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Abstract

This article analyses dealer satisfaction data in the agricultural technology market in Germany. The dealers could rate their suppliers in the 'overall satisfaction' and in 38 questions which can be summarized in 8 dimensions. An ordinal regression model which is also known as the proportional odds model is used to analyse the ordinal scaled rating of the dealers. The ordinal regression model is a well examined method in econometric theory, but many authors prefer using a linear regression model due to better interpretation, even the assumptions of a linear regression do not fit the data. Since the estimated coefficients of an ordinal regression model can not be properly interpreted we show other methods for a better insight of the relationship of the dealer satisfaction and the influencing variables. These methods are easy to use and it is recommended to list some of them in empirical papers.

Keywords: ordinal regression, dealer satisfaction, interpretation

JEL: C25, C51, Q13

Contents

1 Introduction

In the last three decades researchers detected the importance of dealer satisfaction in the subject of vertical marketing. Most articles have not a theoretical but rather an empirical point of view. For a review see (Decker, 2000) and the literature cited there. Franchise systems (Hempelmann and Grunwald, 2003) and the car industry (Meinig, 1995) and (Decker, 2000) are areas where many empirical studies appeared. Usually there is a list of many questions directed to the dealers about their suppliers. The dealers can rate their suppliers in some categories from "very bad" to "very good". The questions get summarized in a few dimensions. Most empirical studies have a pure descriptive character with computing means and range over the questions or/and dimensions. Some extend this with a discriminant analysis (e.g. Meffert *et al.*, 1996) or a factor analysis (e.g Heß, 1994) to assign some dealer-specific variables to the dimensions or respectively to reduce the dimensions to a number up to 3 or 4.

The rating scale in the questionnaire may be treated as ordinal. An ordinal variable has categories which can be ranked but the distance is not interpretable. Grades e.g. can have categories from 1 to 5, but 1 is not double as good as 2. Ordinal variables are often found in questionnaires for rating the most different facts. Rating the taste of food from "excellent" to "very bad" or the importance of fresh air from "very important" to "not at all" are further examples for an ordinal classification. For analysing ordinal scaled data we can recode the answers into numbers from 0 or 1 to the number of categories.

Using a linear regression model (LRM) for analysing dependent ordinal variables violates the assumptions of the LRM (McKelvey and Zavoina, 1975). For handling ordinal outcomes it is much better to use models that avoid the assumption that the distances between categories are equal (Long and Freese, 2003). Winship and Mare (1984) summarize that there are researchers who treat ordinal variables as if they were continuous and use regression, LISREL or other multivariate methods, because the power and flexibility of these models outweigh the small biases that may occur. Many authors prefer using an ordinal regression for ordinal data (e.g. Ananth and Kleinbaum, 1997; Armstrong and Sloan, 1989; Conner-Spady *et al.*, 2004; Enneking *et al.*, 2007; Guisan and Harrell, 2000; Hedeker and Gibbons, 1994; Lall *et al.*, 2002; Lu, 1999; Sun *et al.*, 2000), some of them compare different ordinal models with each other or with non-ordinal models. Long (1997) points out, that researchers have to think carefully before using methods for an ordinal outcome. The possibility of ordering a variable does not mean that

the ordering makes sense in any case. McCullagh and Nelder (1983) show that colors can be arranged according to the electromagnetic spectrum. So if consumers buy a car and prefer a particular color, there is usually not a relation to the arranged colors of the electromagnetic spectrum, but it's rather a matter of taste.
This article deals with the dealer satisfaction of agricultural technology in Germany. Our purpose is to give an overview about the status of the dealer satisfaction and to show which dimensions influence the overall satisfaction of the dealers most. Many articles dealing with an ordinal regression (cited above) don't give a proper interpretation of the estimated coefficients or even don't list the odds ratios. Therefore we give an illustration with graphical and tabulation tools to interpret the results of an ordinal regression properly.

The paper is organized as follows. In section 2 there is an overview of the dataset and some descriptive statistics. In section 3 we give an introduction to the latent variable logit form of the ordinal regression model (ORM), also known as the proportional odds model, which was first presented by McKelvey and Zavoina (1975). In section 4 we interpret the empirical results of the ordinal regression with different tools and a conclusion is given in section 5.

2 Data

A questionnaire directed to dealers of agricultural technology was printed in the 11th edition in the eilbote (eilbote, 2006). Additionally the questionnaire was sent per mail to this group of dealers. 250 dealers of agricultural technology replied.[1] The dealers could rate their suppliers on a scale from 0 (very bad) to 10 (very good) in the 'overall satisfaction' and in 38 questions which can be summarized in the following 8 dimensions:

- product program (4 questions)
- design of the conditions of purchase (3 questions)
- marketing and consumer promotion (8 questions)
- after sales methods and service methods (4 questions)
- support in the garage and at service (10 questions)
- support for second-hand promotions (2 questions)
- future of competition (3 questions)
- relationship to the supplier (4 questions)

[1]The dealers named in total 19 different suppliers.

Additionally dealer-specific questions like the number of employees, number of sites, age of the dealer company or duration of cooperation with the supplier were asked. The dealers could rate five different product groups like tractors, combine harvesters, forage harvesters etc. The ratings for the different product groups were very similar, so we pooled all five groups together. Even if an ORM is appropriate for a rating scale form 0 to 10, it is difficult to interpret the results. Franses and Cramer (2002) point out that a researcher can always reduce the number of outcome categories for practical considerations, but that there is no statistical test that might support this decision. Therefore we rescale the rating for all questions without effecting the main findings. We rescaled ratings from 0 to 5 into 1, 6 and 7 into 2, 7 and 8 into 3 and 9 to 10 into 4. For a quick overview of the data Table 1 gives some summary statistics about the 'overall satisfaction' and the 8 dimensions.

Table 1: Summary statistics (n=247)

Variable	Mean	Std. Dev.
overall satisfaction	2.49	1.12
product program	2.73	0.98
design of the conditions of purchase	2.29	1.12
marketing and consumer promotion	2.44	1.10
after sales methods and service methods	2.05	1.08
support in the garage and at service	2.48	1.03
support for second-hand promotions	1.53	0.92
future of competition	2.74	1.13
relationship to the supplier	2.41	1.16
number of sites	2.16	2.74
total number of employees	27.62	34.26
age of the dealer company	52.18	39.81
duration of cooperation with supplier	23.92	18.28

The highest rating gets 'future of competition' (2.74) followed by 'product program' (2.73), the lowest rating 'support for second-hand promotions' (1.53) is far worse rated than the second lowest 'after sales methods and service methods' (2.05). The mean of 'overall satisfaction' is 2.49. In average a dealer company has 12.8 employees per site and is around 52 years old. The dealers of Eastern Germany rate their suppliers a bit better (2.61) than their western competitors (2.41).

3 Model Specification and Estimation

3.1 Model and Estimation

The latent variable logit form, which was first introduced by McKelvey and Zavoina (1975) is used for the analysis of the data. We define a latent variable y^* ranging from $-\infty$ to $+\infty$ and divide the space into J ordinal categories. The number of categories J of the latent variable is equivalent to the different values of the actual variable y, the 'overall satisfaction'. We get the structural model for one independent variable

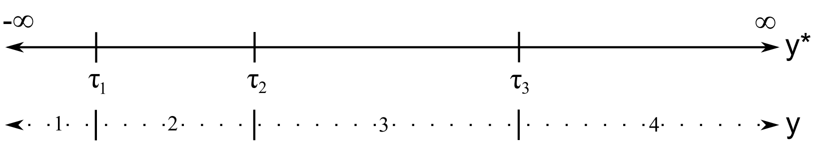
$$y_i^* = \alpha + \beta x_i + \epsilon_i, \qquad i = 1, ..., N \tag{1}$$

where x_i is an independent variable for the ith observation, α is the intercept, β is the slope coefficient and ϵ_i is the error term. The mth outcome of the actual variable y lies between two cut-points of the latent y^*:

$$y_i = m \quad \text{if } \tau_{m-1} \leq y_i^* < \tau_m \quad \text{for } m = 1, ..., J,$$

where τ_{m-1} is the lower limit and τ_m is the upper limit of the latent y^*. To illustrate the relationship between the latent variable y^* and the 'overall satisfaction' y see Figure 1.

Figure 1: The latent variable y^* and the observed categories in y



Source: Long (1997), p. 117

Now we assume that y^* follows a particular probability distribution with density function $f(y^*)$ and cumulative density function $F(y^*)$. The probability that $y = m$ is the area under the density curve $f(y)$ between τ_{m-1} and τ_m (Winship and Mare, 1984).

To get the general form of equation (1) with K independent variables for N observations we write:

$$\mathbf{y}^* = \mathbf{X}\beta + \epsilon \tag{2}$$

where $\mathbf{y}^*$ is a $(N \times 1)$ vector for the dependent variable, $\mathbf{X}$ is a $(N \times (K+1))$ matrix of the K explanatory variables and a unit vector in the first column for the intercept, β is a $((K+1) \times 1)$ column coefficient vector including the intercept as the first element and ϵ is a $(N \times 1)$ vector of the error term.

In case of the latent variable logit form of the ordinal regression model the error term ϵ follows a logistic distribution with mean 0 and variance $\pi^2/3$. The probability distribution function is

$$\lambda(\epsilon) = \frac{\exp(\epsilon)}{(1+\exp(\epsilon))^2}$$

and the cumulative distribution function is

$$\Lambda(\epsilon) = \frac{\exp(\epsilon)}{1+\exp(\epsilon)}.$$

The probability that the 'overall satisfaction' takes one specific value $y = m$ of the J categories for given variables x is

$$\Pr(y_i = m|\mathbf{x}_i) = \Pr(\tau_{m-1} \leq y_i^* < \tau_m|\mathbf{x}_i),$$

where $\mathbf{x}_i$ is a vector of all the independent variables for individual i.
We can substitute $\mathbf{x}_i\beta + \epsilon_i$ for y^* and get

$$\Pr(y_i = m|\mathbf{x}_i) = \Pr(\tau_{m-1} \leq \mathbf{x}_i\beta + \epsilon_i < \tau_m|\mathbf{x}_i)$$

This leads to

$$\begin{aligned}
\Pr(y_i = m|\mathbf{x}_i) &= \Pr(\epsilon_i < \tau_m - \mathbf{x}_i\beta|\mathbf{x}_i) - \Pr(\epsilon_i \leq \tau_{m-1} - \mathbf{x}_i\beta|\mathbf{x}_i) \\
&= F(\tau_m - \mathbf{x}_i\beta) - F(\tau_{m-1} - \mathbf{x}_i\beta), \qquad (3)
\end{aligned}$$

which is in our case for the logistic cumulative distribution function

$$\Pr(y_i = m|\mathbf{x}_i) = \frac{\exp(\tau_m - \mathbf{x}_i\beta)}{1+\exp(\tau_m - \mathbf{x}_i\beta)} - \frac{\exp(\tau_{m-1} - \mathbf{x}_i\beta)}{1+\exp(\tau_{m-1} - \mathbf{x}_i\beta)}.$$

The formulas of interest for J categories are

$$\begin{aligned}
\Pr(y_i = 1|\mathbf{x}_i) &= \Lambda(\tau_1 - \mathbf{x}_i\beta) \\
\Pr(y_i = 2|\mathbf{x}_i) &= \Lambda(\tau_2 - \mathbf{x}_i\beta) - \Lambda(\tau_1 - \mathbf{x}_i\beta) \\
&\vdots \\
\Pr(y_i = J-1|\mathbf{x}_i) &= \Lambda(\tau_{J-1} - \mathbf{x}_i\beta) - \Lambda(\tau_{J-2} - \mathbf{x}_i\beta) \\
\Pr(y_i = J|\mathbf{x}_i) &= 1 - \Lambda(\tau_{J-1} - \mathbf{x}_i\beta),
\end{aligned}$$

since $F(\tau_0 - \mathbf{x}_i\beta) = F(-\infty - \mathbf{x}_i\beta) = 0$ and $F(\tau_J - \mathbf{x}_i\beta) = F(\infty - \mathbf{x}_i\beta) = 1$. For our dealer satisfaction analysis the number of categories J is four and our independent variables in $\mathbf{x}$ are the eight dimensions and the dealer specific variables:

$$
\begin{aligned}
\text{overall satisfaction} \quad = \quad & \beta_1 \times \text{product program} + \beta_2 \times \text{design of the conditions of purchase} \\
+ \quad & \beta_3 \times \text{marketing and consumer promotion} \\
+ \quad & \beta_4 \times \text{after sales methods and service methods} \\
+ \quad & \beta_5 \times \text{support in the garage and at service} \\
+ \quad & \beta_6 \times \text{support for second-hand promotions} \\
+ \quad & \beta_7 \times \text{future of competition} \\
+ \quad & \beta_8 \times \text{relationship to the supplier} \\
+ \quad & \beta_9 \times \text{number of sites} \\
+ \quad & \beta_{10} \times \text{total number of employees} \\
+ \quad & \beta_{11} \times \text{age of the dealer company} \\
+ \quad & \beta_{12} \times \text{duration of cooperation with the supplier}
\end{aligned}
$$

There are two different assumptions which are usually used to identify the model. We can either set the intercept α to 0 or we assume that the cut-point τ_1 is 0.[2] The assumptions don't affect the estimation of the β's. Our data get analysed with Stata which sets the intercept to 0.

The coefficients β and cut-points τ are estimated using maximum likelihood. The likelihood function is

$$L = \prod_{i=1}^{N} \prod_{m=1}^{J} \Pr(y_i = m|\mathbf{x}_i)^{d_{im}},$$

where d_{im} equals one if dealer i rates the overall satisfaction with category m ($y_i = m$) and zero otherwise. Numerical methods have to be used to maximize the likelihood function to estimate the β's and τ's. Stata uses the Newton-Raphson method. Pratt (1981) shows that Newton-Raphson converges to a global maximum. The estimates are consistent and asymptotically efficient.

3.2 Parallel Regression Assumption

Using an ORM implies to accept that the coefficients of all categories m are equal. This is known as the *proportional odds assumption* but rather obvious if we think of *parallel regression lines.* We can rewrite equation 3 to

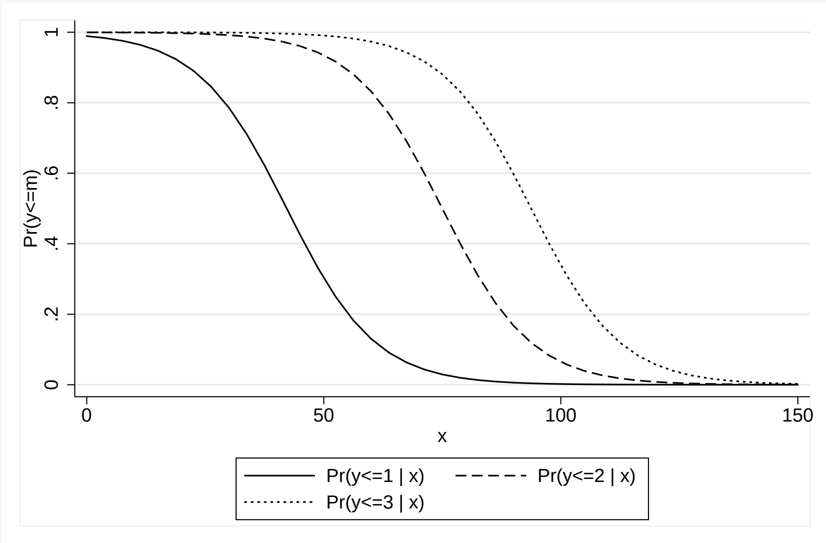
$$\Pr(y_i \leq m|\mathbf{x}_i) = F(\tau_m - \mathbf{x}_i\beta) \quad \text{for } m = 1, ...J - 1. \tag{4}$$

Equation 4 shows that our ordered regression model can be split into $J - 1$ binary regressions with responses in each case less or equal m and greater than m. If we do that for $m = 1, .., J-1$

[2] Long (1997) gives a short explanation about identifying the model.

the β's must be the same for every category m while the cut-points can differ. Figure 2 illustrates this assumption.

Figure 2: Parallel regression lines



Source: Long (1997), p. 141

While τ_m differs for different m (shifting the probability curves to the left or to the right), the slope of the curves are the same for every category m. The assumption can be tested by $J-1$ binary regressions to get $\beta_1, \beta_2, ..., \beta_{J-1}$ from every single regression. The β's in the binary regressions can differ from each other, but if the *parallel regression assumption* holds, β_1 to β_{J-1} have to be very close to each other.

Wolfe and Gould (1998) developed a likelihood ratio test to examine the slope coefficients for all variables at the same time. Brant (1990) constructed a Wald test to test the coefficients for each individual variable.

4 Empirical Results

First we can conclude that all the dealer-specific variables don't affect the 'overall satisfaction'. So the total number of employees, the age of the dealer company, the duration of cooperation with the supplier and the number of sites have no significant influence. Table 2 shows the estimation results of the ordinal regression. Model (1) includes the significant variables of the eight dimensions. The estimated coefficients show that the 'product program' has the highest impact to the 'overall satisfaction', followed by 'marketing and consumer promotion' and 'after sales and service methods'. We carried out a LRM (see Model (2) in Table 2), just to show the different results between the two models, although the assumptions of a LRM don't fit the data. In the regression model the significance of 'after sales and service methods' disappears, while the other dimensions are still relevant. Additionally, 'age of the dealer company' is significant for the 'overall satisfaction'. These small differences show that the results of a regression model with a ordinal scaled dependent variable have to be used with caution.

McKelvey and Zavoina's R^2 for the ORM is about 0.613. Hagle and Mitchell (1992) concluded that McKelvey and Zavoina's R^2 is a good estimate of the OLS R^2. It is relatively unbiased and has together with the corrected Aldrich-Nelson pseudo-R^2 the smallest variances from the OLS R^2. Further they point out that the pseudo-R^2 can't be seen as a OLS-R^2 and therefore misinterpretation is possible and it should be used carefully. So our high R^2 of McKelvey and Zavoina's should not be overvalued. Both, Wolfe and Gould's likelihood ratio test ($\chi^2_6 = 6.19$) and Brant's Wald test ($\chi^2_6 = 5.92$) support the assumption of parallel regression lines, so the analysis with an ORM is appropriate. But how to interpret the results of the ORM?

4.1 Estimated coefficients

The easiest but most meaningless way is to interpret the coefficients as they are got estimated in Table 2 with equation (2). Of course the difference of the strength the dimensions effect the 'overall satisfaction' is seen, but more interpretation is not pssible. The "latent" dependent variable increases by the according estimated β for a one unit increase by the according exogenous variable. This doesn't tell us much, because the actual 4 categories got spanned over the whole space between $-\infty$ and $+\infty$ as they were continuous and it's not possible to see the real categories behind that.

4.2 Log odds ratios

Another way is to interpret the log of the odds:

$$\begin{aligned}
\ln \frac{\Pr(\mathbf{y} \leq 1|\mathbf{x})}{\Pr(\mathbf{y} > 1|\mathbf{x})} &= \tau_1 - \mathbf{x}\beta = 4.192 - 1.269x_1 - 0.875x_3 - 0.293x_4 \\
\ln \frac{\Pr(\mathbf{y} \leq 2|\mathbf{x})}{\Pr(\mathbf{y} > 2|\mathbf{x})} &= \tau_2 - \mathbf{x}\beta = 6.020 - 1.269x_1 - 0.875x_3 - 0.293x_4 \\
\ln \frac{\Pr(\mathbf{y} \leq 3|\mathbf{x})}{\Pr(\mathbf{y} > 3|\mathbf{x})} &= \tau_3 - \mathbf{x}\beta = 8.433 - 1.269x_1 - 0.875x_3 - 0.293x_4.
\end{aligned} \tag{5}$$

On the left hand side of the equations we don't have the latent variable, but rather the log of the ratio of two different categories of the 'overall satisfaction'. There is no transformation of the coefficients necessary, but the interpretation is as meaningless as for equation (2). Due

Table 2: Estimation results : Ordinal Regression

	ORM	LRM
	(1)	(2)
product program	1.269***	0.467***
	(0.209)	(0.070)
marketing and consumer promotion	0.875***	0.365***
	(0.197)	(0.71)
after sales and service methods	0.293*	0.086
	(0.173)	(0.063)
age of the dealer company		0.002*
		(0.001)
τ_1	4.192***	
	(0.472)	
τ_2	6.020***	
	(0.547)	
τ_3	8.433***	
	(0.695)	
Observations	245	237
McFadden's R^2 (ORM), Adj. R^2 (LRM)	0.311	0.593
McKelvey and Zavoina's R^2	0.613	
Log-likelihood	-233.841	-255.407
χ^2	210.644	217.027

Notes: Standard errors in parentheses.
Significance levels : $*$: 10% $**$: 5% $***$: 1%

to the higher estimated coefficient for the 'product program' ($= x_1$) an increase by one unit in that rating dimension lets the log odds decrease more than an increase in 'marketing and consumer promotion' ($= x_3$). It may be confusing that a higher β leads to more decreasing log odds, but decreasing log odds change the probability in favour of the denominator, for a higher category (e.g. from 1 to 2). The change in the log odds itself is very hard to interpret.

4.3 Odds ratios

Instead of the log odds we can use the odds. They look very similar to the array of equations in 5:

$$\begin{aligned} \frac{\Pr(\mathbf{y} \leq 1|\mathbf{x})}{\Pr(\mathbf{y} > 1|\mathbf{x})} &= \exp(\tau_1 - \mathbf{x}\beta) = \exp(4.192 - 1.269x_1 - 0.875x_3 - 0.293x_4) \\ \vdots &= \quad \vdots \qquad\qquad\qquad \vdots \end{aligned} \tag{6}$$

To get this array we just exponentiated the equations in 5. The interpretation is as follows. For a one unit change in e.g. x_1, the rating of the 'product program', the odds of an outcome being higher than m versus being lower or equal to m is $\exp(\beta_1) = 3.56$, given all of the other dimensions in the model are held constant. But why does $\exp(\beta_k)$ explain an increase of the reciprocal of the odds? Let us focus on the odds for category 1. Let

$$\Omega(x_1, x_2, x_3) = \frac{\Pr(\mathbf{y} \leq 1|x_1, x_2, x_3)}{\Pr(\mathbf{y} > 1|x_1, x_2, x_3)} = \exp(\tau_1 - \beta_1 x_1 - \beta_2 x_2 - \beta_3 x_3) \quad \text{and}$$

$$\Omega(x_1 + 1, x_2, x_3) = \frac{\Pr(\mathbf{y} \leq 1|x_1 + 1, x_2, x_3)}{\Pr(\mathbf{y} > 1|x_1 + 1, x_2, x_3)} = \exp(\tau_1 - \beta_1(x_1 + 1) - \beta_2 x_2 - \beta_3 x_3).$$

For a change of x_1 by 1 the odds become

$$\frac{\Omega(x_1 + 1, x_2, x_3)}{\Omega(x_1, x_2, x_3)} = \frac{\exp(\tau_1 - \beta_1(x_1 + 1) - \beta_2 x_2 - \beta_3 x_3)}{\exp(\tau_1 - \beta_1 x_1 - \beta_2 x_2 - \beta_3 x_3)} = \frac{1}{\exp(\beta_1)}.$$

While $\frac{1}{e^{\beta_1}}$ is the factor the odds of a lower or equal outcome ($m \leq 1$) versus a higher outcome ($m > 1$) changes, e^{β_1} is the rate the reciprocal of the standard odds has to be multiplied.
What does the exponent of the estimated coefficient tell us? If $\frac{\Pr(\mathbf{y}>1|x_1=2,x_2,x_3)}{\Pr(\mathbf{y}\leq 1|x_1=2,x_2,x_3)}$ equals one for a 'product program' rating of two, the probability for a higher category than 1 versus the probability the category is less or equal to 1 are both 50 %. Let us now assume that the rating of the 'product program' rises up to three, the other categories are held constant. In that case the odds change from 1 to 3.557 due to the estimated coefficient of $\exp(\beta_1) = 3.557$, that

means the probability for a higher category than 1 increases to 78% versus the probability of 22% for a category less or equal to 1. Table 3 shows the odds ratios $\exp(\mathbf{x})$ and the percentage changes of the significant dimensions for Model (1).

Table 3: Odds ratios and percentage changes of the ORM

Variable	β	e^{β}	percentage change
product program	1.269	3.557	255.7
marketing and consumer promotion	0.875	2.399	139.9
after sales and service methods	0.293	1.341	34.1

4.4 Tables of predicted probabilities

Instead of interpreting the coefficients or a modification, we can tabulate the predicted probabilities for every single category of the 'overall satisfaction'. This can be done by either choosing some for the researcher relevant combinations of some of the variables or by complete tabulation for all variables and all values. The predicted probabilities can be obtained by calculating equation 3 for every category of the 'overall satisfaction'. Table 4-7 list all predicted probabilities for combinations of "product program vs. marketing and consumer production", "product program vs. after sales and service methods" and "after sales and service methods vs. marketing and consumer production" for all categories of the 'overall satisfaction'.

Table 4: Predicted probability of 'overall satisfaction' for category 1

	marketing and consumer production				after sales and service methods			
product program	1	2	3	4	1	2	3	4
1	0.8092	0.6387	0.4243	0.2350	0.6219	0.5509	0.4778	0.4056
2	0.5439	0.3320	0.1716	0.0795	0.3162	0.2565	0.2046	0.1610
3	0.2511	0.1226	0.0550	0.0237	0.1151	0.0884	0.0674	0.0512
4	0.0861	0.0378	0.0161	0.0068	0.0353	0.0265	0.0199	0.0149
after sales and service methods	1	2	3	4				
1	0.3915	0.2115	0.1005	0.0445				
2	0.3243	0.1667	0.0770	0.0336				
3	0.2636	0.1298	0.0585	0.0253				
4	0.2107	0.1001	0.0443	0.0190				

It can be easily seen by the predicted probabilities that the 'product program' influences the overall satisfaction most. For a better illustration we compare the range of the predicted probabilities in the extreme categories 1 and 4. The range of the 'product program' for the

Table 5: Predicted probability of 'overall satisfaction' for category 2

	marketing and consumer production				after sales and service methods			
product program	1	2	3	4	1	2	3	4
1	0.1543	0.2779	0.3966	0.4214	0.2891	0.3332	0.3727	0.4037
2	0.3373	0.4236	0.3914	0.2699	0.4258	0.4256	0.4108	0.3831
3	0.4248	0.3424	0.2109	0.1075	0.3320	0.2878	0.2428	0.2000
4	0.2834	0.1586	0.0763	0.0340	0.1500	0.1184	0.0923	0.0713
after sales and service methods	1	2	3	4				
1	0.4086	0.4137	0.3096	0.1802				
2	0.4248	0.3877	0.2645	0.1441				
3	0.4264	0.3515	0.2203	0.1136				
4	0.4134	0.3089	0.1796	0.0884				

Table 6: Predicted probability of 'overall satisfaction' for category 3

	marketing and consumer production				after sales and service methods			
product program	1	2	3	4	1	2	3	4
1	0.0331	0.0753	0.1599	0.2988	0.0804	0.1043	0.1340	0.1700
2	0.1069	0.2163	0.3720	0.5077	0.2278	0.2779	0.3316	0.3861
3	0.5077	0.4416	0.5359	0.4965	0.4532	0.4945	0.5237	0.5381
4	0.4979	0.5354	0.4397	0.2809	0.5322	0.5094	0.4732	0.4268
after sales and service methods	1	2	3	4				
1	0.1781	0.3239	0.4758	0.4758				
2	0.2218	0.3785	0.5113	0.5293				
3	0.2713	0.4307	0.5331	0.5041				
4	0.3247	0.4764	0.5392	0.4658				

Table 7: Predicted probability of 'overall satisfaction' for category 4

	marketing and consumer production				after sales and service methods			
product program	1	2	3	4	1	2	3	4
1	0.0034	0.0081	0.0192	0.0448	0.0087	0.0087	0.0155	0.0207
2	0.0119	0.0282	0.0650	0.1429	0.0302	0.0401	0.0530	0.0698
3	0.0412	0.0934	0.1982	0.3722	0.2826	0.1293	0.1660	0.2107
4	0.1325	0.2682	0.4678	0.6784	0.2826	0.3456	0.4145	0.4870
after sales and service methods	1	2	3	4				
1	0.0219	0.0510	0.1141	0.2361				
2	0.0291	0.0672	0.1473	0.2929				
3	0.0387	0.0880	0.1880	0.3571				
4	0.0512	0.1146	0.2369	0.4269				

’overall satisfaction’ outcome of 1 varies from 80.92 % for rating into category 1 to 8.61 % for rating into category 4 (range= 72.31 %). ’After sales and service methods’ is set to the average value of 2.05 and marketing and consumer production is set to 1. The ranges of the other dimensions are 57.42 % for ’marketing and consumer production’ and 21.63 % for ’after sales and service methods’. The same can be done for other values of dimensions and for other values of the ’overall satisfaction’ (see Tables 4-7).

4.5 Graphics of predicted probabilities

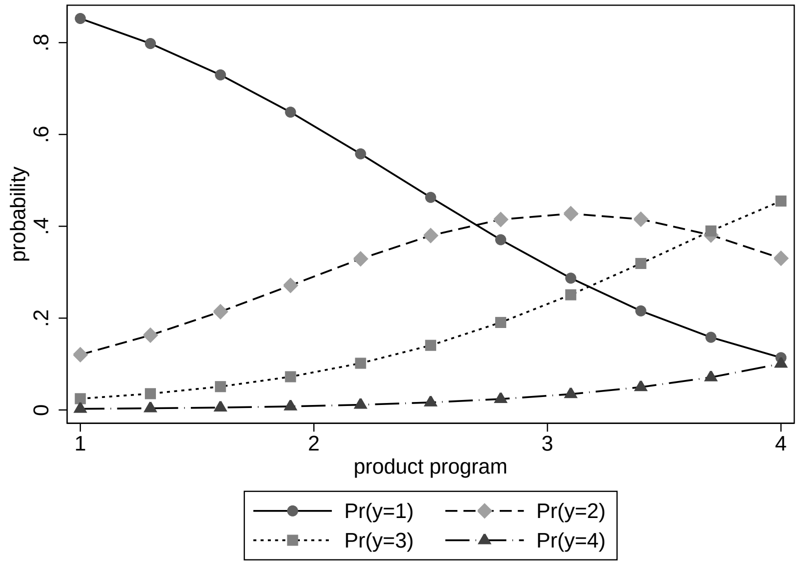
While tables are messy to read, graphics demonstrate the relationship of the variables and the predicted probabilities more obviously. Figure 3 compares the ’product program’ at the top of the figure and ’after sales and service methods’ below.[3] The other dimensions in the Figure are set respectively to 1.[4] The slope of ’after sales and service methods’ declines very slowly for an ’overall satisfaction’ outcome of 1 compared with the slope of the ’product program’. That means that the ’after sales and service methods’ have less influence for increasing rating of the dimension to the change of the probability of the ’overall satisfaction’ than the ’product program’.

Figure 4 compares the two dimensions cited above with other dimensions respectively set to 4. In this case it is most obvious to compare the graphs for an ’overall satisfaction’ outcome of 4. The ’product program’ increases much faster for increasing rating than the ’after sales and service methods’.

[3] The comparison is best seen with these two dimensions, because of the higher difference of the effects on the ’overall satisfaction’.

[4] For ’product program’ the other two significant dimensions ’after sales and service methods’ and ’marketing and consumer production’ are set to 1. For ’after sales and service methods’ the dimensions ’product program’ and ’marketing and consumer production’ are set to 1.

Figure 3: Predicted probabilities of 'overall satisfaction' with other significant variables set to 1. At the top: 'product program'. At the bottom: 'after sales and service methods'.



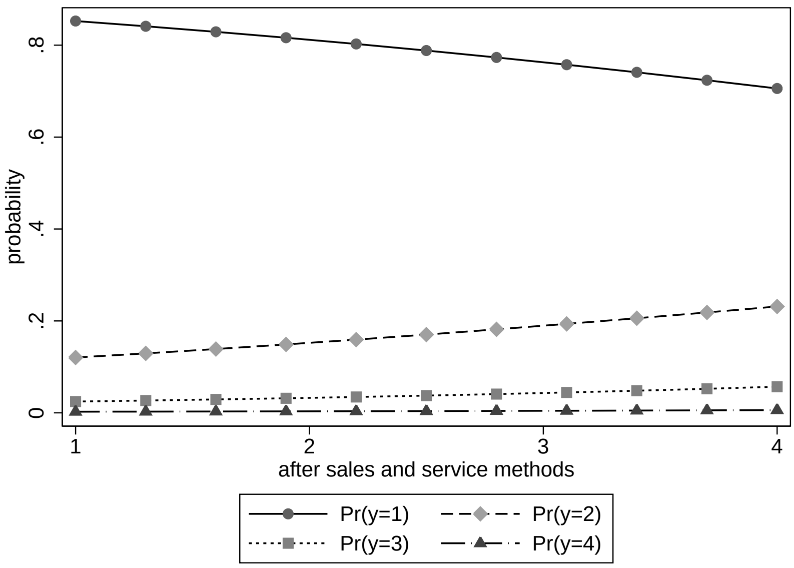
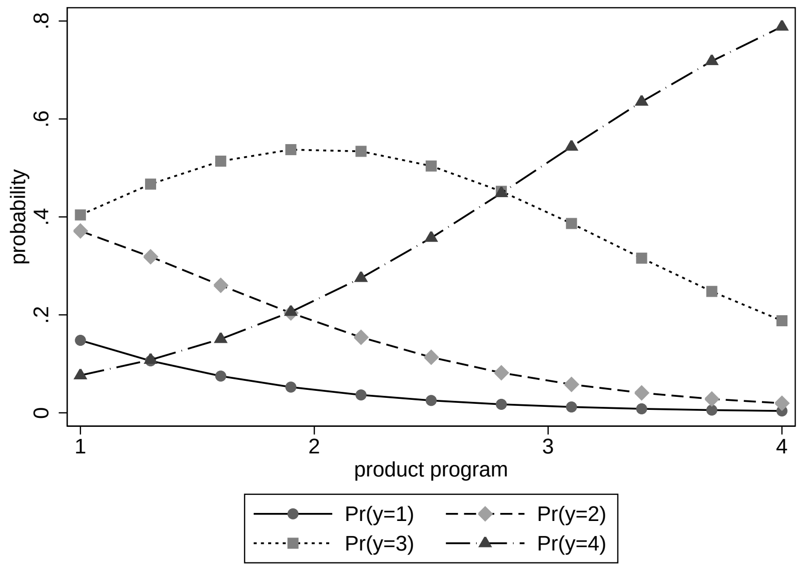
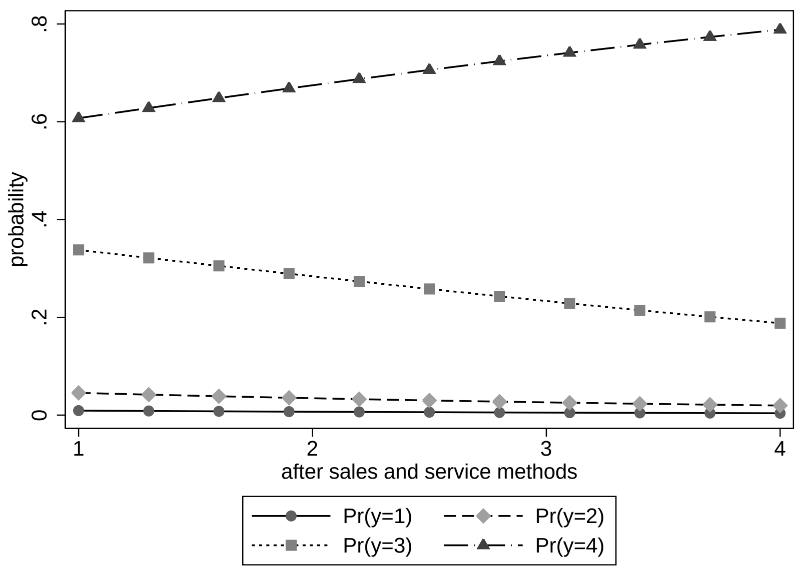


Figure 4: Predicted probabilities of 'overall satisfaction' with other significant variables set to 4. At the top: 'product program'. At the bottom: 'after sales and service methods'..





5 Conclusion

We performed an ordinal regression model using dealer satisfaction data for the agricultural technology market in Germany. The model deals with a ordinal scaled rating between 0 and 10, summarized, without effecting the main results, to a rating between 1 to 4. The significant dimensions for influencing the 'overall satisfaction' are the 'product program', the 'marketing and consumer production' and the 'after sales and service methods'. With a linear regression model for ordinal scaled variables, the results can be misleading and have to be used with caution. Many articles using an ORM list just the estimated coefficients and/or don't proof the assumption of *parallel regression lines*. But the estimated coefficients of the ORM can't be properly interpreted like in the LRM, because of the estimation of a latent variable, so further calculations have to be carried out. To present the log odds is as meaningless as the estimated coefficients themselves. Beginning with the odds or the percentage change of the odds is the first way for a better understanding of the relationship of the significant variables. But still they give only an overview, independently of the other dimensions. With predicted probabilities either for some interesting combinations of values of the explanatory variables or for all possible combinations this problem can be dealed with. The tables are hard to read and even more difficult with a dependent variable with more than 4 categories. Therefore we can illustrate the predicted probabilities by graphs. Within this method it is easy to see by the slope for the according category how much the probability changes with different values of the independent variable. So the odds, the tables and graphs of the predicted probabilities give much more insight into the relationship between the variables. We hope that researcher using an ORM will provide a better interpretation of the empirical study by using the possible techniques instead of listing just the estimated coefficients.

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