therefore, incorporating the development of non-cognitive skills over time when investigating the returns to non-cognitive skills is critical.

[Insert Table A3 about here.]

The findings in Table A3 are robust to various model specifications and estimation methods in the following four ways.[25] First, none of the effects depend on the inclusion of control variables (being a native speaker, mother's education, gender, and age), and the effects are virtually identical when we include controls for occupation. Therefore, our results are similar across occupations and our personal characteristics do not merely pick up differences across occupations. Second, the results do not depend on the applied grouping of personal characteristics. In Table A3 we include two variables for each personal characteristic (treating the Big Five as only two variables, initial values and deltas). However, this grouping has no effect on the results, because the significant effects still remain significant in unconditional models with only one variable at a time. Third, when we estimate probit regressions, all effects remain significant. Given that our outcome is a binary variable, testing for such model specifications is crucial. Fourth, all effects remain significant when we use HC3 standard errors to correct for the limited sample size. Thus our overall conclusions depend on no particular model specification or estimation method, and are robust to several other approaches.

Next, assessing the predictive power of the different characteristics, we find that the Big Five are the most important predictors for receiving a job offer. To display the relative importance of the different personal characteristics, Figure A3 shows *adjusted* R^2s for similar models as in Table A3 but without any control variables. Only the models for grades, Grit, and the Big Five explain the variance in the likelihood of receiving an offer. More specifically, grades and Grit perform about equally well, while the relative predictive power of the Big Five is striking—about six times higher than for grades or Grit. Running a full model with all personal characteristics (figure A3, column 6) shows that Grit, grades, and the Big Five all have incremental predictive power, as the bars of the separate models add up nicely in the full model. This finding shows that grades, Grit, and the Big Five appear to be complements.[26]

[25] In some specifications, the effects for final grade and the Big Five initial values remain significant only at the 15 percent level. Specific results are available upon request.

[26] We test three additional specifications. First, including both measures that capture cognitive ability—intelligence

A simple variance decomposition for the model of Figure A3, column (6), again reveals that the Big Five, grades, and Grit are the important predictors. When we abstract from covariances, intelligence explains 1.8 percent of the explained variance, preferences explain 6.4 percent, Grit explains 11.3 percent, grades explain 16.7 percent, and the Big Five explain 63.8 percent. While these results could be partially due to the different number of variables for each personal characteristic, it again shows the importance of the Big Five.

To better understand the dominant effect of the Big Five, we now investigate the relative importance of the different Big Five traits. Therefore, we again perform a simple variance decomposition but now for the model of Figure A3, column (5). When we abstract from the covariances, conscientiousness explains 32.7 percent of the explained variance, agreeableness explains 26.7 percent, openness explains 22.4 percent, emotional stability explains 17.3 percent, and extraversion explains 0.9 percent. These findings underline the dominant role of conscientiousness as the most important Big Five trait, a result that has been shown across many outcomes (Almlund, Duckworth, Heckman, & Kautz, 2011). Moreover, our findings show that extraversion is not important for job offers, thereby supporting the argument that not all Big Five traits are important for all outcomes (Almlund et al., 2011).[27]

[Insert Figure A3 about here.]

We can compare our results for job offers to the results of studies assessing the relative importance of personal characteristics for educational outcomes. For example, using the same data set, Bessey (2010) shows that Grit and one Big Five trait (emotional stability) are related to the certainty of grad-

and grades—in one model, we obtain a model with basically no predictive power (*adjusted* $R^2 = 0.009$). Second, adding interactions between intelligence and grades to that model, we find a small increase in the predictive power (*adjusted* $R^2 = 0.038$) over the predictive power of the model that uses only grades. This finding might indicate that the power of intelligence may depend on grades, or vice versa. Third, running a model with both measures of non-cognitive skills—Grit and the Big Five—we find a predictive power (*adjusted* $R^2 = 0.1295$) that is about equal to the sum of the powers of the two separate models (i.e., one for Grit and one for the Big Five). The last finding again shows that the two measures of non-cognitive skills appear to be complements.

[27] However, as personality might be valued differentially across occupations (Almlund et al., 2011) and sectors (Hamilton, Papageorge, & Pande, 2014), extraversion might be highly relevant in other settings.

uating from apprenticeship training while finding no significant relationships for intelligence, grades, or economic preferences. However, she provides no F-tests for the joint significance of the Big Five and, as she conducts her analysis at the beginning of the apprenticeship training, does not include changes in non-cognitive skills. Burks et al. (2015), for a sample of U.S. college students, show that conscientiousness and—to a limited extent—patient time preferences are important for grade point average and graduation on time. They find no effect for intelligence when running a full model that includes several non-cognitive skills. In addition, Borghans et al. (2016) show that non-cognitive skills predict test scores and grades above and beyond IQ scores. Therefore, the general pattern of our results, which explain the selection in the labor market, is in line with other studies using educational outcomes: that non-cognitive skills are the most important predictor across a variety of outcomes.

In sum, we show that the Big Five personality traits are by far the most predictive personal characteristic for explaining job offers. Moreover, we show a minor predictive role for Grit, another non-cognitive skill, and for grades, which capture a variety of skills, including non-cognitive ones. In contrast, neither intelligence nor economic preferences predict job offers. Therefore, we show that firms rely heavily on non-cognitive skills when making job offers after apprenticeship training.

3.2 Offers and Labor Market Outcomes

We now analyze the question of whether the job offers we investigate matter for later labor market outcomes. Therefore, we investigate two potential outcomes of receiving an offer: job search behavior directly after training and wages two years after training (table A4). First, individuals who receive an offer at the end of training invest significantly less in their search activities for a job outside the training firm. We observe significant and large differences in the number of job applications sent out (1.1 versus 10.6) and the number of months spent for job search (0.4 versus 1.9).[28] Therefore, job offers appear to be a means for training firms to secure their monopsony power directly after training, because trainees who receive a job offer do not actively search for outside jobs.

Second, we investigate the relationship between offers and wages two years after training. If only

[28]As our survey provides no information on the timing of the offer and the job search activities, we can only describe the correlation, not show a causal effect of the offer on job search activities, i.e., we cannot rule out the possibility that individuals might receive offers only because they do not search for outside jobs.

the "good" workers receive job offers, we should observe higher wages for workers who received an offer. Therefore, we test whether the wages two years after training differ for workers with and without an offer. We find significant higher full-time wages two years after training for workers who received an offer.[29] The wage difference between the two groups is equal to 605 CHF, or about 13 percent (table A4). Therefore, the offers are highly important for the average trainee. While offers might also have a causal impact on wages, we view the wage differences primarily as a result of selection, and the offer as a signal for personality characteristics. In the next section, by looking at the group of retained apprentices in more detail, we further investigate this question. Therefore, we examine what affects the mobility patterns of retained apprentices after training and whether these mobility patterns have an effect on wage differences within this group.

[Insert Table A4 about here.]

3.3 Labor Market Mobility after Accepting Offer

We investigate the more permanent outcome of a job offer by explaining the likelihood of staying with the training firm for at least two years after accepting the offer. At this later stage, when various market forces start to work, the training firm has much less influence. First, the raiding activities of other firms and the training firm's interest in and ability to match outside offers become important (Lazear, 1986; Waldman, 1990).[30] Over time, offers become public knowledge, i.e., employer learning becomes symmetric (Schönberg, 2007). Individuals who received a job offer might use this offer as a credible signal during their subsequent career development. Given the institutional setting of the

[29]The percentage of individuals working full-time is relatively low two years after training (62 percent). The main reason indicated in our survey is "enrollment in further education and training." A high level of further education and training during the period following the initial apprenticeship training is a major characteristic of the Swiss education system (Hoffman & Schwartz, 2015; SERI, 2014).

[30]In line with Waldman (1990), we find that the wage two years after training (mean: 4,525 CHF, sd: 2,053; full-time workers only: mean: 5,340 CHF, standard deviation: 930) varies much more than the retention wage offered (mean: 4,646 CHF, standard deviation: 399). However, this finding might be based on the survey design, as both wages are measured in intervals of 500 Francs and these intervals appear to allow only for limited differentiation between the earlier (lower) wages.

Swiss apprenticeship system, outside firms appear unable to directly observe the training firm's offer or to act on it by giving a counter offer. However, individuals who receive an offer and stay at the training firm reveal their offer by means of their employment patterns, thereby, allowing outside firms to observe it over time.

Second, the apprentices' preferences for employment may become more heterogeneous. While they might be primarily interested in securing any kind of employment at the very end of training, they might later develop further interests, for example, switching employers to obtain different types of working experience or enrolling in further training. Therefore, we expect personal characteristics to be much less important at this later stage.

Conducting the same type of analysis as in section 3.2, we find that higher final grades are associated with staying in the training firm (table A5, column 2). Again, we find no effect for IQ or economic preferences. Moreover, we find basically no effect for Grit or the Big Five.[31] Given that non-cognitive skills are the major selection criterion in the first stage (receiving the job offer), the sub-sample of individuals who receive and accept an offer obviously varies much less in non-cognitive skills than our initial sample. This limited variation might explain the differing results. In a sub-sample replication of the comparison of powers, we again find that grades are the most important predictor for staying in the training firm at least two years after training (figure A4). No other personal characteristic has predictive power for explaining the likelihood of staying in the training firm.

In contrast, the effect for grades in Figure A4 is equal in magnitude to the effect in Figure A3. Given that the most easily observable signal (grades) should become less important as workers stay longer in the labor market (e.g., Altonji & Pierret, 2001), this finding might be somewhat puzzling. However, the investigated workers are still young, and thus firms might rely heavily on their grades, because these constitute an easily observable signal for external firms as well. Moreover, the final grade of the apprenticeship training also measures vocational and occupational skills, which might have an idiosyncratic value to the training firm.

Next, we show that firm movers and firm stayers, both of whom accepted the initial job offer and

[31] Only all Big Five variables, initial values, and changes are jointly significant (table A5, column 4).

started to work for the training firm, do not differ in labor market outcomes (table A6). First, we find no significant differences in job search activities at the end of training—a finding that is not surprising, given that both groups accepted the offer of the training firm. However, this finding also shows that firm movers do not accept the initial offer simply because they could not find a better job. Indeed, at the end of training, neither group searches for jobs outside the training firm. Second, we investigate the wage differences between firm movers and firm stayers two years after training. Again, we focus only on full-time employed workers. Given that firm stayers by definition remain still employed while firm movers could be anywhere, this restriction is crucial for comparing the two groups. In contrast to our findings in section 3.2, we find no statistically significant wage differences between the two groups. In sum, when workers receive and accept an offer, whether they stay with the training firm or move to another firm within two years after the training is irrelevant for labor market outcomes.

4 Discussion and Robustness Checks

This section provides robustness checks that show additional results for the relationship between job offers and firm-related characteristics. Moreover, to address concerns regarding the generalizability of our findings and the reliability of the investigated intelligence measures, we discuss our results in more detail.

4.1 Job Offers and Firm-Related Characteristics

In addition to trainee characteristics, firm-level and macro data could also affect the firms' retention decisions. In this subsection, we provide arguments for the limited confounding influence of these factors in our research design. In addition, we empirically test the relationship between several firm-related characteristics and the likelihood of receiving an offer.

In our research design, firm-level and macro effects should not drive our results for the following two reasons: First, as our sample is very homogeneous and all firms operate in the same region, they all are exposed to the same general macroeconomic conditions, e.g., regional labor market thickness. Therefore, macroeconomic conditions should not affect our results. Second, while firms might use specific retention strategies unrelated to the trainee's personal characteristics, we argue that these types of strategies would clearly downward bias our results, i.e., make finding any significant effect unlikely. At one extreme, a firm could always make each of its trainees an offer regardless of his or her individual characteristics, in which case trainees who received an offer should not have received offers based on their characteristics. At the other extreme, a firm might never make an offer to any of its trainees, in which case some trainees who should have received an offer based on their individual characteristics do not. Both scenarios would decrease the difference in the mean characteristics between those who received an offer and those who do not, thereby causing our results to be downward biased (regression to the mean). Therefore, our estimates consitute only a lower bound for the importance of personal characteristics for firms' retention decisions.

Next, we empirically investigate the relationship between several firm-related characteristics and job offers. Table A7 provides descriptive statistics for the firm-related characteristics in our data set. When investigating trainee retention, research shows that training costs affect retention at the firm level (e.g., Muehlemann et al., 2010) but not necessarily at the individual level (Muehlemann, Braendli, & Wolter, 2013). Indeed, at the individual level, training costs might be endogenous and related to the trainees' personal characteristics (Muehlemann et al., 2013). If firms decide to provide the same level of training to all trainees, then higher-ability trainees might cause fewer training costs. However, firms might also provide more training to their higher-ability trainees in the expectation of retaining them, in which case higher-ability trainees might actually cause higher training costs. However, the extent of this strategy might be bounded by training regulations (for a complete discussion, see Muehlemann et al., 2013). Both levels of analysis—firm and individual—identify firm size and industry/training occupation as two prominent factors affecting training costs. However, we find no statistically significant relationship between firm size or training occupation and the likelihood of receiving an offer (table A8, columns 1 and 2).

Similarly, firms, that want to keep their trainees might already invest more in trainee selection. If so, firms that will keep their apprentices anyway might simply have had better apprentices in the first place. One obvious way of attracting "better" apprentices would be to pay higher training wages.

However, we find no significant correlation between training wages and the likelihood of receiving an offer (table A8, column 3). Finally, we investigate whether the likelihood of receiving an offer depends on the interpersonal relationships of the trainee and his or her training supervisors and co-workers. Again, we find no statistically significant relationship (table A8, column 4). In sum, we find no significant relationship between characteristics related to the training firm and the likelihood of receiving an offer from it. Similarly, for the subsample that accepted an offer we find no significant relationship between firm characteristics and the likelihood of staying in the training firm for at least two years (table A8, columns 5 to 8).

4.2 Initial Selection of Training Firms

Following up on the role of the firm in our setting, we further discuss the potential selection issue that arises because training firms choose their apprentices at the beginning of training and personal characteristics might already influence the selection process. Initially, students apply for apprenticeships with firms; then firms choose their apprentices from the pool of applicants. Ideally, to rule out the possibility that the characteristics that we find unimportant might actually be very important in the initial selection, we would like to replicate our study for the initial selection process. However, for such an investigation, we would need information on the personal characteristics of the full set of applicants, including those who received no apprenticeship position. Even if we had access to this data, such a design would not address the limited observability of non-cognitive skills and thus would most likely yield very different results. Moreover, some of our results indicate that the initial selection process might be less important. First, we find no significant relationship between training wages and offers. Second, we find that changes in Grit during the training are important for receiving an offer.

Nevertheless, taking this potential limitation into account, we have to be clear that we address the question of which skills are valued by employers conditional on having a pre-selected group of workers, i.e., trainees. This question is a common one that researchers investigate when studying all kinds of job promotions. However, when interpreting our results, we need to be aware that all reported effects are conditioned on the first selection into the apprenticeships. Thus we can not rule out the possibility that economic preferences or intelligence might be highly predictive for entering into the apprenticeship training program.

4.3 Reliability of our Intelligence Measures

As we find no significant effects for intelligence, two concerns may arise as to the reliability of our intelligence measures. First, the measures might be of low quality. However, our two measures are extensively used in the economic literature and have proven to be useful (e.g., Dohmen et al., 2010). In addition, with our data set we can empirically test the correlation between our intelligence measures and wages, thereby investigating whether these measures explain an important labor market outcome, i.e., wages. While our IQ score (digit-symbol coding test of the WAIS-III) is unrelated to wages, the CRT score (cognitive reflection test) is significantly related to them: increasing the CRT score by one standard deviation is associated with a 4.9 percent higher full-time wage two years after training. This finding supports our confidence that the CRT score measures important abilities. However, while a higher CRT is valued in the labor market, training firms do not take it into account when making their initial job offers at the end of training.

Second, from a conceptual perspective, our scales might measure other characteristics than intelligence. For example, our IQ measure might be better described as a measure for motivation as it is a relatively simple, unincentivized test (Almlund et al., 2011; Segal, 2012). Furthermore, our CRT measure might asses several skills unrelated to intelligence (for a discussion, see Frederick, 2005). Following only this interpretation of our measures, we would just find insignificant results for another set of (non-cognitive) skills, e.g., motivation. Put differently, our not finding significant results for intelligence could also be due to our measures' limited ability to correctly assess intelligence. Thus we cannot completely rule out the possibility that more complex incentivized intelligence measures might lead to significant results.

5 Conclusion

We find that trainees' final grades and non-cognitive skills (Grit and the Big Five) predict job offers after apprenticeship training. These characteristics develop both before and during training. We show that the Big Five personality traits are the most important predictor. To show that job offers are a relevant outcome, we provide evidence for the labor market importance of the offers we investigate: An offer is associated with fewer job search activities at the end of training and a substantially higher wage two years after training.

However, our results are limited in two ways, both of which provide opportunities for future research. First, our sample size is small. On the one hand, smaller samples make finding significant results less likely. Therefore, finding significant effects in a small sample supports the robustness of our results. On the other hand, our significant results might gain even more credibility when replicated in larger samples for a larger set of occupations. Moreover, in larger samples, not finding statistically significant results for certain characteristics is a stronger argument for the minor role of these characteristics, because missing statistical power is less of a concern. While our small sample size makes our insignificant results—especially for intelligence—less credible, it makes our significant results for the final grade, Grit, and Big Five more credible.

Second, our data provides no long-term labor market outcomes. Given the substantial percentage of part-time workers (38 percent), because many choose further training immediately after the initial apprenticeship, future research should assess the labor market relevance of the offer in the longer term. Large longitudinal data sets with measures of personal characteristics, job offers, and wages would be necessary for overcoming the limitations of this paper.

By showing that firms use primarily non-cognitive skills when making job offers after training, our results have implications for the literature on young workers. By describing the process of hiring decisions after apprenticeship training, we show that hiring after training is non-random (Gibbons & Katz, 1991) and that it is indeed best explained by differences in non-cognitive skills. In this regard, the results of our study show that accounting for the non-randomness of hiring is crucial when identifying the causal effect on wages of moving versus staying (e.g., von Wachter & Bender, 2006). However, we show that the worrisome selection is based on non-cognitive skills, not on cognitive ability, in line with recent research emphasizing the importance of skills other than cognitive ability (e.g., Deming, 2016; Heckman & Kautz, 2012).

Our results have implications for both firms and policy makers. We show that firms base their job offers after apprenticeship training primarily on hard-to-observe non-cognitive skills. One way in which firms take this phenomenon into account is by extensively offering specific programs to entry-level workers, programs that allow them to screen these workers (e.g., internships, traineeships, or apprenticeships). Using these programs, firms screen primarily for non-cognitive skills. As another way of learning about applicants' non-cognitive skills, firms could also simply use personality tests with scales similar to those we use in this study. However, faking personality tests is very easy, and one always needs to consider test-takers' incentives when interpreting such test results (for a general discussion, see Almlund et al., 2011). Job applicants in particular frequently fake personality tests and—with individual differences in the tendency to fake such tests—this behavior heavily affects hiring decisions based on such tests (Rosse, Stecher, Miller, & Levin, 1998). In sum, our results show the importance of non-cognitive skills for firms' hiring decisions and—as personality tests are no convincing alternative—of extensive screening periods for learning about these hard-to-observe skills.

For policy makers, our study provides a guideline for the preparation of young people for the labor market. Indeed, once young people have attained a certain level of education, such efforts should focus on programs targeting the formation of non-cognitive skills. Moreover, policy makers may facilitate training programs that include substantial screening periods, thereby allowing individuals to communicate their valuable non-cognitive skills to potential employers.

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Appendix

Figures

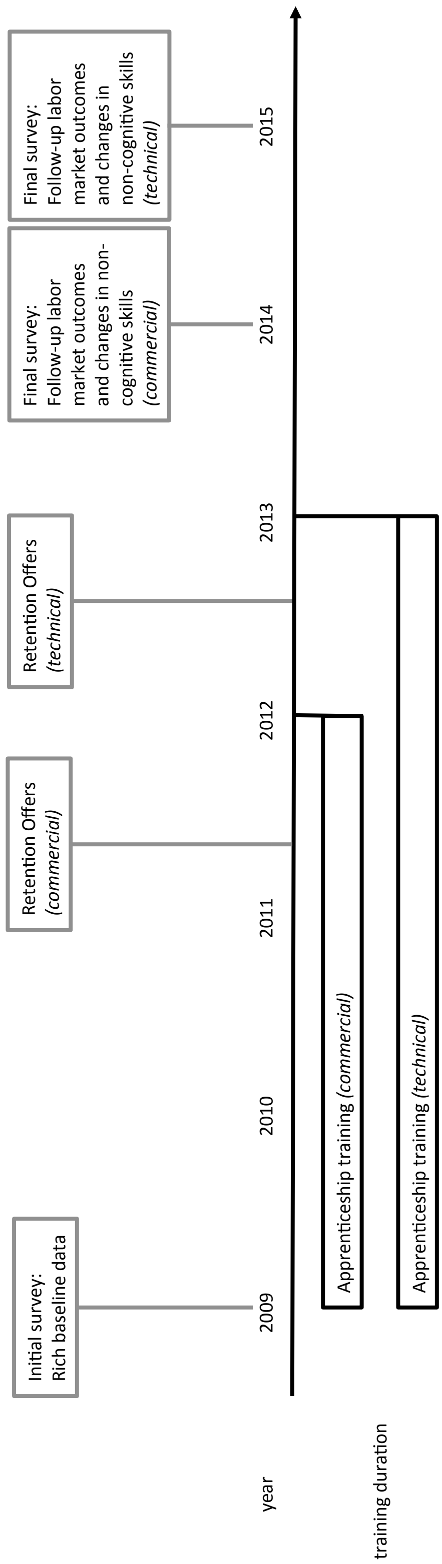

Figure A1: Time Structure

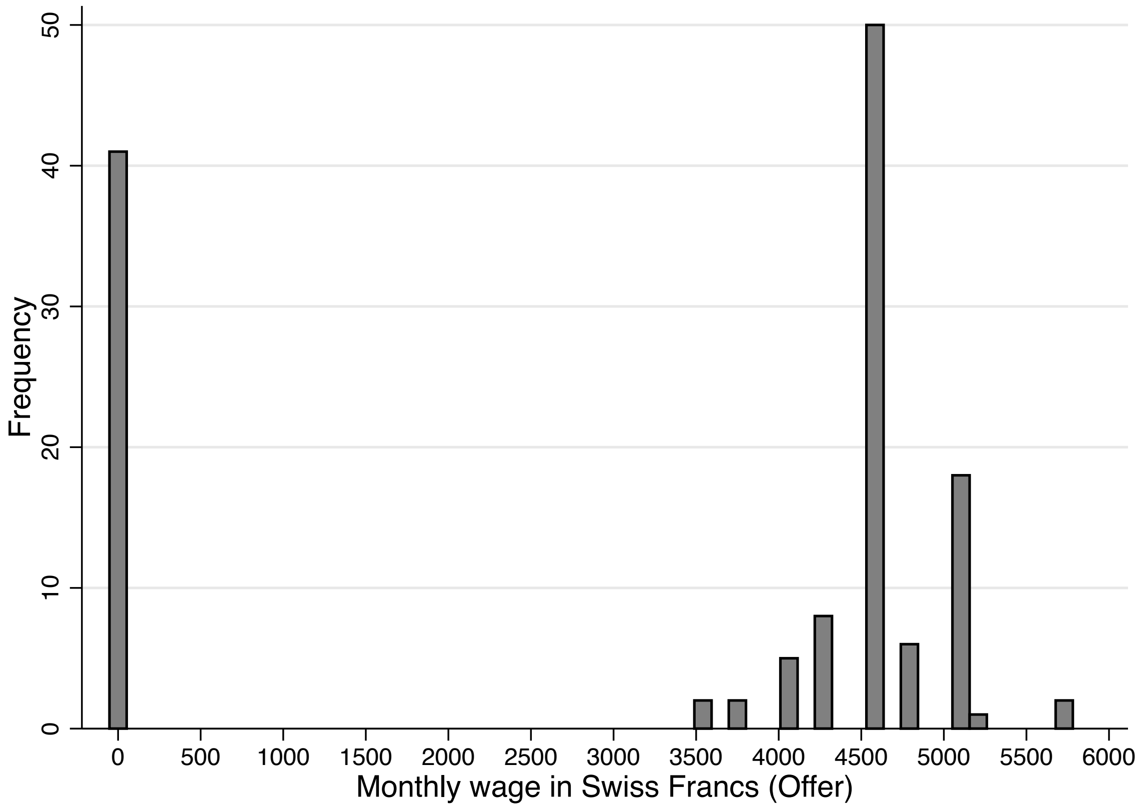

Figure A2: Distribution of Offers

Notes: The reported monthly wages may include additional yearly payments calculated on a monthly base.

Leading House Apprenticeship Panel, Authors' calculations.

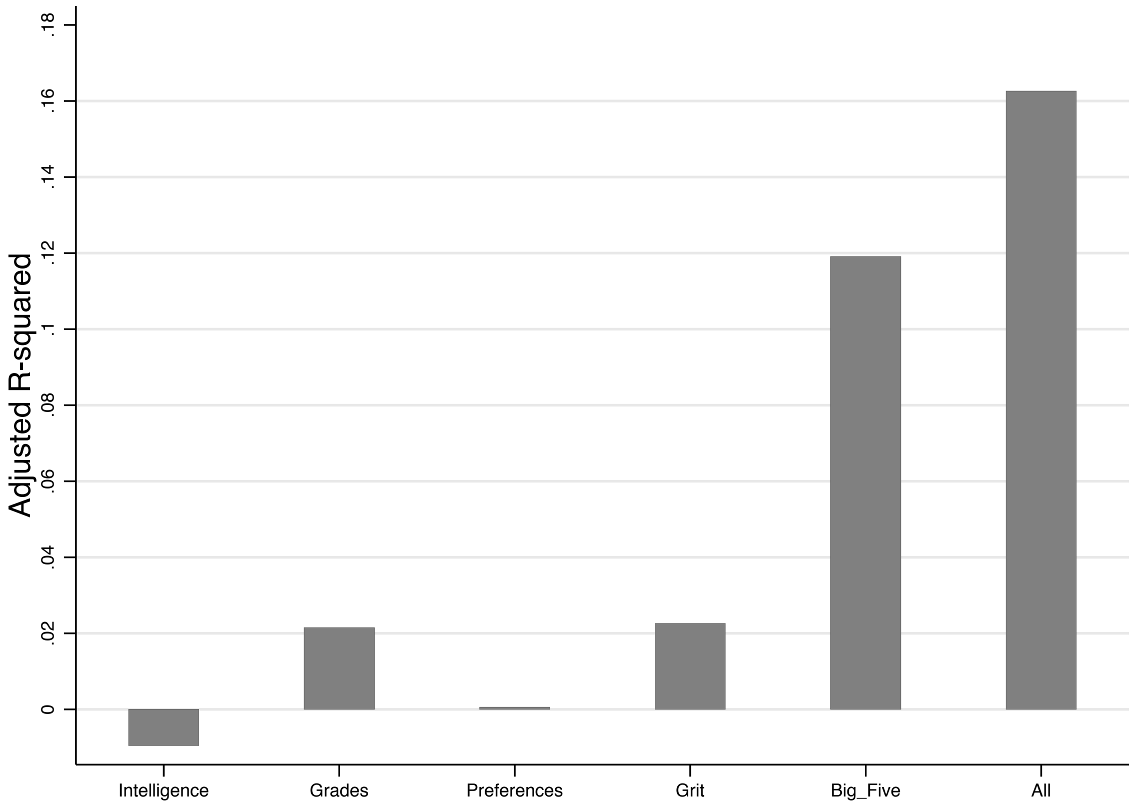

Figure A3: Relative Predictive Power for Job Offers

Notes: Column 1 to 5 show *adjusted* R^2 values of five individual regressions without control variables, one regression for each category of personal characteristics, i.e., one regression for each of the following: intelligence, grades, (economic) preferences, Grit, or Big Five (for a list of all variables included in each category, see table A1). For example, column 1 shows the *adjusted* R^2 of a regression of IQ and CRT on offer. Column 6 reports the *adjusted* R^2 of the full model (without control variables) including all measures of personal characteristics (for a full list, see table A1).

Leading House Apprenticeship Panel, Authors' calculations.

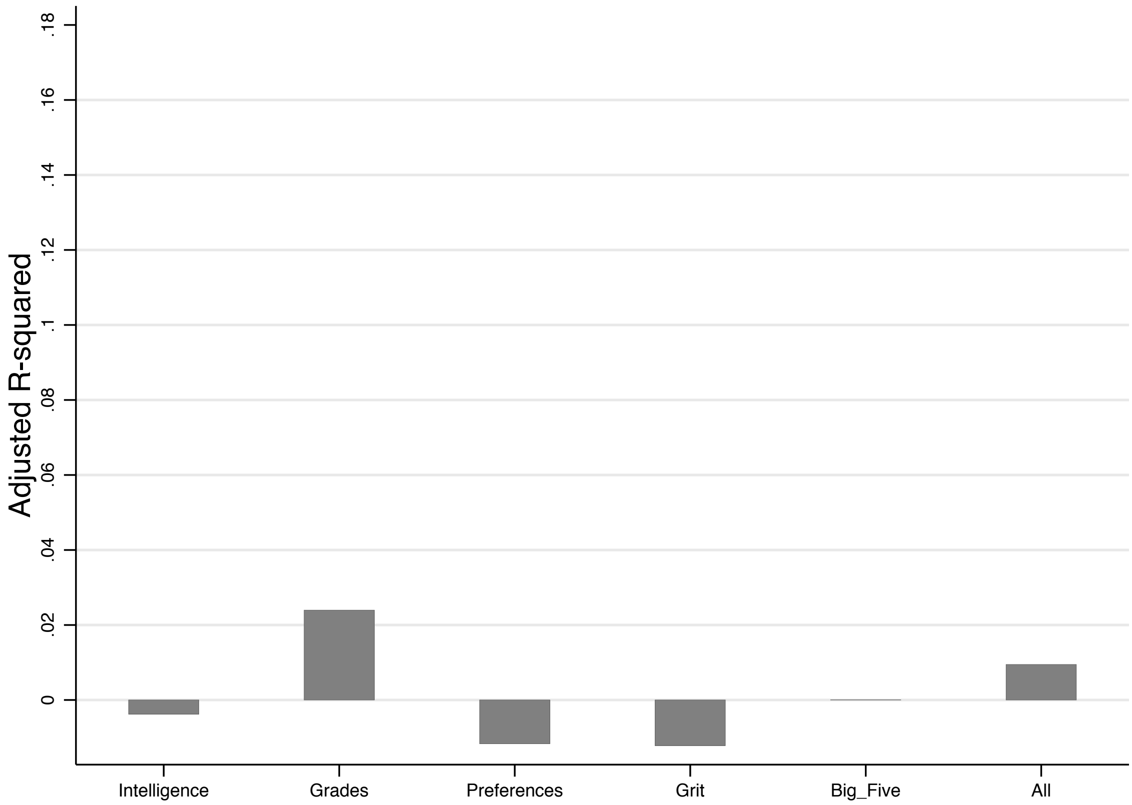

Figure A4: Relative Predictive Power for Staying - Retained Apprentices Only

Notes: Column 1 to 5 show *adjusted* R^2 values of five individual regressions without control variables, one regression for each category of personal characteristics, i.e., one regression for each of the following: intelligence, grades, (economic) preferences, Grit, or Big Five (for a list of all variables included in each category, see table A1). For example, column 1 shows the *adjusted* R^2 of a regression of IQ and CRT on offer. Column 6 reports the *adjusted* R^2 of the full model (without control variables) including all measures of personal characteristics (for a full list, see table A1).

Leading House Apprenticeship Panel, Authors' calculations.

Tables

Table A1: Summary Statistics of Personal Characteristics

	Descriptive Statistics (1)				Correlation with Offer (2)
	mean	sd	min	max	coefficient
Intelligence					
IQ	75.326	14.097	14.000	116.000	0.0199
CRT	0.807	0.926	0.000	3.000	0.0716
Grades					
Grade Middle School	4.883	0.399	3.667	5.667	-0.0602
Final Grade APT	4.779	0.268	4.200	5.400	0.1588*
Economic Preferences					
Willingness to Take Risks	5.881	1.588	1.000	10.000	0.0930
Patience	76.037	20.462	10.000	100.000	0.0771
Grit					
Grit_Initial	19.222	4.119	9.000	29.000	-0.0467
Grit_Delta	1.963	4.821	-11.000	14.000	0.1827**
Big Five					
Conscientiousness_Initial	11.556	3.173	2.000	18.000	0.1925**
Extraversion_Initial	12.430	3.939	0.000	18.000	-0.0303
Agreeableness_Initial	8.437	2.323	0.000	12.000	-0.1328
Openness_Initial	11.222	3.220	3.000	18.000	-0.1551*
Emotional Stability_Initial	8.800	3.568	1.000	18.000	-0.1323
Conscientiousness_Delta	1.778	3.409	-7.000	10.000	-0.0906
Extraversion_Delta	0.178	3.663	-9.000	10.000	0.1028
Agreeableness_Delta	0.785	2.107	-5.000	7.000	0.0782
Openness_Delta	-0.096	3.498	-11.000	11.000	0.1250
Emotional Stability_Delta	1.570	3.686	-8.000	10.000	0.1683*

Notes: N=135. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. IQ is the number of successively correctly matched symbols on the digit symbol-coding test of the WAIS-III. CRT is the number of correctly answered questions on the cognitive reflection test. The values for economic preferences indicate switching points in choice tables. The grit measure is the sum of eight Likert scale items (0-4). The agreeableness measure is the sum of two Likert scale items (0-6). Each of the other Big Five measures is the sum of three Likert scale items (0-6). Emotional stability is calculated as the reverse of neuroticism. The delta for each non-cognitive skill represents the difference between the respective final value and the initial value.

Leading House Apprenticeship Panel, Authors' calculations.

Table A2: Descriptives of Transitions

Sample	N	Offer	Acceptance	Staying
Offer=1	94	100.0%	93.6%	52.1%
Acceptance=1	88	100.0%	100.0%	**55.7%**
Total	135	**69.6%**	65.2%	36.3%

Notes:
Leading House Apprenticeship Panel, Authors' calculations.

Table A3: Job Offers and Personal Characteristics (OLS)

	(1) Offer	(2) Offer	(3) Offer	(4) Offer	(5) Offer
IQ	0.0404				
	(0.0451)				
CRT	0.0044				
	(0.0424)				
Grade Middle School		-0.0382			
		(0.0355)			
Final Grade APT		0.0760*			
		(0.0437)			
Willingness to Take Risks			0.0405		
			(0.0357)		
Patience			0.0474		
			(0.0411)		
Grit_Initial				0.0374	
				(0.0458)	
Grit_Delta				0.1063**	
				(0.0477)	
Conscientiousness_Initial					0.1378**
					(0.0535)
Extraversion_Initial					0.0418
					(0.0516)
Agreeableness_Initial					-0.1449***
					(0.0550)
Openness_Initial					-0.1193**
					(0.0465)
Emotional Stability_Initial					-0.0996*
					(0.0541)
Conscientiousness_Delta					-0.0068
					(0.0511)
Extraversion_Delta					0.0393
					(0.0470)
Agreeableness_Delta					-0.0740
					(0.0488)
Openness_Delta					0.0126
					(0.0482)
Emotional Stability_Delta					0.0363
					(0.0475)
Controls	YES	YES	YES	YES	YES
F-test Joint	0.6318	0.1666	0.3021	0.0702	0.0002
F-test Joint Initial Values					0.0011
F-test Joint Deltas					0.6097
R-squared	0.055	0.073	0.065	0.087	0.213
N	135	135	135	135	135

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Coefficients are indicated. Robust standard errors are in parentheses. All personal characteristics are standardized to have mean 0 and standard deviation 1. Controls include being a native speaker, mother's education, gender, and age. Listed is the p-value from a F-test for the joint significance of the indicated personal characteristics. Leading House Apprenticeship Panel, Authors' calculations.

Table A4: Labor Market Relevance of Offer

	Count	Offer=0	Offer=1	Difference	p-value
Job Search Behavior					
Search Time in Months	130	1.923	0.385	1.538	0.000
Number of Applications	130	10.641	1.110	9.531	0.000
Wages Two Years Later					
Wage	132	3278.312	4409.955	-1131.643	0.006
Wage (full-time equivalent)	132	3630.743	4822.652	-1191.910	0.007
Wage (only full-time employed)	82	4740.079	5345.492	-605.412	0.007

Notes: Monthly wages in CHF including any bonus payments or other additional yearly payments calculated on a monthly base.

Leading House Apprenticeship Panel, Authors' calculations.

Table A5: Staying and Personal Characteristics - Retained Apprentices only (OLS)

	(1) Staying	(2) Staying	(3) Staying	(4) Staying	(5) Staying
IQ	-0.0640				
	(0.0499)				
CRT	0.0311				
	(0.0557)				
Grade Middle School		0.0474			
		(0.0547)			
Final Grade APT		0.1064*			
		(0.0539)			
Willingness to Take Risks			-0.0334		
			(0.0498)		
Patience			0.0796		
			(0.0551)		
Grit_Initial				0.0290	
				(0.0658)	
Grit_Delta				0.0760	
				(0.0638)	
Conscientiousness_Initial					-0.0564
					(0.0793)
Extraversion_Initial					-0.0359
					(0.0709)
Agreeableness_Initial					0.1259
					(0.0893)
Openness_Initial					0.0619
					(0.0726)
Emotional Stability_Initial					-0.0081
					(0.0686)
Conscientiousness_Delta					0.0255
					(0.0632)
Extraversion_Delta					0.0828
					(0.0670)
Agreeableness_Delta					0.1473**
					(0.0694)
Openness_Delta					-0.0721
					(0.0645)
Emotional Stability_Delta					0.0241
					(0.0684)
Controls	YES	YES	YES	YES	YES
F-test Joint	0.4232	0.0333	0.2009	0.4732	0.0843
F-test Joint Initial Values					0.5053
F-test Joint Deltas					0.1569
R-squared	0.068	0.113	0.083	0.070	0.183
N	88	88	88	88	88

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Coefficients are indicated. Robust standard errors are in parentheses. All trainee characteristics are standardized to have mean 0 and standard deviation 1. Controls include being a native speaker, mother's education, gender, and age. Listed is the p-value from a F-test for the joint significance of the indicated personal characteristics.

Leading House Apprenticeship Panel, Authors' calculations.

Table A6: Labor Market Relevance of Staying with the Training Firm - Retained Apprentices only

	Count	Staying=0	Staying=1	Difference	p-value
Job Search Behavior					
Search Time in Months	85	0.432	0.292	0.141	0.469
Number of Applications	85	1.027	0.646	0.381	0.442
Wages Two Years Later					
Wage	87	3955.329	4987.788	-1032.459	0.019
Wage (full-time equivalent)	87	4177.952	5426.878	-1248.927	0.008
Wage (only full-time employed)	60	5431.391	5269.745	161.646	0.510

Notes: Monthly wages in CHF including any bonus payments or other additional yearly payments calculated on a monthly base.

Leading House Apprenticeship Panel, Authors' calculations.

Table A7: Summary of Firm-Related Characteristics

	Descriptive Statistics (1)					Correlation with Offer (2)
	count	mean	sd	min	max	coefficient
Small Firm	124	0.387	0.489	0.000	1.000	-0.0105
Occupation						
Electrician	135	0.111	0.315	0.000	1.000	0.1310
Polymechanic	135	0.237	0.427	0.000	1.000	0.0272
Commercial	135	0.652	0.478	0.000	1.000	-0.1107
Training Wage	121	1188.017	257.312	800.000	1650.000	0.0215
Conflict at Work	132	0.333	0.473	0.000	1.000	0.0233

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Small firms have below 100 employees (median of firm size = 100). Training wage is measured in CHF per month. Conflict at work indicates any conflict with master craftspeople or co-workers.

Leading House Apprenticeship Panel, Authors' calculations.

Table A8: Transitions and Firm-Related Characteristics (OLS)

	(1) Offer	(2) Offer	(3) Offer	(4) Offer	(5) Staying	(6) Staying	(7) Staying	(8) Staying
Small Firm	-0.0011				0.1833			
	(0.0832)				(0.1130)			
Polymechanic		-0.1325				-0.0479		
		(0.1222)				(0.1869)		
Commercial		-0.1197				0.1142		
		(0.1290)				(0.1970)		
Log(training wage)			0.2302				-0.2322	
			(0.2219)				(0.3091)	
Conflict at Work				-0.0070				0.0336
				(0.0867)				(0.1176)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
F-test Joint		0.5124				0.5804		
R-squared	0.051	0.055	0.055	0.046	0.080	0.065	0.066	0.055
N	124	135	121	132	81	88	79	88

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Coefficients are indicated. Robust standard errors are in parentheses. Controls include being a native speaker, mother's education, gender, and age. The base group in columns 3 and 6 is electrician. Listed is the p-value from a F-test for the joint significance of the occupation dummies.

Leading House Apprenticeship Panel, Authors' calculations.