Requirements towards and Discrimination against Agricultural Workers – Evidence from a Discrete Choice Experiment among East German Farms

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Abstract

Using a discrete choice experiment on the basis of stated preference data from East Germany, attributes of workers are evaluated. Relevant attributes for the experiment were derived from earlier studies and a vocational classification system. Results show that reliability is the most preferred attribute of a worker, followed by having graduated from vocational school with an A and interest in the occupation. Older, female and workers with a migration background are discriminated against. Significant differences in preferences can be found by introducing four subject-specific variables – type of farming, farmer's sex and education as well as farm acreage.

Keywords: *workforce, requirements, discrimination, discrete choice.*
JEL classification: *Q1, C25, J24, J71.*

Introduction

Due to structural change, hired labour in agriculture still gains significance. Family farms become larger and thus the need for non-family workers increases. At the same time, educational needs for these workers rise since working in agriculture becomes more complex, not only because of more sophisticated farm equipment but also due to a higher degree of rules and requirements by authorities.

Stakeholders in German agriculture are increasingly concerned about an imminent skills shortage among the workforce on the production level. This personnel-related risk constitutes a problem for farms because the workforce's qualifications are going to match the requirements to an increasingly lesser degree. East Germany's agricultural sector features a high degree of division of labour and a very qualified and specialised workforce. Qualifications of a farm's employees can be seen as a competitive advantage while making the farm dependent on it at the same time. Management of the farm must ensure that an employee's qualification match the functional and technical requirements of the position.

Generally, it is the main task of educational and extension institution in agriculture to avoid a too high share of miss-qualified workers. An analysis of respective preferences on the production level is therefore needed.

The paper at hand should be understood as a contribution to tackle this problem. The paper at hand features a double focus. First, competences of workers shall be evaluated in order to provide a solid basis for policy makers in educational contexts. Furthermore, also socio-demographic attributes of workers are subject to evaluation in order to detect certain discrimination patterns among farms. The latter aspect, however, is not the main

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focus of this paper but can be seen as additional result that might be of interest for rural sociology.

Preferences of employers with respect to employees in agriculture have not been researched very comprehensively. Ricard et al. (2008) employed a survey for workers in American arboriculture. The study of Kitchen et al. (2002) was geared towards the requirements for using precision agriculture equipment. Hansen, Holmes, and Jimmerson (1989), Gerds (2010), and Petty and Stewart (1983) surveyed concerning desired backgrounds of workers. Most research in the field is either out-of-date or neglects the production level by more focusing on agribusiness as a whole, e. g. Onianwa et al. (2005), Radhakrishna and Bruening (1994) or Litzenberg, Gorman, and Schneider (1983).

The aforementioned papers rather employed a standard survey design. Workers could thus not be considered as a whole by the decision maker, meaning that employers did not have to perform trade-offs while considering desired worker attributes. This aspect is a feature of discrete choice settings. Utilization of discrete choice or conjoint analysis approaches for the evaluation of employer's preferences with respect to employees cannot be considered extensive. Biesma et al. (2007) asked employers in the Dutch health business to evaluate students. Moy and Lam (2004) employed conjoint analysis for employer's evaluation of employees for different economic sectors (without agriculture) in China. A similar approach was used by Floyd and Gordon (1998) in New Zealand. Here agriculture was part of the sectors under study. Without considering agriculture, Arora and Stoner (1992) deployed adaptive conjoint choice for employer's assessment of MBA students.

The same is true for Boatwright and Stamps (1986). Similar studies which are more geared towards agriculture are sparse. Norwood and Henneberry (2006) conducted a discrete choice survey in which employers had to choose between different fictitious graduates. However, the focus was only laid onto academic educated employees. Farms accounted for only 3% of the sample.

It can be safely said that preferences of employers on the agricultural production level have been neglected by scientists and policy makers – at least for the last 20 years. Thus, newer, more sophisticated methods were not applied to this field.

Data and descriptive statistics

In the following sections, the sample is characterized. Furthermore, derivation of relevant worker attributes as well as generation of choice sets are explained.

Sample

As area under study, the German state of Mecklenburg-Western Pomerania was chosen. This federal state—a former part of the socialistic German Democratic Republic—is located in the very north-east of Germany, bordering the Baltic Sea in the north and Poland in the east. It was chosen for two reasons: 88.2% of all people working in agriculture and forestry in 2008 were employees (as opposed to self-employed farmers or family labour), which was the highest share in Germany (national average: 53.3 %). In Bavaria, for instance, the respective share was only 25.8 %. Additionally, Mecklenburg-Western Pomerania featured also the highest rate of full-time employment (97.1 %; national average: 92.5 %), while having the second lowest standard deviation (0.14 %). However, it is assumed that the selection of the study area do not cause biases.

Table 1: Farmer demographics and farm characteristics (sample size = 737)

	% of respondents
Type 1	
Crop Farming	35.97
Fodder Production	20.57
Mast	4.09
Permanent Crop	1.63
Mixed	33.65
Other	4.09
Type 2	
Conventional	83.22
Organic	16.50
Position of farmer	
Farm employee	
no shares in the farm	12.69
ownership of most shares	5.86
ownership of some shares	10.18
Self-employed	
sole owner	52.02
part owner	19.25
Farm acreage in hectare	
< 100	16.81
100–399	29.86
400–699	19.58
700–999	10.97
1000–1999	18.06
2000–2999	3.75
> 3000	0.97
No. employees (full time)	
0–1	38.47
2–3	19.44
4–6	12.50
7–10	10.56
11–20	9.17
21–30	4.44
> 31	3.33
Farmer's sex	
female	18.06
male	81.94
Farmer's education	
academic	56.45
non-academic	43.55
Farmer's age	
< 20	0.14
20–29	3.36
30–39	15.13
40–49	35.99
50–59	33.05
60–69	9.94
> 70	2.38

In October 2010 questionnaires were sent to all farms in Mecklenburg-Western Pomerania, with the exception of part-time farmers. Addresses were provided by the state's Ministry of Agriculture, the Environment and Consumer Protection. 3,031 farms could thus be reached. 737 valid questionnaires were sent back until January 2011, resulting in a response rate of 24.32 %. A pretest was conducted a few weeks earlier. It was sent to a randomly drawn sub sample of twenty farms, attached with an evaluation form with questions concerning the quality of the questionnaire. Resulting eight answers were used to edit the final questionnaire which was then shortened and made more comprehensible. The final questionnaire promised a free one-year subscription of a monthly farmer's magazine in case the respondent wished it.

In the questionnaire, farmers were asked to repeatedly choose between three different fictitious employees, stating which worker they prefer most. Overall, 18 choice sets were presented. All employees within a set differed in levels of their respective attributes. Four attributes were presented simultaneously in order to describe an employee. Since the choice model consisted of 14 attributes, only partial profiles were presented to the respondents. Furthermore, farm-specific questions were asked, which compromised not only questions concerning the farm itself but also socio-demographic data of the farmer. See table 1 for descriptive statistics of the sample. The respective difference to 100% correspondents to missing values. It must be noted that an independent one-sample t-test revealed that the sample is not representative in terms of farm acreage because average farm acreage is considerably higher in the sample than in reality (635 vs. 250 ha, $T = 15.45$, $p < 0.0001$). Larger farms tended to answer the questionnaire more than smaller ones—a phenomenon that is consistent with similar studies.

Attached to all questionnaires, the farmers found a covering letter describing the purpose of the study. Additionally, each questionnaire began with a cheap talk text, stating that the respondent should imagine a situation where he or she needs a new worker for the production level of the farm, regardless of the fact whether they actually needed one at that moment. They faced three different applicants who—they were told—were equal with the exception of four attributes and they had to base their decision only on those four attributes presented. Furthermore, the text underlined that the respondents should check the one worker they preferred the most.

Defining of Worker's Characteristics

A crucial part in every discrete choice experiment is the question, which attributes shall be used. A high share of research studies neglect this question by using attributes the respective researcher sees fit, therefore bringing a highly subjective factor in the research design. Although not being completely objective, this approach seems to be less subjective than similar studies. Different sources for possible attributes were used in the study at hand in order to minimize subjectivity and thus avoiding respective biases. Please refer to figure 1 for a schema of attribute sources. These issues shall be elaborated on in the following.

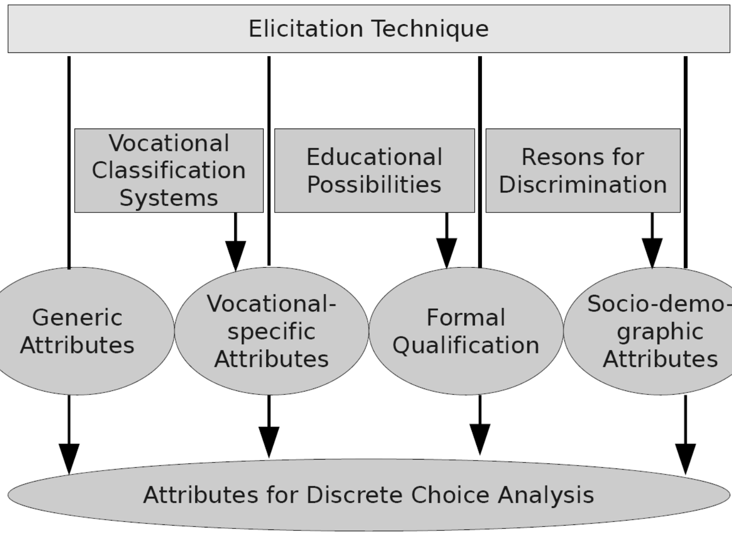

Figure 1: Generation of attributes

Four categories were defined for which attributes were to be created:

- generic attributes
- vocational-specific attributes
- formal qualifications
- socio-demographic attributes

While generic attributes can be applied in various business and economic sectors due to their non-specialized character, vocational-specific competences are in most cases specialized abilities for the respective field of work. The category of formal qualification was included in order to analyse the impact of different vocational degrees. Socio-demographic attributes were included for the detection of certain discrimination patterns among agricultural employers.

Generic Attributes

The generation of generic attributes drew on the results of Gerds (2010), who employed an open question by means of elicitation technique. Farmers were asked to state which attributes of agricultural workers they deem important. In this study, order and number of attributes were used to compute an importance score. Since mostly generic attributes were named there, the four most important attributes were used for the discrete choice analysis in this paper. These were:

- interest
- reliability
- independence
- flexibility

Gerds (2010) identified "specialized knowledge" as most import attribute. In contrast, in the study at hand, this attribute is going to be further differentiated instead of dealing with this rather general, aggregated attribute.

Vocational-specific Attributes

In order to do so, a vocational classification system was utilized. Reviewing different classification systems, the Occupational Information Network (O*NET)

(United States Department of Labor 2006) was found the most suitable, since it contained quantified data about necessary competences for every occupation. The International Standard Classification of Occupation of the International Labor Organization (ILO) as well as an adapted version by the European Union ("ISCO-88 (COM)") provided not enough information for the purpose of this study due to their lack of quantified data.

O*NET replaced the Dictionary of Occupational Titles (DOT) in the 90s. Every occupation in the database featured a vocational definition and respective tasks as well as information on necessary knowledge, skills, abilities, and physical requirements. Furthermore, detailed information regarding work activities, work content, occupational interest, and work values were available here.

The O*NET data on the vocational class "General Farmworkers" (Code 79855) was the most appropriate in the case of the study at hand. Entries concerning knowledge and skills were compared with respect to their different importance values. The three most important attributes were selected from the O*NET category "knowledge". The first five elements of the skills list were aggregated to the attribute "operating machinery", since all these elements dealt with operation, controlling, and maintaining of equipment and machinery. The respective values for the five elements were averaged to obtain a value which could be compared to other elements of the vocational description. See table 2 for an overview of vocational-specific attributes selected from the O*NET data base.

Table 2: Vocational-specific attributes

Attribute	**Relevance**
Comprehension of work processes[2]	100.0
Technical comprehension	71.0
Operating Machinery	69.4
Biological comprehension	67.0

These four attributes represented the dimension of vocational-specific attributes in the discrete choice questionnaire. The next important attributes—which were not included—were "Building and Construction" (relevance of 63) and "Chemistry" (58).

Formal Qualifications

Generation of attributes for formal qualification was straight-forward. All degrees and qualifications were considered which were relevant for agricultural employees on the production level. These were mainly:

- existence of a finalised vocational education[3]
- existence of a finalised professional school[4]

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[2] Originally labelled as "Food Production". However, this term is misleading since it is not clear. The O*NET description is more specific: "Knowledge of techniques and equipment for planting, growing, and harvesting of food for consumption including crop rotation methods, animal husbandry, and food storage/handling techniques". This clearly is a different kind of food production than the one of, say, a baker.

[3] German: "Berufsschule". An apprenticeship in this kind of vocational education institution is normally attended twice a week over a duration of (in most cases) three years. The rest of the days are spent working at the farm.

[4] German: "Fachschule". This kind of educational institution offers vocational extension and further qualifies workers in their respective occupation. A finalised vocational education is a prerequisite.

- work experience

Work experience is itself not a formal qualification, but was nevertheless included here due to its similarity with the other attributes in this section.

Socio-demographic Attributes

Concerning socio-demographic attributes, such characteristics were used that contain a certain potential for discrimination. An integration of these attributes in the discrete choice analysis seemed feasible in order to analyse prejudices. In this respect, discrete choice analysis provides a suitable framework because workers are considered as a whole and social desirability biases are less likely.

These attributes were derived from certain anti-discrimination acts, like the German General Equal Treatment Act of 2006 or the Civil Rights Act and its subsequent updates in the United States. They were:

- age
- sex
- migration background

The attribute age was expressed relatively since different farms feature different age structures among their work force. This structure can be different for different regions in the area under study. This issue was addressed by introducing age in relative rather than in absolute terms.

Overview

All attributes are displayed in table 3. Assumptions regarding respective utility model are also presented. If a linear relationship between the attribute level and utility is assumed, that is a vector model, implementation of two levels suffices. In cases where this cannot reasonably be assumed, e. g. concerning age, at least three levels must be integrated.

Generation of Choice Sets

Out of the 14 attributes, only four were presented simultaneously to the respondents. It is obvious that a presentation of all attributes would have placed a too high cognitive burden upon the respondents. However, it was intended to present a broad range of attributes which can be used to describe an agricutural worker. Four or five attributes are clearly too less for covering possible characteristics.

For this reason, a partial profile choice design was created using the partprof macro, together with corresponding macros, of SAS Software. It will be provided upon request. The author drew heavily on the code provided by Kuhfeld (2009, p. 555f.). According to Chrzan and Elrod (1995), partial profile designs are less efficient than full-profile designs. However, respondents can answer simpler questions more consistently. Therefore, partial profile designs allow more precise estimation of the model. Street and Burgess (2007, p. 243) argue that respondents will not answer consistently in the presence of a high number of attributes and partial profiles should be used in this case.

The resulting profile of the partprof macro can be assessed as efficient, both in orthogonality and balancedness. Furthermore, order of attribute representation was randomised in each choice set in order to avoid respective biases. It is assumed that the order of the alternatives in the choice set does not have an impact on the respondent's choice itself. No "none" option was introduced in the design due to concerns that farmers may choose this option in case they do not require hired labour at that moment. An example is provided in figure 2.

Table 3: Attributes for discrete choice

Attribute	Utility Model
Generic Attributes	
1 Interest[a]	Vector
2 Reliability[a]	Vector
3 Independence[a]	Vector
4 Flexibility[a]	Vector
Vocational-specific Attributes	
5 Comprehension of work processes[a]	Vector
6 Technical comprehension[a]	Vector
7 Operating Machinery[a]	Vector
8 Biological comprehension[a]	Vector
Formal Qualifications	
9 Vocational education[f]	Part worth
10 Professional school[b]	Vector
11 Work experience[c]	Vector
Socio-demographic Attributes	
12 Age[d]	Ideal point
13 Sex[e]	Part worth
14 Migration background[b]	Part worth

a Levels: **normal**, superior
b Levels: yes, **no**
c Levels: **sparse**, plenty
d Levels: young, **middle-aged**, old
e Levels: female, **male**
f Levels: **none**, grade C, grade A
(Base level bold)

Choice Decision 8

Three workers only differ in these attributes:

	Worker 1	Worker 2	Worker 3
Professional school	Yes	No	No
Reliability	superior	normal	superior
Migration background	Yes	No	No
Operating machinery	normal	superior	normal

I prefer this worker most (please check only **one**):
☐ ☐ ☐

Figure 2: Example of a choice set

Methodology

In this section, properties of the discrete choice approach shall be elaborated on. The rationale for employing a multinomial logit model stems from its well-known advantages. The assumption concerning Independence of Irrelevant Alternatives (IIA) holds in this case since the alternatives are generic in a sense that there is no alternative label. Thus, it is unlikely that they share a common unobserved attribute which may cause correlation (like the well-known blue-bus/red-bus-problem). The respondents only have the information given as attributes in the choice sets and cannot derive information from other sources. Thus, utility is not dependent on other alternatives' attributes.

The multinomial logit model is too powerful to simply jeopardize it for a more flexible but also rather less powerful model like probit or mixed logit. A further assumption is that there is no correlation of unobserved factors on the side of the respondents during the repeated choice situation – that is, these unobserved factors are independent over time.

According to the concept of random utility, utility can be decomposed into a deterministic and a stochastic part (Train 2009, p. 14f.; Ben-Akiva and Lerman 1985, p. 48f.; Hensher, Rose, and Greene 2005, p. 82f.; Garrow 2010, p. 22f.; Raghavarao, Wiley, and Chitturi 2011, p. 10f.), as displayed in (1).

(1) $U_{ik} = v_{ik} + \delta_{ik}$

with

U_{ik}: utility of worker i for respondent k; $i = 1, \ldots, I$; $i \in A_k$; $k \in K$, where index k denotes the utility structure of population K and A_k the set of alternatives (Evoked Set of Alternatives) of respondent $k \in K$; $A_k \subseteq A$ with A as amount of all alternatives,

v_{ik}: deterministic component of utility of worker i for respondent $k \in K$,

δ_{ik}: stochastic component of utility of worker i for respondent $k \in K$

A linear-additive utility function is assumed for the deterministic utility component v_{ik}:

(2a) $v_{ik} = \sum_{p=1}^{P} \sum_{m=1}^{M_p} v_{ikmp}$

(2b) $\quad = \sum_{p=1}^{P} \sum_{m=1}^{M_p} \beta_{ikmp} x_{ikmp} = \beta'_{ik} x_i$

with

v_{ikmp}: utility of attribute level m of attribute p of worker i for respondent $k \in K$,

M_p: number of levels for attribute p

x_{imp}: attribute level m of attribute p of worker i,

β_{ikmp}: utility parameter of attribute level m of attribute p of worker i for respondent $k \in K$

Due to the assumption of an utility-maximizing decision maker, the alternative with the highest utility is chosen by the respondent. Comparing two workers i and j, where i is superior with respect to utility for respondent k and under the condition that $i \neq j$, the behavioural rule is:

(3) $U_{ik} > U_{jk}$

Inserting (1) and (2a) in (3) yields after transposing:

(4) $\sum_{p=1}^{P} \sum_{m=1}^{M_p} (v_{ikmp} - v_{jkmp}) > \delta_{jk} - \delta_{ik}$

The difference between both stochastic utility components in (4) is not observable since both represent probability distributions. Therefore, statements concerning choice of respondent k in favour of an alternative can only be made with a certain probability. In case of a logistic distribution, the probability P_{ik}, that a respondent $k \in K$ chooses an alternative i, can be modelled as

$$\text{(5a)}\quad P_{ik} = \frac{\exp(v_{ik})}{\sum_{j=1}^{I} \exp(v_{jk})}$$

$$\text{(5b)} = \frac{\exp\left(\sum_{p=1}^{P}\sum_{m=1}^{M_p} \beta_{ikmp} x_{imp}\right)}{\sum_{j=1}^{I} \exp\left(\sum_{p=1}^{P}\sum_{m=1}^{M_p} \beta_{jkmp} x_{jmp}\right)}$$

with

P_{ik}: probability, that respondent $k \in K$ chooses worker i,

j: index of another alternative j from the alternative set of respondent $k \in K$, which can be equally chosen, with $j \in A_k$.

Maximum likelihood was used for parameter estimation. Computations were performed with R (R Development Core Team 2010) and its mlogit-package (Croissant 2011).

Subject-specific variables were modelled as interaction effects within a common model for each subject variable. This is true for both categorical and metric scaled subject-specific variables. A division into categorical subgroups with a subsequent computation of a multinomial logit model for each subgroup (an approach applied by Norwood and Henneberry (2006) to compare the preferences of two different groups) was not conducted in this study since modelling as interaction effects can be considered more accurate. Otherwise, the only option would be to just compare the coefficients from two different models. A more direct approach was employed here which also causes a harder to grasp interpretation of the results. Categorical subject-specific variables were:

- type of farming (conventional vs. organic)
- sex of farmer (male vs. female)
- education of farmer (academic vs. non-academic)

The only metric subject-specific variable was farm acreage.

Results and Discussion

Results of the computations are presented in the following sections. Interpretations are provided.

Main Effects

A computation of a multinomial logit model with only main effects—that is, without any interactions with subject-specific variables—entering the model yielded results which are displayed in table 4.

Table 4: Main effects model (n = 737)

Variable	$\hat{\beta}$	Std. Error	t-value	$\exp(\hat{\beta})$
Interest				
normal → superior	1.5497***	0.0690	22.48	4.71
Reliability				
normal → superior	2.4964***	0.0749	33.32	12.14
Independence				
normal → superior	1.1617***	0.0823	14.12	3.20
Flexibility				
normal → superior	1.2891***	0.0673	19.14	3.63
Comprehension of work processes				
normal → superior	1.4149***	0.0487	29.04	4.12
Technical comprehension				
normal → superior	1.0143***	0.0600	16.90	2.76
Operating Machinery				
normal → superior	1.4514***	0.0559	25.96	4.27
Biological comprehension				
normal → superior	0.1617 **	0.0599	2.70	1.18
Vocational education				
none → grade A	1.6480***	0.1036	15.91	5.20
none → grade C	0.5344***	0.0641	8.34	1.71
Professional school				
no → yes	0.6151***	0.0467	13.17	1.85
Work experience				
sparse → plenty	1.2220***	0.0548	22.29	3.39
Age				
middle-aged → old	-0.4013***	0.1042	-3.85	0.67
middle-aged → young	0.3959***	0.0845	4.69	1.49
Sex				
male → female	-0.3897***	0.0679	-5.74	0.68
Migration background				
no → yes	-0.2223***	0.0454	-4.90	0.80
AICc: 21,356.00				
Log-Likelihood: -10,661.53				
Likelihood-ratio test: x^2 =7566:2***				
p: ***<0.001; **<0.01; *<0.05				

All variables have a significant impact on the choices of the decision makers. Goodness of fit indicators are reported, including the corrected Akaike's Information Criterion with a correction for finite sample sizes (Burnham and Anderson 2004).

One cannot look at the actual estimates in order to evaluate the impact of each variable because of the absence of a linear relationship– only the sign can be used as evidence for the direction of influence. Thus, the respective odds ratio of each variable

$\exp(\hat{\beta}) = \exp\left(\sum_{p=1}^{P}\sum_{m=1}^{M_p}\beta_{ikmp}x_{imp}\right)$ is presented in the table. It allows the interpretation of the variable's impact.

For example, a change in a worker's interest from normal to superior level raises his/her likelihood of being preferred by 4.71 times, all else being equal. An odds ratio of <1 indicates a declining likelihood, like in the example of level change from a middle-aged to an old worker. Here an old worker has a 33% less chance of being preferred than a middle-aged one.

All estimates have the expected sign. Eye-catching is the high estimate for a superior reliability, resulting in a more than 12 times higher chance of being preferred compared to workers with only a normal level of this attribute. All generic competences have high impacts on the farmer's choice, having at least an odds ratio of greater than 3. The same is true for the vocational-specific attributes, with technical comprehension still more than doubling the likelihood. Biological comprehension has by far the least impact, indicated by its relatively small estimate. It is thus an exception among the generic and vocational competences.

Vocational education seems to play an important role in the choice process. A relatively high odd for grading with an A in relation to no vocational education at all underlines the important role of good grades. Grading with a C results in only a small benefit, increasing the odds by only 71% in relation to no vocational education. Compared to a very good grade, graduation from an professional school has a relatively small impact, raising the likelihood of being preferred over non-graduates by only 85 %. Of course, 85% still seems high, but is has to be evaluated in the context of the other odds. Plenty of work experience has a fairly high impact, raising the odds by more than three times compared to workers with only a sparse amount.

Concerning socio-demographic attributes of a worker, it is not surprising that old workers suffer a penalty compared to middle-aged ones, while young workers are preferred over their middle-aged counterparts. It can be noted that the absolute values of both estimates are somewhat equal, thus suggesting a linear-like relationship. It could be argued that this fact does contradict common sense since middle-aged workers seem more preferable due to their often higher degree of experience. In this regard, one has to take into account that work experience was included as a separate attribute in the model, thus a worker's age did not serve as a proxy for work experience, making the estimates for age comprehensible.

As a further result in this regard, it can be observed that female workers have a 32% lesser likelihood of being preferred than male workers. Therefore, one can draw the conclusion that women are indeed discriminated against in agriculture. The same is true for workers with a migration background (odds ratio penalty of 20 %).

Subject-specific Effects

In the following sections, subject-specific characteristics of farmers and their farms are taken into account in order to analyse whether different subgroups of farms and farmers possess different preference patterns. This is done by integrating interaction effects into the main model. Interaction terms specify the difference in coefficients between subgroups of the sample (Hilbe 2009, p. 191f.).

Only one subject-specific variable is introduced at a time. An introduction of more than one subject-specific variable in the same model does not yield significant interaction effects at all since values for standard errors become very high. This is mainly caused by the limited number of observations in the collected data set. Thus, one cannot include subject-specific variables where one expects correlation due to heterogeneity. Existence of unobserved heterogeneity among the respondents is indeed crucial in this context. There may be unobserved effects which are correlated among alternatives – leading to non-zero diagonal covariances. Heterogeneity is a special type of serial correlation (Louviere, Hensher, and Swait 2000, p. 141).

According to Hensher, Rose, and Greene (2005, p. 619), all data sets, regardless of the number of choice situations per sampled individual, may feature unobserved heterogeneity. The explanatory variables that are included in the model may be insufficient to capture all heterogeneity across individuals (Garrow 2010, p. 22f.). This is especially true in this case

where only one subject-specific variable enters the model separately. The author is aware of the strong underlying assumption. In this context, results can be seen as reasonable approximations of a certainly more complex relationships (Ben-Akiva and Lerman 1985, p. 285). Louviere, Hensher, and Swait (2007, p. 181) point out that a great number of observations are needed to satisfy asymptotic theory of such complex models which in some cases even requires sample sizes that exceeds available human populations.

The impact and magnitude of unobserved effects is obviously not clear. We can only assume that in case of unobserved heterogeneity, it is not complex in a sense that it disturbs or even invalidate the estimated results.

Another point which has to be considered is the fact that the underlying utility function in this case is generic (as opposed to alternative-specific). According to Louviere, Hensher, and Swait (2000, p. 221), this constitutes a vastly lower dimensional choice problem in terms of unobserved heterogeneity. Greene (2008, p. 26) points out that ”ignoring the heterogeneity (random effect) is not so benign here as in the linear regression model.“ Estimators that ignore unobserved heterogeneity still produce an appropriate estimator of the average partial effects (Greene 2008, p. 26) since it is averaged over the individuals in the sample.

In addition, Train (2009, p. 36) regards using the logit model as an option when unobserved heterogeneity is suspected. In this case, the model has to be considered as an approximation. Here, logit is able to produce estimates fairly well even in the presence of unobserved heterogeneity since the logit formula is fairly robust to misspecifications. ”The researcher might therefore choose to use logit even when she knows that tastes have a random component, for the sake of simplicity“ (Train 2009, p. 44). Louviere, Hensher, and Swait (2000, p. 15) underline that the multinomial logit model “is often very robust (in terms of prediction accuracy) to violation of the very strong behavioural assumptions imposed on the profile of the unobserved effects, namely that they are independently and identically distributed (IID) amongst the alternatives in the choice set”. Considering this, the following results are best understood as approximation of reality which in fact all scientific models are.

Type of Farming

In the first model which incorporates subject-specific effects, the variable "type of farming" was included. The model for conventionally and organically producing farms are presented in table 5. Organic in this sense means production according to European Union regulation No. 2092/91 (often referred to as EU-Eco-Regulation).

Table 5: Interaction terms (type of farming)

Var.[a] X TY02[b]	$\hat{\beta}$	$\exp(\hat{\beta})$	$1/\exp(\hat{\beta})$
INTsup	-0.1162	0.89	1.12
RELsup	-0.1469	0.86	1.16
INDsup	0.0352	1.04	0.97
FLEXsup	-0.0802	0.92	1.08
CO_Psup	-0.0374	0.96	1.04
T_COsup	-0.1892 *	0.83	1.21
OP_MAsup	-0.1932 **	0.82	1.21
B_COsup	0.1475	1.16	0.86
VOC_A	-0.2612 *	0.77	1.30
VOC_C	0.0038	1.00	1.00
PR_Syes	-0.1883 **	0.83	1.21
EXPplenty	-0.1711 *	0.84	1.19
AGEold	0.1147	1.12	0.89
AGEyoung	0.0207	1.02	0.98
SEXfem	0.3270 ***	1.39	0.72
MIGyes	0.1094	1.12	0.90

*p: ***<0.001; **<0.01; *<0.05*

Please note that only interaction effects are displayed. The full model is presented in table A.1 in the appendix

[a] See table 4 for full variable names and respective base level.
[b] base level: conventional (displayed: organic relative to conventional)

The coefficients $\hat{\beta}$ of the interaction terms specify the difference of organic farms compared to conventional farms (since conventional is the base level). For example, among organic farms, $\hat{\beta}$ for superior technical comprehension (T_COsup) over a worker with a normal level of this attribute is 0.1892 lesser than for conventional farms.

Expressed in odds ratios, the likelihood of choosing a worker with superior technical comprehension is multiplied by factor 0.83 (exp(-0.1892) = 0.83) as compared to organic farms. Among conventional farms, this factor is 1.21 (exp(0.1892) = 1.21 = 1/0.83).

One can compute the likelihood of preferring a worker with such an attribute by adding $\hat{\beta}$ of the interaction term to the non-interaction term ($\hat{\beta}$ of the counter group) in the model (Hilbe 2009, p. 191f.). Please refer to the full model in table A.1. For organic farms, the coefficient is thus 0.9173 – 0.1892 = 0.7281, resulting in an odds ratio of exp(0.728) = 2.07. Therefore, organic farms feature twice the likelihood of preferring a worker with superior technical comprehension as for a worker with only a normal level (all else being equal). Please note, that this odds ratio is actually higher for conventional farms. Among the latter, the likelihood is multiplied by 2.5 times, since exp(0.9173)= 2.5. See table 9 for a comparison of odds ratios. The ratio of both likelihoods for organic and conventional farms equals exp($\hat{\beta}$) in table 5.

In this model, interaction effects with generic competences are not significant. Among vocational attributes, there is a significant difference concerning the two technical skills. Both technical comprehension—as already pointed out—and operating machinery are much more important on conventional farms. This does not seem surprising since a high degree of mechanization is typically a feature of conventional farms.

Major differences of both subgroups are clearly to observe concerning formal qualifications. These attributes generally play a more important role among conventional farms. Respective interaction terms concerning vocational education graded with an A and work experience enter the model significantly. Jansen (2000) argues that the activities of a worker employed by an organic farm is very different from activities of conventional farms. Processing and direct marketing become much more important once a farm converts to organic production. However, theses task are traditionally not a part of the curriculum of vocational schools where education is more geared towards immediate plant and animal farming. Thus, workers who graded from vocational schools with an A are more desired by conventional farms since their education matches the position on these farms to a higher degree. However, graduating with a C from vocational school is not an attribute that distinguishes preferences of organic and conventional farms.

The picture is not that clear with respect to socio-demographic attributes. While a worker's age and his/her migration background do not differ between the two subgroups, the sex of a worker enters the model highly significant. Organic farms are much more likely to prefer a woman over a man than conventional farms are. In fact, the corresponding likelihood of organic farms is multiplied by the factor 1.39 as compared to conventional farms. This is especially interesting since the high interaction coefficient of 0.3270 actually more than compensates the "male" effect coefficient of -0.1963, thus resulting in an coefficient of 0.1307. This implies that organic farms prefer female over male workers – the analogous likelihood is multiplied by 1.14, thus a woman has a 14% higher chance of being preferred than a man (ceteris paribus). A reason for that lies in the fact that organic farms tend to engage more in livestock husbandry than conventional farms. In the sample, the farm type "fodder production" (which involves mainly dairy or mother cow husbandry) has the highest share among organic farms (37.29 %), while only accounting for 17.65% among conventional farms. Traditionally, female workers are more deployed to husbandry (European Commission 2002, p. 12). Background is the assignment of certain gender roles in which men tend to work in more technical field work while women are deployed to tasks which involve caring due to an assumed higher degree of empathy (Symes 1991). Gasson (1980) argues that this fact is caused by male prejudice rather than by lack of physical strength or education.

Sex of Farmer

Another subject-specific effect which was included as interaction in a separate multinomial logit model was the sex of the respondent. Results are presented in table 6.

Table 6: Interaction terms (farmer's sex)

Var.[a] X SEX[b]	$\hat{\beta}$		$\exp(\hat{\beta})$	$1/\exp(\hat{\beta})$
INTsup	0.0459		1.05	0.96
RELsup	0.0326		1.03	0.97
INDsup	-0.0031		1.04	1.00
FLEXsup	0.0389		1.00	0.96
CO_Psup	-0.1139		0.89	1.12
T_COsup	-0.0386		0.96	1.04
OP_MAsup	0.0510		1.05	0.95
B_COsup	0.0678		1.07	0.93
VOC_A	0.0825		1.09	0.92
VOC_C	-0.0863		0.92	1.09
PR_Syes	0.0478		1.05	0.95
EXPplenty	0.0173		1.02	0.98
AGEold	-0.2136	**	0.81	1.24
AGEyoung	0.1073		1.11	0.90
SEXfem	-0.2296	**	0.79	1.26
MIGyes	-0.0155		0.98	1.02

*p: ***<0.001; **<0.01; *<0.05*
Please note that only interaction effects are displayed. The full model is presented in table A.1 in the appendix

[a] See table 4 for full variable names and respective base level.
[b] base level: female (displayed: male relative to female)

Evidently, there are very few significant differences among both sexes with respect to worker's characteristics. Vocational, generic and formal attributes do not differ significantly between male and female farmers. This is consistent with common sense since disparity in this attributes among sexes would not make much sense.

However, major differences originate from socio-demographic attributes of a worker. Male farmers find older workers and female workers less desirable as compared to female farmers. Among male farmers, the likelihood of choosing an old worker over a middle-aged one is multiplied by the factor 0.81 as compared to female farmers. An old worker has an odds ratio of being preferred over a middle-aged one of 0.62 among male farmers while having an odds ratio of 0.77 being preferred by female farmers. It is obvious that both male and female farmers prefer middle-aged workers over older ones. However, this preference is much stronger among male farmers. This fact implies that female farmers tend to discriminate less against workers of old age than male farmers do. Research suggests that women have a higher degree of social empathy (Riggio, Tucker, and Coffaro 1989) than men and may therefore be reluctant to prefer a middle-aged worker over an old one. However, little research has been done on this subject in agricultural settings and interpretation has to be used cautiously. The same is true for female vs. male workers. The corresponding interaction term is statistically significant and negative for male farmers.

Female workers face a 1.26 higher odds ratio of being preferred by a female farmer than by a male farmer. Although a female worker has an overall odds ratio of being preferred smaller than 1 (0.78), it is much higher than being preferred by a male farmer (odds ratio: 0.62). This is consistent with findings from other studies investigating gender discrimination in small firms (Carrington and Troske 1995).

Education of Farmer

In order to take into account the respondent's education, all levels were categorized into two basic groups: academic (sample share: 56.45 %) and non-academic (43.55 %) . This was not only done for reasons of simplicity but also considering the assumption that differences between different levels of education within each basic group are not distinct. Results for the model including respondent's education are displayed in table 7. "Academic" in this sense means graduating with a higher education degree (undergraduate and postgraduate).

Table 7: Interaction terms (farmer's education)

Var.[a] X EDU[b]	$\hat{\beta}$	$\exp(\hat{\beta})$	$1/\exp(\hat{\beta})$
INTsup	0.2043 **	1.23	0.82
RELsup	0.2359 **	1.27	0.79
INDsup	0.0643	1.07	0.94
FLEXsup	0.0831	1.09	0.92
CO_Psup	0.0102	1.01	0.99
T_COsup	0.0887	1.09	0.92
OP_MAsup	0.2165 ***	1.24	0.81
B_COsup	-0.0326	0.97	1.03
VOC_A	0.2513 *	1.29	0.78
VOC_C	0.0194	1.02	0.98
PR_Syes	0.1768 ***	1.19	0.84
EXPplenty	0.1248 *	1.13	0.88
AGEold	-0.1468 *	0.86	1.16
AGEyoung	0.0534	1.05	0.95
SEXfem	-0.1888 **	0.83	1.21
MIGyes	-0.0206	0.98	1.02

*p: ***<0.001; **<0.01; *<0.05*

Please note that only interaction effects are displayed. The full model is presented in table A.1 in the appendix

[a] See table 4 for full variable names and respective base level.
[b] base level: female (displayed: academic relative to non-academic)

Generic qualities are generally more preferred by academically educated farmers with all signs being positive. Interest in the vocation and reliability enter the model significantly, with a superior level of it resulting in a 23% and 27% greater odds ratio, respectively, of being chosen by a academic rather than a non-academically educated respondent.

Among vocational-specific competences, only the operation of farm machinery features a significant interaction term with farmer's education. Being more preferred by academically educated farmers, a superior level of this attribute multiplies the odds ratio of being preferred over a normal level by 5.36 for academically educated farmers and 4.31 for non-academic farmers (see table 9).

As can be suspected, the education of a farmer influences the preferences with regard to a worker's formal qualification. Having graduated from vocational school with grade A let a worker possesses a 29% higher chance of being chosen by an academic farmer rather than a non-academic one. Contrary, grading with a C does not have a significant impact, which is consistent with the general weak influence of this attribute over all models including the main effects model. Successfully completing a professional school is highly appreciated by farmers with an academic background. Such workers have a 2.19 higher odds ratio of being chosen among academically educated farmers, while this factor is 1.84 for non-academic farmers. While still being preferred by both groups, the likelihood is obviously higher among the academically educated respondents. The same is true for a high degree of work experience. It can thus be concluded that formal education and experience is considerably more appreciated within the group of farmers with an academic background.

Furthermore, there are some impacts of subject-specific variables concerning socio-demographic attributes of workers. Older and female workers are significantly less preferred by academically educated farmers. For female workers, the odds ratio of being chosen by a non-academically educated farmer is multiplied by 0.67, while it is nearly cut in half for academic farmers (0.55). This fact seems surprising to some extent since common sense suggests that discrimination tends to be less developed among better educated persons. However, the results presented here imply that the more practical-orientated a farmer's background is, the more he or she tends to emphasize real competences rather than the sex of a worker.

Farm Acreage

The only continuously scaled, subject-specific variable which is taken into account is farm acreage. Interaction terms are displayed in table 8.

Since a continuous instead of a categorical variable is now considered, interpretation is different than discussed above. The coefficient of each interaction term now refers to the change in $\hat{\beta}$ and $\exp(\hat{\beta})$, respectively, with a one unit change in the subject-specific variable. Please note that the results do not refer to a single unit of hectare but to 100 hectare in this case. This is simply for scaling up the coefficients for the reader's convenience. For example, an increase in farm acreage of 100 hectare results in a 4.88% higher likelihood of being chosen for a worker with superior interest in the vocation as compared to a worker with a normal level of this attribute.

As before, in order to compute the overall odds ratio of a worker with a certain attribute level, coefficients of non-interaction effect and interaction effect have to be added. For example, a farm with an acreage of 400 hectare features a 4.40 times greater odds ratio of preferring a worker with superior interest over an normally interested worker since $\exp(4 * 0.0477 + 1.2919) = \exp(1.4827) = 4.40$ (see table A.4).

Table 8: Interaction terms (farm acreage)

Var.[a] X ACR x 100	$\hat{\beta}$		$\exp(\hat{\beta})$
INTsup	0.0477	***	1.0488
RELsup	0.0455	***	1.0465
INDsup	0.0001		1.0001
FLEXsup	0.0228	*	1.0230
CO_Psup	0.0155		1.0156
T_COsup	0.0185		1.0187
OP_MAsup	0.0400	***	1.0408
B_COsup	-0.0078		0.9922
VOC_A	0.0565	**	1.0581
VOC_C	-0.0010		0.9990
PR_Syes	0.0383	***	1.0391
EXPplenty	0.0229	*	1.0231
AGEold	-0.0985	***	0.9062
AGEyoung	0.0597	***	1.0615
SEXfem	-0.0392	***	0.9615
MIGyes	-0.0162	*	0.9840

*p: ***<0.001; **<0.01; *<0.05*

Please note that only interaction effects are displayed. The full model is presented in table A.1 in the appendix

[a] See table 4 for full variable names and respective base level.

The model features a high share of statistically significant interactions. With the exception of independence, all preferences for generic competences highly depend on the farm's size measured in acreage. Similar to the attribute interest, a superior level of reliability is by trend more appreciated by larger farms. The same is true for flexibility but the impact here is only half as strong as among both aforementioned attributes. These results contradict recent results of Gerds (2010) who found that smaller farms prefer generic competences more than larger farms because of a more distinctive division of labour and specialization among the latter. However, one can explain this fact with the principal-agent problem. In this context, generic competences prove more useful on larger farms because due to the larger size, monitoring of employees is harder (that is, more costly in terms of transaction costs) compared to smaller farms. Workers should thus have very good generic competences, like reliability, to perform their tasks since they cannot be continuously instructed by supervisors.

Among vocational-specific competences, only operating machinery has a significant interaction effect with farm acreage. Further increasing a farm's acreage by 100 hectare increases its likelihood of choosing a superior machinery operator over a normal one by 4.08 %. Please note that while handling farm equipment enters the interaction model significantly, technical comprehension does not. This is not surprising since larger farms usually feature a higher degree of mechanization and specialization (Eastwood, Lipton, and Newell 2010) which makes operating respective equipment a highly appreciated attribute compared to smaller farms. Simultaneous non-significance of technical comprehension can be seen as an indication of a higher degree of division of labour among larger farms. Following this interpretation, a worker must be highly skilled with farm machinery on these farms but actual comprehension of it is not that important since he or she only has to do what the supervisor instructs. Furthermore, repairing of farm equipment is usually done by on-farm repair shops or is sourced out to external service providers.

Formal qualifications also enter the model significantly. Again, grading with a C from vocational school does not have a significant effect which is consistent with the other results so far. However, leaving vocational school with a very good grade has a very strong interaction effect with farm acreage. Every increase in 100 ha raises the odds ratios of preferring such workers by 5.81% over workers who did not grade at all. This is strong evidence that larger farms prefer a very good grade. This applies also to grading from a professional school, albeit the effect is not that strong. Even lesser is the effect of work experience but it is still elevating the respective odds ratios by 2.31% per 100 hectare.

Socio-demographic characteristics prove to have the highest interaction effects – all attributes enter the interaction model significantly. The attribute of being of old age has the highest coefficient (in absolute value) in this model. Each 100 hectare increase in farm size results in a nearly 10% lesser chance of being chosen for an old worker compared to a middle-aged one. In contrast, a younger worker increases his/her likelihood of being preferred over a middle-aged one by 6.15% for every 100 hectare increase. Thus, the penalty for older workers seems to be higher than the benefit of being a young worker. However, the implication is much higher for younger workers, since the odds ratio curve is asymptotically approaching zero considering old workers while there is no restriction for young workers (see figure 3).

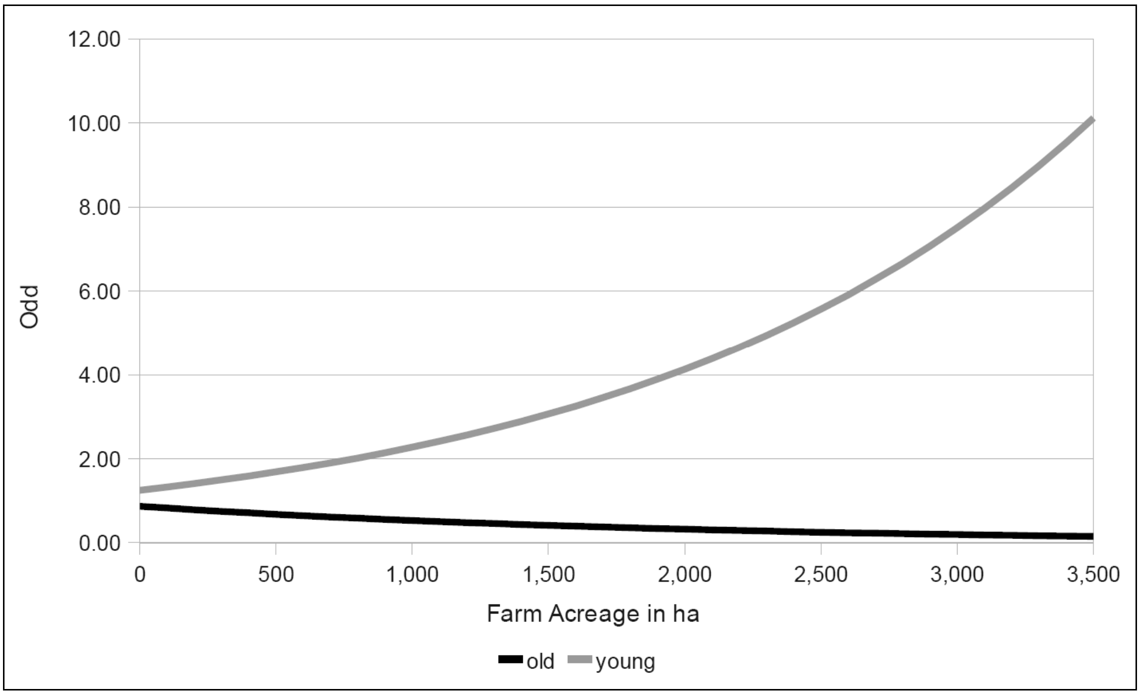

Figure 3: Odds ratios of preferring an old and young worker, respectively, over a middle-aged worker against farm acreage

Furthermore, female workers and workers with a migration background are less preferred by larger farms as compared to smaller farms. Although both coefficients do not suggest an equally high impact as age of a worker, discrimination against these two types tends to increase with increasing farm size. A reason for that can be seen in the fact that larger farms are more likely to have a separation of ownership and management. In the sample, the average acreage of farms which are managed by an employed manager is 1091.04 hectare while being 448.14 hectare for self-employed farmers. Farm managers who are employees themselves do not benefit from a change in farm profits to the same extent as farm owners do (Jensen and Murphy 1990). Thus, non-owners tend to discriminate more since they do not bear the full cost of discrimination (Carrington and Troske 1995) which can be considerable according to Becker (1971).

Conclusion

Table 9 features an overview of all subject-specific variables, which proved to be statistically significant. A comparison of respective ratios of odds is presented in order to show where the biggest differences between the different subgroups lie. A main result is that farms do not represent a homogeneous entity but are very diverse with respect to their preferences for farm workers.

Table 9: Overview of significant, categorical, subject-specific variables

Variable[a]	$\exp(\hat{\beta})$		
TY02	conventional		organic
T_COsup	2.50	>	2.07
OP_MAsup	3.74	>	3.09
VOC_A	4.54	>>	3.50
PR_Syes	1.66	>	1.37
EXPplenty	3.10	>	2.61
SEXfem	0.82	<<	1.14
SEX	male		female
AGEold	0.62	<	0.77
SEXfem	0.62	<	0.78
EDU	acad.		non-acad.
INTsup	5.93	>	4.83
RELsup	15.62	>>	12.34
OP_MAsup	5.36	>	4.31
VOC_A	6.92	>>	5.39
PR_Syes	2.19	>	1.84
EXPplenty	3.92	>	3.46
AGEold	0.57	<	0.66
SEXfem	0.55	<	0.67

Ratio of both respective odds:
<<: <0.75; <: 0.75–0.9; >: 1.1–1.25; >>: >1.25
[a] *See table 4 for full variable names and respective base level.*

Goodness of fit indicators—in this case loglikelihood and AICc—suggest that the subject-specific models surpass the main model. Nevertheless, results of main model appear very stable, even after the introduction of subject-specific variables. Although there are a number of significant interaction effects, deviations from the estimates of the main model are fairly small.

Resulting preferences with respect to generic and vocational-specific attributes should be noted by educational institutions in agriculture. They can check whether their range of educational offers match requirements of farmers and also create new curriculum modules. Extension institutions can react to the different preferences of certain farm subgroups by offering curricula which are adopted to local agricultural structure.

Of course, generic competences are more difficult to teach than vocational-specific competences. However, the most preferred characteristics can be found among the first, with reliability as especially outstanding. In contrast, other attributes, e. g. work experience, offer a great preference bonus and are relatively easy to achieve, for example by introducing more practical experience on farms in respective curricula.

A common feature over all models was the fact that grading from vocational school with a C has little benefit compared to no vocational education at all. On the other hand, grading with an A offers a high preference benefit. This underlines how important good grades are not only for farmers but also for the workers themselves. This is a known fact since the job-market signaling model of Spence (1973).

Form a policy point of view, these results are noteworthy especially for policy makers in agricultural education. Vocational education should be geared toward matching farm's requirements. The results presented here can be seen as basis for this undertaking. Farms can only achieve high utility from their work force when there is a match between supply and demand of competences.

Some brief remarks concerning socio-demographic attributes of worker shall be made in the following. Results make clear that agricultural workers with certain attributes are subject to discrimination. This is true for old, female and non-German originated workers – that is, all socio-demographic attributes which were included in order to test hypotheses about discrimination. Because of the fact that they are less preferred, even though they are the same in every other attribute, a pattern of systematic discrimination emerges. No normative statement should be given here. However, these results should be noted by rural sociology. Furthermore, Becker (1971) argues that discrimination of a firm's workforce raises its costs, thus reducing its competitiveness. Therefore, reducing discrimination is also in the interest of farms and their managers.

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Appendix

Table A.1: Interaction Model (Type of Farming)

Variable[a]	$\hat{\beta}$	Std. Error	t-value
INTsup	1.4741	0.0866	17.0152
RELsup	2.3970	0.0947	25.3138
INDsup	1.1668	0.1036	11.2620
FLEXsup	1.2545	0.0879	14.2781
CO_Psup	1.3985	0.0647	21.6022
T_COsup	0.9173	0.0780	11.7602
OP_MAsup	1.3203	0.0720	18.3315
B_COsup	0.2550	0.0800	3.1879
VOC_A	1.5130	0.1323	11.4389
VOC_C	0.5266	0.0854	6.1691
PR_Syes	0.5049	0.0620	8.1476
EXPplenty	1.1307	0.0677	16.7008
AGEold	-0.3447	0.0715	-4.8208
AGEyoung	0.4084	0.0569	7.1787
SEXfem	-0.1963	0.0861	-2.2790
MIGyes	-0.1617	0.0601	-2.6920
Interaction effects (x TY02[b])			
INTsup	-0.1162	0.0866	-1.3416
RELsup	-0.1469	0.0947	-1.5515
INDsup	0.0352	0.1036	0.3396
FLEXsup	-0.0802	0.0879	-0.9127
CO_Psup	-0.0374	0.0647	-0.5781
T_COsup	-0.1892	0.0780	-2.4259
OP_MAsup	-0.1932	0.0720	-2.6824
B_COsup	0.1475	0.0800	1.8442
VOC_A	-0.2612	0.1323	-1.9745
VOC_C	0.0038	0.0854	0.0447
PR_Syes	-0.1883	0.0620	-3.0395
EXPplenty	-0.1711	0.0677	-2.5271
AGEold	0.1147	0.0715	1.6042
AGEyoung	0.0207	0.0569	0.3638
SEXfem	0.3270	0.0861	3.7960
MIGyes	0.1094	0.0601	1.8217
n=715; AICc=20,723.23; LL= -10,329.53*			

* Likelihood-ratio test shows statistic significance (tested against null model)

[a] See table 4 for full variable names and respective base level.

[b] base level: conventional

Table A.2: Interaction Model (Farmer's Sex)

Variable[a]	$\hat{\beta}$	Std. Error	t-value
INTsup	1.5192	0.0864	17.5815
RELsup	2.4810	0.0949	26.1427
INDsup	1.1813	0.1047	11.2819
FLEXsup	1.2673	0.0869	14.5854
CO_Psup	1.4928	0.0645	23.1380
T_COsup	1.0421	0.0774	13.4600
OP_MAsup	1.4202	0.0712	19.9466
B_COsup	0.1142	0.0788	1.4505
VOC_A	1.6073	0.1360	11.8224
VOC_C	0.5892	0.0835	7.0573
PR_Syes	0.5850	0.0608	9.6172
EXPplenty	1.2208	0.0686	17.7957
AGEold	-0.2676	0.0699	-3.8272
AGEyoung	0.3318	0.0574	5.7789
SEXfem	-0.2509	0.0867	-2.8921
MIGyes	-0.2086	0.0580	-3.5951
Interaction effects (x SEX[b])			
INTsup	0.0459	0.0864	0.5310
RELsup	0.0326	0.0949	0.3436
INDsup	-0.0031	0.1047	-0.0295
FLEXsup	0.0389	0.0869	0.4479
CO_Psup	-0.1139	0.0645	-1.7659
T_COsup	-0.0386	0.0774	-0.4983
OP_MAsup	0.0510	0.0712	0.7169
B_COsup	0.0678	0.0788	0.8614
VOC_A	0.0825	0.1360	0.6069
VOC_C	-0.0863	0.0835	-1.0331
PR_Syes	0.0478	0.0608	0.7858
EXPplenty	0.0173	0.0686	0.2516
AGEold	-0.2136	0.0699	-3.0543
AGEyoung	0.1073	0.0574	1.8691
SEXfem	-0.2296	0.0867	-2.6465
MIGyes	-0.0155	0.0580	-0.2676
n=731; AICc=21,147.30; LL= -10,541.57*			

* Likelihood-ratio test shows statistic significance (tested against null model)

[a] See table 4 for full variable names and respective base level.

[b] base level: female

Table A.3: Interaction Model (Farmer's Education)

Variable[a]	$\hat{\beta}$	Std. Error	t-value
INTsup	1.5751	0.0705	22.3332
RELsup	2.5129	0.0765	32.8668
INDsup	1.1527	0.0836	13.7893
FLEXsup	1.3245	0.0687	19.2738
CO_Psup	1.4304	0.0496	28.8438
T_COsup	1.0409	0.0612	17.0123
OP_MAsup	1.4617	0.0571	25.5867
B_COsup	0.1630	0.0610	2.6710
VOC_A	1.6838	0.1057	15.9323
VOC_C	0.5304	0.0652	8.1330
PR_Syes	0.6084	0.0475	12.7943
EXPplenty	1.2401	0.0559	22.2012
AGEold	-0.4200	0.0571	-7.3510
AGEyoung	0.4007	0.0443	9.0457
SEXfem	-0.4013	0.0689	-5.8277
MIGyes	-0.2091	0.0462	-4.5250
Interaction effects (x EDU[b])			
INTsup	0.2043	0.0705	2.8961
RELsup	0.2359	0.0765	3.0853
INDsup	0.0643	0.0836	0.7692
FLEXsup	0.0831	0.0687	1.2092
CO_Psup	0.0102	0.0496	0.2051
T_COsup	0.0887	0.0612	1.4490
OP_MAsup	0.2165	0.0571	3.7904
B_COsup	-0.0326	0.0610	-0.5348
VOC_A	0.2513	0.1057	2.3778
VOC_C	0.0194	0.0652	0.2975
PR_Syes	0.1768	0.0475	3.7190
EXPplenty	-0.1248	0.0559	2.2348
AGEold	-0.1468	0.0571	-2.5696
AGEyoung	0.0534	0.0443	1.2058
SEXfem	-0.1888	0.0689	-2.7414
MIGyes	-0.0206	0.0462	-0.4450
n=730; AICc=20,838,27; LL= -10,387.05*			

* Likelihood-ratio test shows statistic significance (tested against null model)

[a] See table 4 for full variable names and respective base level.

[b] base level: non-academic

Table A.4: Interaction Model (Farm Acreage)

Variable[a]	$\hat{\beta}$	Std. Error	t-value
INTsup	1.2919	0.0960	13.4581
RELsup	2.2721	0.1038	21.8890
INDsup	1.1582	0.1156	10.0195
FLEXsup	1.1826	0.0940	12.5810
CO_Psup	1.3388	0.0689	19.4241
T_COsup	0.9377	0.0842	11.1429
OP_MAsup	1.2427	0.0774	16.0518
B_COsup	0.2125	0.0850	2.5014
VOC_A	1.3250	0.1466	9.0400
VOC_C	0.5441	0.0908	5.9895
PR_Syes	0.3860	0.0660	5.8521
EXPplenty	1.1121	0.0757	14.6835
AGEold	-0.1388	0.0792	-1.7530
AGEyoung	0.2253	0.0623	3.6173
SEXfem	-0.1487	0.0939	-1.5837
MIGyes	-0.1215	0.0638	-1.9048
Interaction effects (x ACR)			
INTsup	0.0477	0.0133	3.5823
RELsup	0.0455	0.0137	3.3184
INDsup	0.0001	0.0151	0.0042
FLEXsup	0.0228	0.0113	2.0167
CO_Psup	0.0155	0.0082	1.8942
T_COsup	0.0185	0.0100	1.8480
OP_MAsup	0.0400	0.0097	4.1421
B_COsup	-0.0078	0.0102	-0.7654
VOC_A	0.0565	0.0183	3.0772
VOC_C	-0.0010	0.0109	-0.0931
PR_Syes	0.0383	0.0079	4.8520
EXPplenty	0.0229	0.0094	2.4269
AGEold	-0.0492	0.0114	-4.3134
AGEyoung	0.0597	0.0079	7.5696
SEXfem	-0.0392	0.0112	-3.5079
MIGyes	-0.0162	0.0075	-2.1497
n=720; AICc=20,751.06; LL= -10,343.45*			

* Likelihood-ratio test shows statistic significance (tested against null model)

[a] See table 4 for full variable names and respective base level.