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Remaining value development of tractors – a call for the application of a differentiated market value estimation

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Estimates of market values are important for decisions about type and economic useful life of tractors as well as for assessing appropriate used prices. In this context, a linear relationship between the value and both the intensity of use and the age is often assumed. Differences between manufacturers, power classes or configuration are insufficiently considered. This paper shows that market values and thus also the development of remaining values can be better described with nonlinear functions, in particular with exponential functions. It shows that the development differs between manufacturers and power classes. On the basis of online advertisements we estimate market values using multiple linear regression models. They are validated with auction results and compared with the remaining value formula of the KTBL. The models based on online advertisements appear to be suitable to represent real sales. In some cases substantial differences in the devaluation costs of individual power classes but also manufacturers arise from a differentiated consideration of the remaining value based on the market value. In simple applications, average considerations are sufficient, but in the case of short usage periods, low utilization rates and small power classes, we recommend to estimate an individual remaining value. For this purpose as well as for an objective assessment of the market values of used tractors we provide the respective parameters in the appendix.

Keywords
Tractors, remaining values, depreciation, auctions, online advertisements

An objective and accurate market value estimate for used tractors or remaining value development is significant for decision makers in the agricultural environment for at least two reasons. On one hand, the forecasts are needed to assess whether an offer for the purchase or sale of a used tractor is close to a market price, which is insufficiently known due to a lack of market transparency. Furthermore, objective estimates are helpful for agricultural appraisers or for balance sheet analyses. On the other hand, exact estimates are needed for the calculation of machinery costs. For many agricultural services, machinery costs are the largest cost item (Hoop et al. 2014). For the determination of machinery costs, assumptions about the remaining value and thus about prices achievable on the second-hand market are essential.

There are various approaches for determining the value of a used tractor. The German income tax law uses a linear depreciation to approximate the loss in tractor value. The depreciation equals the acquisition value minus the remaining value divided by the period of use (cf. also § 7 I EStG). Eight years after acquisition the depreciation tables of the tax authorities assume a remaining value of zero. Another option for determining the remaining value for cost calculation or for estimating prices

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for used tractors is the standard data of the KTBL. It assumes a linear depreciation over 12 years to a remaining value of 20%. Since 2017, the KTBL is using a formula that, in addition to age, also takes the intensity of use into account. This formula and its parameters are considered a "working hypothesis" (Schroers et al. 2020). The formula is presented in the method section and used as a benchmark. This article can be seen as a supplement to that of Schroers et al. (2020). The formula of KTBL and the other mentioned options have in common that they assume a linear relationship between remaining value and age as well as intensity of use. Furthermore, none of the methods distinguishes between different manufacturers or different power classes. Such manufacturer-specific differences and nonlinear depreciation of tractors have been suggested in the past for international tractor markets (Wilson and Tolley 2004; Perry et al. 1990, Fenollosa Ribera and Guadalajara Olmeda 2007; Wilson 2010; Daninger and Gunderson 2017). For the German market, Uppenkamp (1998) conducted regressions of the natural logarithm of age on remaining value and estimated correction factors for the average annual utilization and different manufactures. However, differences in engine power were not considered. Previous publications use multiple years of auction results (cf. Perry et al. 1990; Cross and Perry 1996, Wu and Perry 2004; Daninger and Gunderson 2017), collections of advertisements in agricultural magazines (cf. Wilson and Tolley 2004; Wilson 2010), or other multi-year price collections (cf. Fenollosa Ribera and Guadalajara Olmeda 2007, Unterschultz and Mumey 1996). Due to such time series (and the use of different auction formats) biases in the estimation arise and have to be controlled for changes in macroeconomic variables over time as in the work of Perry et al. (1990), Cross and Perry (1996) and Daninger and Gunderson (2017). Although the mentioned publications highlight differences between manufacturers, they do not focus on manufactures that are currently relevant in Germany.

Objectives and Hypotheses

This paper aims to extend the analyses mentioned above. In the process, current functions for describing the market value of used tractors in Germany are to be estimated. These functions can be used for price assessment in the sense of market transparency and for remaining value estimation in internal accounting. It focuses on manufacturer differences and differences in engine powers. In addition, this article is the first to exclusively use online advertisements as the data basis for estimating market values. The intention is to provide a valid and easily updatable estimate of real market events. Online advertisements were not available to all of the previous publications mentioned above. Online advertisements provide current data for the German market. Thus, current value developments, including those of individual manufactures, can be mapped in a more specific manner. Only Wilson (2010) uses offers from the websites of various agricultural machinery dealers in his remaining value estimates. He does not provide any information about their scope and combines them with advertisements from various magazines. The data used here, on the other hand, comes from the same online portal. Given this background, the following hypotheses are addressed:

- A linear relationship is not appropriate for describing the depreciation or devaluation of tractors from a business perspective.
- The devaluation of tractors in Germany differs between manufacturers within the same power class.
- Estimation models based on online advertisements are suitable to represent real sales events.

Data and method

We test these hypotheses by estimating regression models for market values of used tractors. The models take different manufacturers and power classes into account. For a valid test, the largest possible data set with tractors of different manufacturers and power classes with information on age and total operating hours would be needed. Data sets with market prices from actual sales would be ideal. Such data are only publicly available in small numbers in the form of auction results. The latter, due to their comparatively small number, do not allow for sufficiently valid estimates to make statements about manufacturer-specific differences in devaluation. Therefore online advertisements are used as a basis for estimating various models for market values and devaluation trends. Online advertisements have the advantage to be available in large numbers. However, advertisement prices do not represent actual sales prices. At best, they come close to these in the form of systematically higher values. Therefore, in a second step, different models are used to predict auction results with actual purchase prices (cf. fig. 3). This answers whether the relations found in the listings can be transferred to real sales events and thus form a valid foundation to estimate actual prices. In addition, the comparison of models with and without manufacture-specific devaluation makes it possible to test whether the manufacturer has a measurable influence on the prediction of real sales prices. Furthermore, the auction results are compared with the predictions of the linear remaining value function of the KTBL.

The data has been obtained from the online advertisements of “traktorpool.de” active on 27.02.2020 using R-Studio and the “rvest” package. According to its own information, “traktorpool.de” is the leading German marketplace for used agricultural machinery and tractors. According to the AgriMa 2019, a media usage analysis with more than 3000 participating farmers, “traktorpool.de” is the most known and most used German agricultural website (Traktorpool.de 2019). The sample used here initially included all tractors advertised on “traktorpool.de” at that time. It therefore also includes advertisements that were published before 27.02.2020. An advertisement on “traktorpool.de” is subject to a fee and either expires after 28 days or causes ongoing costs. This indicates the validity of the data. Only tractors with a location in Germany, an age of up to 20 years and a maximum of 12,000 operating hours were considered. This is to prevent a bias due to vintage vehicles. Furthermore, tractors were excluded if they obviously had engine or transmission damage or were to be sold in combination with other agricultural equipment. For the evaluation, only data records with information on offer price, engine power in kW, operating hours, year of manufacture and type designation were included. Only the manufacturers “Case” (including “Steyr”), “Claas”, “Fendt”, “John Deere” and “New Holland” were considered. These manufacturers had the highest shares of registrations of tractors with 36 kW and above in Germany in 2018 and represented a total of 65.5% of registrations (Stirnimann and Renius 2020). Based on their engine power the tractors were assigned to a power class according to KTBL (2020). Classes do not overlap, so each tractor belongs to one class. Compared to the use of the exact values of the engine power, the classes have the advantage to level out inaccuracies in the power data from the advertisements. In addition, the power class-specific repair costs of the KTBL can still be used for cost calculations based on the models. Table 1 shows the distribution of tractors across power classes and manufacturers. Due to the small sample sizes of less than 20 tractors per manufacturer, the power classes 45, 54, 275, 338 and 400 kW were excluded from further considerations. Which left 2667 tractors in the sample. This limitation of the power classes effectively excludes all track-laying tractors (e.g. “Case Quadtrac” or the RT series from “John Deere”). The results largely refer to four-wheel drive utility tractors. The locations of the tractors are spread all over Germany. With the exception of a few large cities, all of the German two-digit zip code areas are represented in the sample. 357 auction results for tractors that meet the above criteria for manufacturer, age, operating hours and power class (67-233kW) are used for validation. Again, tractors with engine and transmission damage were excluded. The results were obtained from eight auctions conducted in Meppen (Germany) by „Ritchie Bros.“. These auctions took place from March 2019 to November 2020. The age of the auctioned tractors is calculated from the difference between the year of the auction and the year of manufacture.

Table 1: Composition of the online advertisements used by manufacturer and power class

Power class (kW)	Total number and per manufacturer						Average value of		
	total	Case	Claas	Fendt	JD[1)]	NH[1)]	price[2)] in Euro	engine hours	age in years
45	21	5	0	1	8	7	25.042	426	6
54	77	8	15	9	33	12	30.663	1665	6
67	230	36	68	28	71	27	35.100	3220	9
83	255	28	61	48	86	32	41.463	4200	9
102	288	50	71	35	109	23	54.950	4325	7
120	354	23	114	49	117	51	64.621	3425	6
138	334	36	77	75	105	41	68.700	4348	7
157	301	32	88	39	116	26	74.900	4500	6
176	334	21	74	110	89	40	85.500	4117	6
200	335	25	43	143	90	34	92.000	4070	6
233	236	26	30	78	80	22	93.658	4420	7
275	272	8	54	114	84	12	113.250	4450	7
338	61	5	40	7	7	2	146.000	2720	5
400	33	12	8	9	3	1	199.000	3855	6

[1)] JD = John Deere, NH = New Holland
[2)] The price is the average advertised offer price

Various previous works conclude that a linear relationship does not adequately reflect the depreciation of agricultural machinery. There are different opinions on which transformation is most appropriate for describing agricultural machinery depreciation. Cross and Perry (1996) and Wu and Perry (2004) obtained the best results with Box-Cox transformations. For each, the dependent variable was the ratio to the list price. In their work, the next best fit was provided by transforming dependent and independent variables with the square root. They refer to this as “double square root” transformation and recommend it for practical use because of its simpler handling. Daninger and Gunderson (2017) also prefer this transformation, which in their study also yields only slightly worse results than the Box-Cox transformation. In their work a model with interaction terms between age and power class as well as between operating hours and the power class using the transformation of the price with the natural logarithm performs similarly well. Unterschultz and Mumey (1996) and Fenollosa Ribera and Guadalajara Olmeda (2007) also transform the price with the natural logarithm to estimate devaluation models. The latter three articles use the absolute price as the dependent variable (Unterschultz and Mumey 1996; Daninger and Gunderson 2017; Fenollosa Ribera and Guadalajara Olmeda 2007). The estimate of absolute value excludes price policy influences of list prices. The main argument against the Box-Cox transformation mentioned above is that the results are difficult to interpret (Wu and Perry 2004; Wilson 2010).

In this article, multiple linear regressions are fitted for different transformations to describe the absolute price. The one with the best fit is selected. In addition to a linear model (untransformed price (equation 1)) the natural logarithm (exponential functions) (equation 2) and the double square root (equation 3) are used. In each case, the full model can be described as follows:

$$y = v_{k,f} + h_{k,f} * x_1 + a_{k,f} * x_2$$ linear model Eq. (1)

$$y = e^{v_{k,f}} * e^{h_{k,f} * x_1} * e^{a_{k,f} * x_2}$$ natural logarithm Eq. (2)

$$y = (v_{k,f} - h_{k,f} * {x_1}^{0,5} - a_{k,f} * {x_2}^{0,5})^2$$ double square root Eq. (3)

y = estimated value of the offer price of the used machine
v = parameter to be estimated for the as-new price
h = devaluation parameter to be estimated against the operating hours
a = devaluation parameter to be estimated against age
f = manufacturer
k = power class
x_1 = operating hours
x_2 = age

In the full model, the parameters a and h differ between the manufacturers (*f*) and the power classes (*k*). The as-new price, respectively its parameter (*v*), is also estimated endogenously. In addition to the full models shown above, all reduced models of these are fitted (all subsets regression). The fit is estimated using ordinary least squares estimation. For the three remaining models, one per transformation, the sum of squared deviations of the back-transformed estimate to the advertisement price is calculated. The sums of squared deviations are compared between the models. The model with the lowest sum of squared deviations is selected and used further on. The preferred model is tested for the statistical significance of the included variables by an analysis of variance. Then, the statistical significance of the individual parameters is tested using t-tests. These tests are one-sided, since only positive values can be expected for the estimated as-new price v and only decreases in value with increasing age and operating hours. This is particularly convincing since the restriction to tractors not older than 20 years excludes vintage vehicles, which value can increase with age. The parameters of the devaluation (*h* and *a*) for individual manufacturers of the same power class are tested with F-tests for differences between the manufacturers. In each case, the individual parameters for tractors of different manufacturers within the same power class are compared in pairs. Due to the accumulation of type I errors by multiple testing, the p-values are corrected with the Benjamini-Hochberg procedure (Benjamini and Hochberg 1995). The proportion of false positive rejections of the null hypothesis is thus limited to a proportion to be specified, in this case 0.05. The number of pairwise comparisons, that is 180 (twice 10 comparisons per class), was used as the basis for the correction. For comparison with the auction results, the next best model with the same transformation but without manufacturer influence selected by AIC is used. Additionally, the remaining value formula of the KTBL was included (cf. Schmid and Krön 2018 and Schroers et al. 2020):

$$R = A * (a - b * \frac{ND}{NDpot} - c * \frac{NU}{NUpot}) \qquad \text{Eq. (4)}$$

R = Absolute remaining value
A = Acquisition price
a = Percentage remaining value after being put into operation
ND = Actual duration of use in years
NDpot = Total potential duration of use in years
NU = Actual amount of use in hours
NUpot = Total potential use in hours
b und c = Weighting factors for use in years and hours

For tractors, the parameters have the following values: a, 0.74; b, 0.27; c, 0.27; *NDpot*, 12 years; *NUpot*, 10000 hours (Schmid and Krön 2018). The value for A assigned to each tractor was the acquisition value from the corresponding year of construction according to different years of "KTBL-Betriebsplanung" or "Taschenbuch Landwirtschaft" (KTBL 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018). In each case, the value for powershift transmissions was selected. As mentioned, for the estimation models based on advertisements, a systematic overestimation of real prices is to be expected. To correct for this, if necessary, a percentage discount between auction results and the prediction of the models is estimated. The correction factor is chosen to minimize the sum of squared deviations between the estimation result of the respective model and the actual price. A percentage discount seems more appropriate than a constant absolute discount given the range of variation in auction results (137,000 € to 9,000 €). The calculated discount provides information about the price ratio of auctions to advertisements. Only one correction factor is estimated for each model. Due to the small number of auction results, no attempt is made to adjust a more specific discount, e.g. by manufacturer or power class. To address possible biases due to the nearly two-year period from which the auction results are drawn, a multiple linear regression model is constructed to explain the discrepancy between the auction results and the associated estimated results. Secondly, the comparison with a model without the influence of a manufacturer is intended to show whether statistically significant differences between the manufacturers are also "economically significant" in the form of an improved representation of the auction results.

Results

In each case, the best fit according to the AIC is provided by the full model shown (1, 2 and 3). The smallest sum of squared deviations of the back-transformed estimates was provided by the exponential model (2) (transformation with the natural logarithm). The further presented results are limited to this transformation. In the model selection, across all transformations, the models with manufacturer specific devaluation factors have lower values for the AIC than those without. For the exponential model, the difference in the AIC of the full model from the next best model is 7.43. A difference in this magnitude suggests that this model is indeed the most appropriate of the selected models for representing market values in the sample (Burnham and Anderson 2004). The estimates of the regression parameters from the selected model (2) as well as the standard errors and p-values are presented in full in the appendix. All three influencing factors are statistically significant in the analysis of variance (*p-value* <0.05). In the selected model the parameters of operating hours (h) are all statistically significant (*p-values* <0.05) less than zero (t-test). The parameters for age (a) are also mostly statistically significantly smaller than zero at this level, except for four cases. Since the

Breusch-Pagan test indicates the presence of heteroskedasticity for the selected model, the estimation of the robust standard errors according to White (1980) were used. Figure 1 shows the estimated relative remaining values (y/v) of the different manufacturers for the various power classes. To enable a two-dimensional representation, a fixed number of operating hours per year was assumed. In this case, this is 833 h/a, which corresponds to so called "utilization threshold" (Auslastungsschwelle) defined by the KTBL (cf. KTBL 2018). The remaining value formula of the KTBL is plotted as a red line in the figure. In some cases, the curves differ considerably between the manufacturers. Differences also occur between the power classes. In the classes above 138 kW, the curves approach a remaining value of about 20% at 10,000 operating hours, as assumed by the KTBL. The utilization threshold might not reflect the utilization to be found in farm practice, especially in the smaller power classes (the present sample has an average utilization of 358 h/a in the 67kW power class). Therefore, a representation for varying utilization rates for the 67kW power class is given in the appendix. The difference to the estimate of the KTBL formula increases with a lower utilization.

In the two power classes with the lowest engine power (67 and 83kW), the relative remaining value at the end of the use period (12 years and 10,000h) is much higher than 20%. It does not converge with the KTBL values. Depending on the manufacturer, the relative remaining value can be between 40% and 50%. The order of the manufacturers in the devaluation levels differs between the power classes. Table 2 shows for each power class, separately for the parameters of devaluation (*h* and *a*), the proportion of corrected p-values that were smaller than 0.05 in the pairwise comparison by F-test.

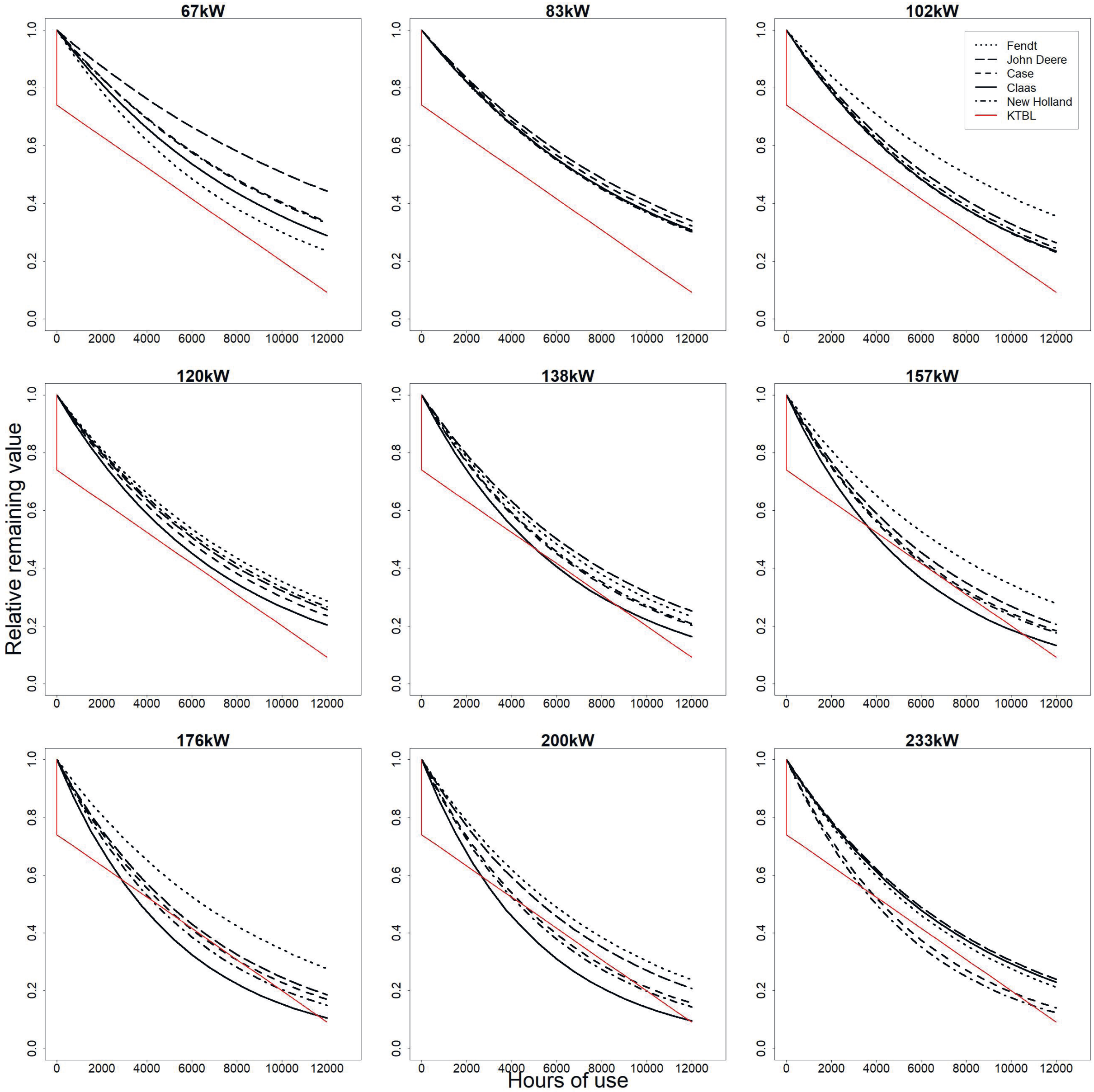

Figure 1: Estimated relative remaining value by power classes and manufacturers as a function of operating hours based on the utilization of 833 hours per year

Table 2: Proportion of statistically significant F-tests (a = 0.05) after application of the Benjamini-Hochberg procedure for differences in devaluation parameters (h and a) by power classes.

		Power classes								
		67	**83**	**102**	**120**	**138**	**157**	**176**	**200**	**233**
Parameter	**h**	0%	50%	0%	20%	0%	50%	50%	50%	10%
	a	0%	20%	0%	30%	0%	20%	10%	30%	0%

In every power class, each of the two devaluation parameters was compared between all manufacturers. Taking the 176 kW class as an example, the 50% share for the parameter h means that a statistically significant difference was found in half of the comparisons. The proportion varies between the classes and the parameters. In some classes none of the null hypotheses could be rejected. Thus, no statistically significant differences could be shown there. For the parameter h (devaluation with increasing operating hours) more statistical significant differences can be shown. As a comparison to evaluate the "economic significance" of the manufacturer differences, the next best model according to the AIC without manufacturer influence is used. This model can be described as follows:

$$y = e^{v_k} * e^{h_k * x_1} * e^{a_k * x_2} \quad \text{Eq. (5)}$$

The naming of the variables is the same as in the methodology, for example see (2). Figure 2 shows the estimations of the auction results by the models before adjusting a correction factor. The actual auction results are plotted on the x-axis and the corresponding estimates are plotted on the y-axis. Points above the plotted bisector indicate overestimation of the actual price, points below indicate underestimation.

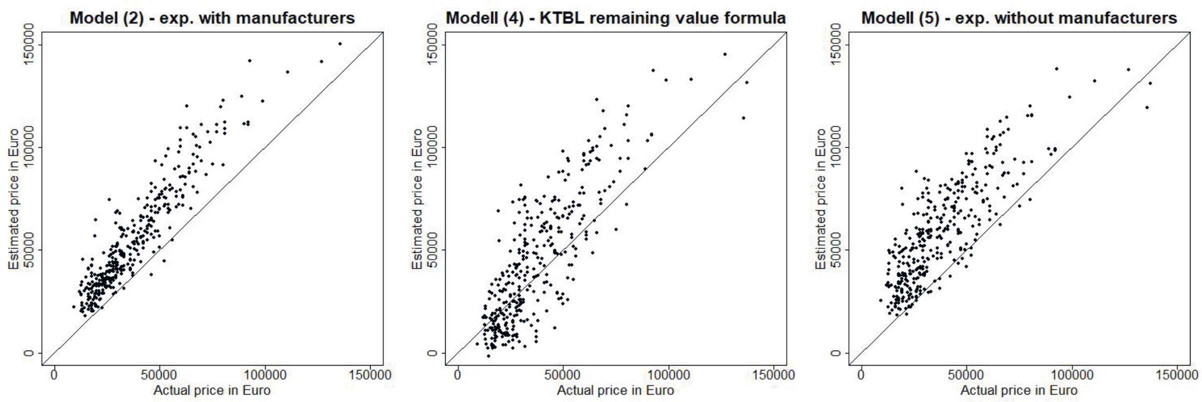

Figure 2: Estimation deviation of auction results without percentage discount

As expected, there is a systematic overestimation of auction results by the models based on advertisements (2, 5). Model (2) overestimates the actual price in 98.5% of the cases. A conspicuous feature of the KTBL formula is the systematic underestimation for older tractors. Therefore, the correction factor described in the methodology was adjusted. Table 3 shows the correction factor and various key figures on the quality of the estimates (after application of the correction factor). The correction factor ranges from 66 to 76%, depending on the model.

Table 3: Key figures on the quality of the estimation of auction results with a percentage discount.

Model	Correction factor	Mean absolute deviation in Euro	Mean absolute deviation in Euro	SD of the deviation in Euro	Correlation coefficient between estimated and actual price
(2) - exp. with manufacturers	69,9%	5.388,00	11%	7.458,28	0,943
(4) - KTBL remaining value formula	75,5%	11.036,64	28%	13.077,47	0,851
(5) - exp. without manufacturers	66,2%	8.781,74	19%	11.682,97	0,853

For each of the figures, model (2) provides the best score. On average, its estimates deviates from the actual result by 5388 euros. In addition to the values shown, it should be added that the percentage deviation of the 75% quantile for model (2) is 19.6% whereas model (4) reaches 74.6%. The comparison between model (2) and model (5) shows that the differences between the manufacturers are not only statistically significant, they also improve the actual price estimate considerably. The results from Table 3 further show that not only the manufactures differences account for the improved estimation of the exponential models over the linear models. Model (5) also shows better estimation performance than the KTBL formula (4). The median percent deviation is nine percentage points lower in model (5) than with the KTBL formula. The exponential model, with only power class specific new prices and uniform parameters for age and hours of operation (not shown in Figures 2 and 3) has a median of 22% in this metric. From this perspective the estimates of the exponential models are superior to the linear approach, even with the same number of parameters.

Analogous to Figure 2, Figure 3 shows the corrected estimation results. In particular, model (2) shows a considerable improvement due to the correction factor. On average, the KTBL residual value formula does not show much improvement due to the correction factor. This is because the discount cannot improve the already occurring underestimation of various tractors, especially old and heavily used ones. But even here the estimation of relatively young tractors can be improved. Based on the

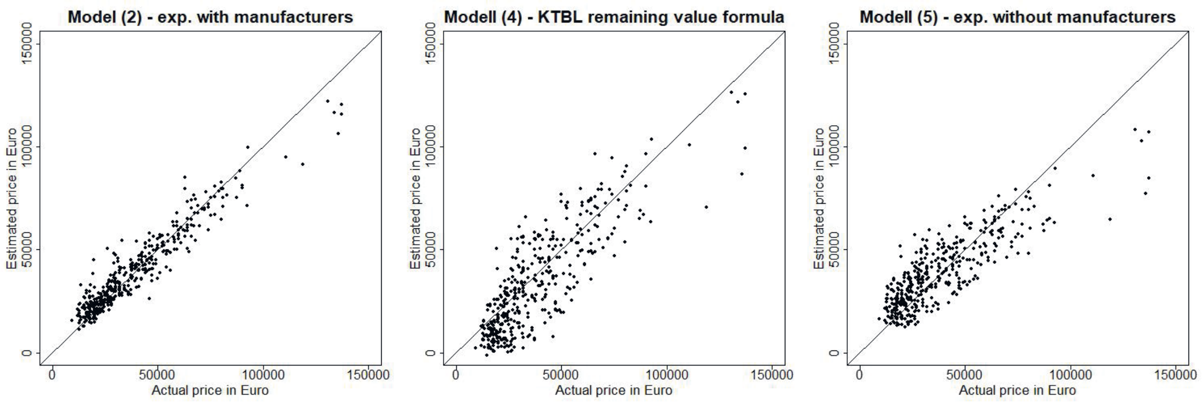

Figure 3: Forecast deviation of auction results with percentage discount

correction factor of 0.699 for model (2), the average discount between advertisements and auction results is 30.1%.

Figure 4 shows the forecast errors of the corrected models plotted against operating hours. The red line represents an ordinary least squares fitted regression line of the operating hours against the divergence of the estimates from Figure 3. While for the exponential models the divergence appears to be almost unrelated to the operating hours, this is the case for KTBL remaining value formula. The higher the number of hours, the more underestimated is the value of the tractor, this can also be shown against age. The slope of the line in Figure 4 is not statistically significantly different from zero either for model (2) nor model (5). This was tested with a t-test with the regression parameters and the robust standard errors according to White (1980). The robust standard errors prevent a possible bias due to variance heterogeneity.

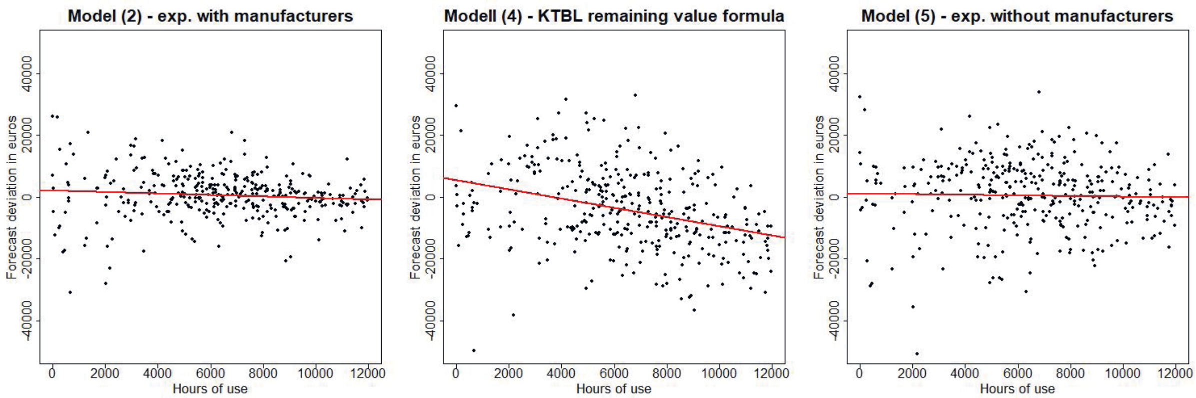

Figure 4: Forecast divergence of the auction results by the models against the operating hours.

However, in a multiple linear regression model, when age, operating hours and auction year are jointly fitted against the deviations from figure 3, the parameters for age and operating hours turn out to be statistically significantly different from zero (t-test with robust standard errors). In this regression the parameters for age and operating hours have opposite signs, so that the effects on the deviation balance out at 765h/a. In sum, they only explain deviations in the three-digit euro range. The longer auction period does not lead to any distortions.

The hypotheses can be addressed as follows: We agree with the first hypothesis. A linear relationship is not appropriate for describing the individual depreciation for cost calculations or predicting prices in the used tractor market. The linear model (1) provides a inferior fit to the advertisement data than the non-linear transformations (2,3). Similarly, the improved estimation of the auction data by the exponential models compared to the KTBL remaining value formula suggests that a linear relationship does not represent depreciation properly (see Figure 3). This is also evident in Figure 4. A weakness of the linear relationship is, among other things, the constant negative slope. With such an approach, theoretically even negative remaining values would be conceivable, which would continue to decrease with continued use.

The second hypothesis is also in line with our results. The devaluation differs by manufacturers. Models with manufacturer specific devaluation consistently have lower values for the AIC in the model selection. This indicates that the inclusion of manufacturers in the model improves the estimation of advertisement prices. In addition, some statistically significant differences were demonstrated between the devaluation parameters for operating hours (h) and age (a) within the same power class. In conclusion, the estimation of the auction data shows that the consideration of manufactures improves the prediction. In particular, the dispersion is reduced (Figure 3).

Regarding the third hypothesis, after fitting a correction factor, the models based on the online advertisements provided good estimates of the auction results in terms of the amount of divergence and dispersion. These estimates are subject to almost no bias against the parameters of devaluation (see Fig. 4). It follows that there is a close correlation between the level of advertisement prices and actual sales prices, in the form of auction results.

Discussion and conclusions

In this section, individual implications from the results will be pointed out. A comparison with the remaining value formula of the KTBL will also be conducted. This is followed by a presentation of the differences to previous work on remaining value development and a methodological discussion of this article.

Implications from the results

The results have various implications both for cost calculations and for estimating market values of used tractors. They are first illustrated by an example of cost calculation. We do not follow the separation into variable and fixed components proposed by Schroers et al. (2020). But this kind of separation is possible with the proposed model. A John Deere in the 176 kW power class is considered (the results are basically independent of the tractor model chosen here, the differences are considerably larger in the smaller power classes). A price of 120,000€ for a new tractor and 12 years of usage are assumed. Two cases are considered: in case 1 a utilization of 800 h/a and in case 2 of 400 h/a is assumed. Table 4 shows the average costs per hour due to the devaluation for the exponential model (2), the remaining value formula of the KTBL (4) and for a linear depreciation with a remaining value of 20%. In each case, the calculated remaining value at the end of the assumed usage was determined and the resulting loss divided by the total operating hours (9,600 h or 4,800 h). The calculated remaining values according to Schroers et al. (2020) (model 4) as well as the values of our proposed model (2) approach 20% of the new price when the utilization is close to the "utilization threshold" (cf. Figure 1). Therefore, the calculated remaining values and costs in case 1 are at roughly similar levels for all three methods. Considerable differences arise for case 2, which often occurs in practice as our data show. The calculated costs for the remaining value formula of the KTBL, but especially for model (2), are much lower than those for linear depreciation by years. For both alternative models (2 and 4), the remaining value turns out to be higher due to the lower utilization of 400 h/a. The evaluation of online advertisements confirms this; tractors with low annual usage achieve higher remaining values. Since only devaluation according to age leads to fixed costs, the effect of fixed cost degression decreases in comparison to linear depreciation, when taking into account the operating hours. With linear depreciation on a fixed remaining value of 20%, the costs per hour can be halved from 20€/h to 10€/h by doubling the utilization. Model (2) describes the remaining or market value of tractors more accurately (i.e., in this case, determining higher values) than linear approaches. In this example, the linear depreciation method overestimates the fixed cost degression. Therefore, it must be assumed that in agricultural practice the economic advantage of a higher utilization rate is lower than assumed by usual calculations with linear depreciation, because less heavily used machines can be sold at higher prices. This also means that farms that do not reach full capacity utilization can be economically more successful than assumed. In principle, this effect results from the devaluation with operating hours, as it is also presented in Schroers et al. (2020). They make the assumption that for a use at the "utilization threshold" half of the devaluation is attributable to the use in years and half to the operating hours. This assumption is not supported, at least for tractors, on the basis of our analyses. Our results lead to the suggestion that the loss in value due to the actual hours of operation accounts for the greater share in most cases.

Table 4: Devaluation costs and remaining value using the example of a John Deere tractor in the 176kW power class, new purchase and use for 12 years

	Exponential model with manufacturer influence (2)		**KTBL remaining value formula(4)**		**Linear depreciation, remaining value 20%**	
	Cost of devaluation per h	relative remaining value	Cost of devaluation per h	relative remaining value	Cost of devaluation per h	relative remaining value
Case 1: 800h/a	9,28€/h	25,8 %	9,87€/h	21,1 %	10,00€/h	20,0 %
Case 2: 400h/a	14,32€/h	42,7 %	16,49€/h	34,0 %	20,00€/h	20,0 %

Another phenomenon occurring in agricultural practice can be better explained with model (2) and its degressive course than with linear models: The purchase of used tractors. Consider the "John Deere" from case 2. The period of use is divided into two equal segments. The convex course of the remaining value development (Figure 1) results in different values for the average devaluation costs per hour. In the first six years, they amount to 17.28 €/h. In the following six years, they are only 11.36 €/h. These values make a second-hand purchase seem economically advantageous. It is difficult to explain this with uniform linear losses in value. Regarding the advantageousness of second-hand purchases, it should be noted that repair costs for tractors increase with increasing age and operating hours (cf. Morris 1988 and Calcante et al. 2013). The shorter period of use also shows a greater difference to the remaining value formula of the KTBL. While model (2) assigns the John Deere a percent remaining value of 65.4% after the first six years, the KTBL formula estimates a value of 54% (not shown in Table 4). In this example, this is a difference of over 13,500€ or 5.7 €/h, which means an increase in the loss of value per hour by one third. Based on the example calculation, it becomes clear when and for what purpose one should use the exact remaining value estimates as they are possible with the functions shown in this article. The remaining value formula of KTBL is good in calculation of average cost under the following conditions: power classes 138kW and above, useful life in the range expected by the KTBL and utilization at the utilization threshold. However, considerable distortions result for smaller power classes, for a shortened period of use or for a lower utilization rate. We therefore advocate that, at least in these cases, an individual residual value differentiated according to the intended period of use, intensity of use and manufacturer should be used in the operational cost calculation. The use of standard residual values of 20% or even zero should be avoided in farm cost accounting, apart from tax law. For this estimation of remaining values, but also for the estimation of market values, our estimation model (calculation example in the appendix) can be used.

However, we are not advocating the use of different devaluation costs for each year. Average costs should still be used. The KTBL remaining value formula offers advantages beyond the operational calculation, e.g. in model calculations. It provides a better description of devaluation costs than linear depreciation (Table 4) and, as our contribution shows, rightly takes into account devaluation by operating hours. Furthermore, this contribution shows that there are indeed close correlations between real prices and the remaining value formula (Table 3.) However, based on our results, the KTBL could consider adjusting the devaluation in the smaller power classes (67, 83 and presumably also 45 and 57kW) in order to reflect higher (more realistic) remaining values. For the estimation of current market values, the linear methods are less suitable and a differentiated estimation should be made.

Placement of the results within the literature

Although this article is different from previous publications due to the data basis of online advertisements and the focus on the German market, there are overlaps in the results with regard to devaluation differences of manufacturers and power classes. The fact that manufacturers have an influence on the remaining value of tractors has been noted in most of the previous publications on this topic. However, the value stability of manufactures in devaluation differs between the papers. In the present study, "John Deere" tractors are more stable in value than "Case" tractors in most power classes as measured by relative remaining value (Figure 1). Unterschultz and Mumey (1996) comparably show for the North American market in the years 1972 to 1992 that "Case" tractors depreciate more strongly with age than "John Deere" tractors. In the period from 1996 to 2016, the average devaluation of these two manufactures for the U.S. appears to be about the same (Daninger and Gunderson 2017). However, in the analyses of Fenollosa Ribera and Guadalajara Olmeda (2007) for Spain and Wilson (2010) for the UK, "Case" tractors are shown to be more stable in value than "John Deere" tractors. This is remarkable because in the previous analysis by Wilson and Tolley (2004) the relationship was reversed. In our article, Fendt tractors are shown to be relatively stable in value in most power classes. This tendency is equally found in Wilson and Tolley (2004) and Wilson (2010), but not in Fenollosa Ribera and Guadalajara Olmeda (2007). This underscores the need for up-to-date market-specific estimates such as those made in this article. This is especially true in the context of substantive differences between the recent analyses for Spain and the UK.

The observation that lower powered tractors lose value more slowly was also made by Perry et al. (1990) and Fenollosa Ribera and Guadalajara Olmeda (2007). The cubic model of Wilson (2010) suggests that this is not a monotonically decreasing relationship, but that tractors regain value stability above about 260 kW. Daninger and Gunderson (2017) differentiate this trend by age and hours of operation and find that the loss in value by hours increases steadily with increasing engine size, while it decreases with age from about 260 kW. Perry et al. (1990) suggest that larger tractors are more likely to be used on farms where downtime costs are higher. As a result, reliability matters more. Reliability decreases with length of use or age and justifies the valuation discount. Smaller tractors, on the other hand, are more likely to be used for less critical work in their view, so this aspect is less important. This paper can confirm these findings for the German market in 2020. The discount of about 30% between advertisements respectively sales offers and auction results determined in this study differs from the 10% assumed by Wilson and Tolley (2004). However, they only consider commercial dealers, some of whom are obliged to provide a warranty, which may justify a lower discount.

Discussion of the methodology

An alternative measure in model selection between transformations would have been the “mean absolute percentage error” (MAPE). This measure has been used in several of the articles cited here (Wilson 2010; Daninger and Gunderson 2017). The MAPE for fitting model (2) to the advertisements is 10.9% and for model (3) it is 11.4%. Hence the choice of model (2) would have been the same. In Daninger and Gunderson (2017), the logarithm transformation also shows a slightly lower value for the MAPE than the “double square root transformation” in a model with interaction terms for the power classes. In theory, MAPE values would be comparable across different studies (Wilson (2010) makes such comparisons). However, MAPE values vary according to how tightly the sample is delimited at the maximum age (Daninger and Gunderson 2017). The cutoff by age is not identical in the literature. Further, it is likely that our MAPE values, which are comparably good, stem in part from the fact that we did not aggregate manufacturers as much (Daninger and Gunderson (2017) aggregate all AGCO brands) or did not create an “other” category for manufacturers not explicitly considered, as Wilson (2010) did. Thus, we abstain from further comparisons. While MAPE values are more interpretable, the sum of squared deviations approach used here has the advantage of favoring transformations whose fitting produces fewer outliers. The article cannot show whether an exponential model is actually the best model form. A Box-Cox transformation could provide better fits, as addressed in the methods section. However, it would be more difficult to interpret and would make it more difficult to transfer the findings to farming practice and consulting. Therefore, exponential functions provide good and unbiased estimates of market values.

Since the advertisements were extracted on one day, they represent a temporary snapshot of the German tractor market. Although there are no distortions over time within the two auction years used for validation, this does not mean that the presented estimation parameters are time invariant. But the good fit to the auction results suggests that the functions represent the market well at this point in time. The estimates need to be updated periodically. The online advertisement based method presented here simplifies such updating. The time series-based estimation models cited above are no less subject to future market changes and would also need to be updated.

List prices were avoided as a reference because they do not represent actual new prices obtainable in the market. For example, Wilson and Tolley (2004) report discount margins up to 40% on the list price. These discounts can vary between manufacturers, creating a further distortion. Therefore, the model used implicitly estimates a new price with the parameter v. This approach of not using a list price at the same time makes it difficult to estimate a discount that could be linked to the start of use, as assumed by the KTBL.

The used advertisements could not be differentiated by warranty. Tractors with warranty could achieve a higher price, as this would reduce the expected values of repair costs in the warranty period and the buyers concern about hidden defects at the time of purchase. The likelihood of adverse selection decreases. Wilson and Tolley (2004) address this problem by considering only listings from commercial dealers. However, at least for the German market, this separation cannot be equated with a separation along warranty lines. This is because liability for material defects can be excluded between commercial market participants (such as farmers, contractors and dealers). Such an exclusion is also part of the model contract of “traktorpool.de” (Traktorpool.de 2016). However, it cannot be assumed that the results on manufacturer differences and non-linearity would be fundamentally different if warranty features could be taken into account. The correction factor would presumably be affected in particular. The results of Daninger and Gunderson (2017) show that the presence of a warranty has at best a very small positive effect on the price.

The shown manufacturer differences give rise to a follow-up research question, which is of great importance for manufacturers: Why do these differences exist and how can they be influenced? One possible answer would be that different repair cost curves between manufactures exist. Then the manufacturer influences shown here could indicate that the expected repair costs are priced into the second-hand market. This hypothesis is contradicted by the fact that farmers in Germany rate the repair and maintenance costs of “Fendt” tractors significantly worse than those of “Claas” tractors (Granoszewski and Spiller 2012), but “Fendt” tractors in most power classes show themselves to be more stable in value than those of “Claas” in this article. As an alternative explanation, brand image could positively influence market value and thus the remaining value development. Here, “John Deere” and “Fendt” perform better than “Claas”, at least for tractors (Granoszewski and Spiller 2012). Walley et al. (2007) conclude in a study with English farmers that manufacturer or brand has a greater influence on tractor purchase decisions than the price. Even if the reputation of the manufacturer has a significant influence on the market value, it would be important to quantify this influence and that of the repair costs.

Appendix

Calculation example:

John Deere tractor, power class 176kW, age 5 years, 4000 operating hours

$$Estimated\ remaining\ value = e^{v_{176,JD}} * e^{h_{176,JD}*4000} * e^{a_{176,JD}*5} * 0.699$$

$$65{,}650€ \approx e^{12.0152} * e^{-0.000105*4000} * e^{-0.029*5} * 0.699$$

Corresponds to a relative residual value of 56.8% compared to 52% in the KTBL formula, which in the present case represents a difference of about 5000€). If one has an actual purchase price, this replaces the first multiplier and the percentage discount for the advertisement (correction factor).

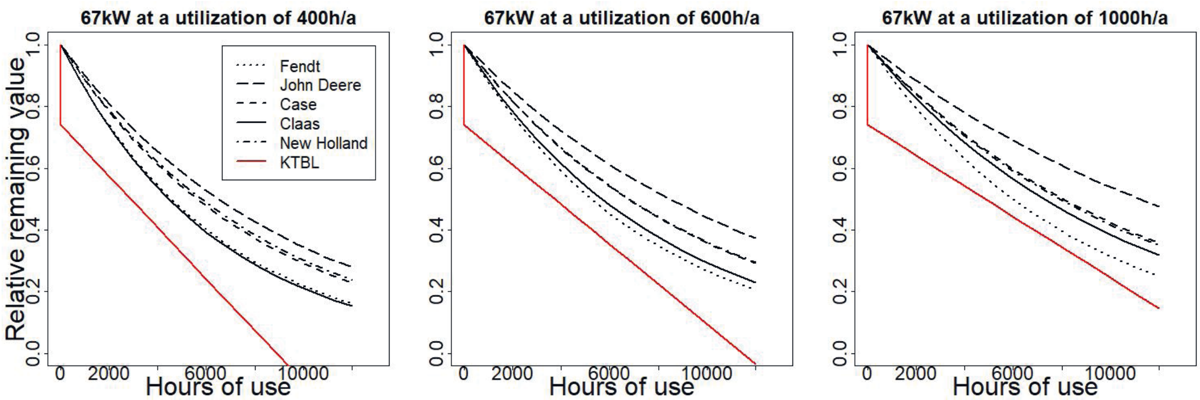

Figure A-1: Relative remaining value in the 67kW power class at different utilization rates

Table A-1: Regression results, robust standard errors and one-sided p-values (a = 0.05) for model (2)

Parameter	Predicted value	Robust standart Error	p-value (one-sided)
$v_{67,Case}$	10,8107	0,084962	1,1E-16
$v_{67Claas}$	10,9322	0,050695	1,1E-16
$v_{67,Fendt}$	11,3472	0,03684	1,1E-16
$v_{67,JD}$	10,9693	0,040809	1,1E-16
$v_{67,NH}$	10,7565	0,089213	1,1E-16
$h_{67,Case}$	-0,000061	1,84E-05	0,000464
$h_{67,Claas}$	-0,000055	1,29E-05	9,62E-06
$h_{67,Fendt}$	-0,000091	2,71E-05	0,000382
$h_{67,JD}$	-0,000032	8,78E-06	0,000127
$h_{67,NH}$	-0,000066	2,06E-05	0,000659
$a_{67,Case}$	-0,0250	0,007923	0,00082
$a_{67,Claas}$	-0,0402	0,007142	1,02E-08
$a_{67,Fendt}$	-0,0242	0,011425	0,01703
$a_{67,JD}$	-0,0298	0,004706	1,45E-10
$a_{67,NH}$	-0,0214	0,008625	0,006625
$v_{83,Case}$	11,0484	0,110642	1,1E-16
$v_{83,Claas}$	11,1272	0,059207	1,1E-16
$v_{83,Fendt}$	11,4141	0,024028	1,1E-16
$v_{83,JD}$	11,3206	0,029361	1,1E-16
$v_{83,NH}$	11,0061	0,065154	1,1E-16
$h_{83,Case}$	-0,000080	1,79E-05	3,76E-06
$h_{83,Claas}$	-0,000029	1,35E-05	0,017209
$h_{83,Fendt}$	-0,000087	1,14E-05	1,2E-14
$h_{83,JD}$	-0,000056	6,68E-06	7,1E-17
$h_{83,NH}$	-0,000075	1,19E-05	1,33E-10
$a_{83,Case}$	-0,0117	0,010802	0,139239
$a_{83,Claas}$	-0,0580	0,009607	8,73E-10
$a_{83,Fendt}$	-0,0097	0,005322	0,034237
$a_{83,JD}$	-0,0286	0,003594	1,38E-15
$a_{83,NH}$	-0,0202	0,007363	0,003018
$v_{102,Case}$	11,4573	0,035344	1,1E-16
$v_{102,Claas}$	11,3691	0,025841	1,1E-16
$v_{102,Fendt}$	11,5986	0,030435	1,1E-16
$v_{102,JD}$	11,5902	0,0257	1,1E-16
$v_{102,NH}$	11,3495	0,025937	1,1E-16
$h_{102,Case}$	-0,000081	1,27E-05	1,47E-10
$h_{102,Claas}$	-0,000061	1,15E-05	6,94E-08
$h_{102,Fendt}$	-0,000042	1,31E-05	0,000695
$h_{102,JD}$	-0,000072	7,29E-06	8,45E-23
$h_{102,NH}$	-0,000081	1,32E-05	5,98E-10
$a_{102,Case}$	-0,0341	0,006157	1,63E-08
$a_{102,Claas}$	-0,0501	0,006835	1,6E-13
$a_{102,Fendt}$	-0,0367	0,007894	1,72E-06
$a_{102,JD}$	-0,0328	0,004151	1,97E-15
$a_{102,NH}$	-0,0303	0,008322	0,000141
$v_{120,Case}$	11,442	0,072647	1,1E-16
$v_{120,Claas}$	11,5025	0,028862	1,1E-16
$v_{120,Fendt}$	11,8711	0,019091	1,1E-16
$v_{120,JD}$	11,7029	0,025617	1,1E-16
$v_{120,NH}$	11,4040	0,036275	1,1E-16
$h_{120,Case}$	-0,000087	9,31E-06	6,85E-21
$h_{120,Claas}$	-0,000078	8,5E-06	2,9E-20
$h_{120,Fendt}$	-0,000037	8,01E-06	2,74E-06
$h_{120,JD}$	-0,000078	1,03E-05	2,75E-14
$h_{120,NH}$	-0,000072	1,67E-05	9,66E-06
$a_{120,Case}$	-0,0275	0,005807	1,11E-06
$a_{120,Claas}$	-0,0452	0,005674	1,16E-15
$a_{120,Fendt}$	-0,0562	0,00533	8,36E-26
$a_{120,JD}$	-0,0294	0,007128	1,9E-05
$a_{120,NH}$	-0,0320	0,010049	0,000737
$v_{138,Case}$	11,6780	0,05047	1,1E-16
$v_{138,Claas}$	11,6553	0,02721	1,1E-16
$v_{138,Fendt}$	12,0264	0,030189	1,1E-16
$v_{138,JD}$	11,7738	0,033619	1,1E-16
$v_{138,NH}$	11,6516	0,048521	1,1E-16
$h_{138,Case}$	-0,000062	2,1E-05	0,001563
$h_{138,Claas}$	-0,000101	1,18E-05	1,03E-17
$h_{138,Fendt}$	-0,000072	7,73E-06	8,51E-21
$h_{138,JD}$	-0,000069	1,08E-05	9,35E-11
$h_{138,NH}$	-0,000069	1,23E-05	1,09E-08
$a_{138,Case}$	-0,0592	0,012308	7,85E-07
$a_{138,Claas}$	-0,0419	0,007528	1,43E-08
$a_{138,Fendt}$	-0,0407	0,005473	6,71E-14
$a_{138,JD}$	-0,0381	0,008963	1,12E-05
$a_{138,NH}$	-0,0511	0,008009	1,06E-10
$v_{157,Case}$	11,7939	0,041851	1,1E-16
$v_{157,Claas}$	11,8126	0,024412	1,1E-16
$v_{157,Fendt}$	11,9697	0,032951	1,1E-16
$v_{157,JD}$	11,9374	0,025654	1,1E-16
$v_{157,NH}$	11,7532	0,059893	1,1E-16
$h_{157,Case}$	-0,000060	1,24E-05	8,07E-07
$h_{157,Claas}$	-0,000079	1,07E-05	8,42E-14
$h_{157,Fendt}$	-0,000072	1,05E-05	3,81E-12
$h_{157,JD}$	-0,000099	8,15E-06	3,76E-33
$h_{157,NH}$	-0,000054	1,25E-05	7,71E-06
$a_{157,Case}$	-0,0678	0,013582	3,16E-07
$a_{157,Claas}$	-0,0740	0,007539	1,2E-22
$a_{157,Fendt}$	-0,0289	0,009147	0,00081
$a_{157,JD}$	-0,0275	0,007025	4,55E-05
$a_{157,NH}$	-0,0756	0,010884	2,45E-12
$v_{176,Case}$	11,8483	0,030456	1,1E-16
$v_{176,Claas}$	11,9880	0,042402	1,1E-16
$v_{176,Fendt}$	12,0523	0,01399	1,1E-16
$v_{176,JD}$	12,0152	0,042791	1,1E-16
$v_{176,NH}$	11,8617	0,054257	1,1E-16
$h_{176,Case}$	-0,000078	8,24E-06	3,55E-21
$h_{176,Claas}$	-0,000096	1,36E-05	1,05E-12
$h_{176,Fendt}$	-0,000069	6,31E-06	7,04E-28
$h_{176,JD}$	-0,000105	8,55E-06	2,9E-34
$h_{176,NH}$	-0,000088	8,46E-06	6,86E-25
$a_{176,Case}$	-0,0583	0,005165	4,01E-29
$a_{176,Claas}$	-0,076	0,012584	9,01E-10
$a_{176,Fendt}$	-0,0314	0,004552	3,31E-12
$a_{176,JD}$	-0,029	0,009706	0,001437
$a_{176,NH}$	-0,0593	0,009124	4,84E-11
$v_{200,Case}$	11,9187	0,060616	1,1E-16
$v_{200,Claas}$	12,0910	0,033793	1,1E-16
$v_{200,Fendt}$	12,1702	0,020477	1,1E-16
$v_{200,JD}$	12,0084	0,038797	1,1E-16
$v_{200,NH}$	11,9106	0,057126	1,1E-16
$h_{200,Case}$	-0,000145	2,12E-05	4,05E-12
$h_{200,Claas}$	-0,000088	1,68E-05	8,84E-08
$h_{200,Fendt}$	-0,000087	4,71E-06	2,47E-72
$h_{200,JD}$	-0,000075	9,9E-06	1,8E-14
$h_{200,NH}$	-0,000075	1,59E-05	1,44E-06
$a_{200,Case}$	-0,0078	0,019141	0,341114
$a_{200,Claas}$	-0,0893	0,012302	2,51E-13
$a_{200,Fendt}$	-0,0269	0,005484	5,07E-07
$a_{200,JD}$	-0,0461	0,005824	1,89E-15
$a_{200,NH}$	-0,0726	0,013789	7,58E-08
$v_{233,Case}$	12,0685	0,100539	1,1E-16
$v_{233,Claas}$	11,9076	0,053199	1,1E-16
$v_{233,Fendt}$	12,2975	0,030756	1,1E-16
$v_{233,JD}$	12,0871	0,032001	1,1E-16
$v_{233,NH}$	12,1221	0,038361	1,1E-16
$h_{233,Case}$	-0,000120	2,75E-05	6,36E-06
$h_{233,Claas}$	-0,000104	1,34E-05	5,96E-15
$h_{233,Fendt}$	-0,000095	7,64E-06	7,04E-35
$h_{233,JD}$	-0,000074	1,12E-05	1,65E-11
$h_{233,NH}$	-0,000080	3,62E-05	0,013657
$a_{233,Case}$	-0,0357	0,022239	0,054207
$a_{233,Claas}$	-0,0155	0,010175	0,064511
$a_{233,Fendt}$	-0,0282	0,007438	7,69E-05
$a_{233,JD}$	-0,0372	0,0069	3,92E-08

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