Market depreciation rates. A case study for construction machinery

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ABSTRACT

Depreciation of industrial and construction assets is a key accounting concept that helps organizations make decisions on asset replacement and tax management, while it also determines companies' operating margins significantly.

Today's increasing amount of market information allows us to analyze the behavior of the asking price as a function of the machine's age instead of applying the theoretical depreciation patterns provided by accounting.

By means of econometric methods, cross-validation, and bootstrap techniques, in this paper, we obtain depreciation models and rates for construction machinery and show the inadequacy of the predominant straight-line depreciation method.

Keywords

Cross-validation; OLS regression, construction machinery, depreciation, quantile regression, bootstrap

INTRODUCTION

The search for efficiency by companies may affect all the company's subsystems and, consequently, analytical accounting has great relevance for controlling a company's production structure and when establishing its operating, financial, and global margins (Fuentes, 1996). In this regard, Kachelmeier and Granof (1993) highlighted the effect of depreciation on the operating margin. They also considered that depreciation might serve as a cognitive reminder for decision-makers in governmental organizations of the need to replace long-lived assets as they deteriorate physically. Furthermore, together with net profit, they define the self-financing capacity of a company, and any change in depreciation may cause inverse effects on profit tax (Croitoru *et al.*, 2015). This implies that depreciation methods can influence the tax and financial performance of companies.

In the same way, Al-Chalabi *et al.* (2014) acknowledged that depreciation determines the appropriate investment policy for the company. Indeed, selecting the proper depreciation method is relevant in order to ensure that the equipment and machinery replacement takes place at the right time. Wrong decisions regarding the replacement of assets will increase operating and maintenance costs. Different authors, like Chisholm (1974), have analyzed the acknowledgment of machinery costs (through their depreciation). Chisholm proposed that an optimal policy would be to keep a machine until the marginal cost of maintaining it for a further year exceeded the amortized cost. Watts and Helmers (1981), for their part, argued that annual machinery cost estimates are useful when comparing different machine costs, for exploring alternatives regarding ownership, analyzing tradeoffs between labor and machinery, estimating the optimal machinery replacement time, or for making hedging decisions based on production costs.

The International Accounting Standard (IAS) No. 16 on Property, Plant, and Equipment (IASB, 2009) outlines the accounting treatment for most types of fixed assets. These assets are initially measured at their cost. Subsequently, they are measured using either a cost model or a revaluation one and then, they are depreciated so that their depreciable amount is allocated on a systematic basis over their useful life. According to this standard, the depreciation method used shall reflect the pattern in which the asset's future economic benefits are expected to be consumed by the entity. These methods include the straight-line method, the diminishing balance method, and the units of production method.

These methods do not reflect the market value neither the fair value as defined by the International Financial Reporting Standard No. 13 (IASB, 2012). Thus, we should take into account that depreciation methods were developed in times when information sources were scarce. Currently, a substantial amount of information on values and prices in secondary or second-hand markets is available. Despite this, depreciation accounting methods have not changed.

Notwithstanding the above, there is an extensive body of literature that studies the relationship between the market value of fixed assets and several explanatory variables. Table 1 synthesizes the relevant literature on this subject.

Author	**Year**	**Data sample**	**Data source**	**Variables**
Peacock and Brake	1970	2,521	*Official Tractor and Farm Equipment Guide (National Farm and Power Equipment Dealers Association NFPDA) and National Farm Tractor*	Age

Author	Year	Data sample	Data source	Variables
			and Implement Blue Book Evaluation Guide (National Market Reports Incorporated)	
McNeil	1979	32	*Dealers from the southern inland of British Columbia*	Age and state
Leatham and Baker	1981	2,538	*Official Guide: Tractors and Farm Equipment (NFPEDA)*	Age, power, motor type, traction, and manufacturer
Reid and Bradfor	1983	411	*National Farm and Power Equipment Dealers Association*	Age, power, manufacturer, increasing usage, and technological changes
Hansen and Lee	1991	1,612	*Official Guide: Tractors and Farm Equipment (NFPEDA)*	Age, year of manufacture, and purchase year
Cross and Perry	1995	n.a.	*Farm Equipment Guide. Auction sale prices reported by Hot Line Inc.*	Age, usage, manufacturer, care, type of auction, region, and macroeconomic variables
Arias	2001	1,211	Guía de Marketing Ocasión Maquinaria Agrícola (MOMA)	Horsepower and price
Dumler *et al.*	2003	n.a.	Purchase prices from Agricultural Prices (USDA, National Agricultural Statistics Service)	Age, inspection year, power, manufacturer, and depreciation method
Tozer	2006	183	Machinery dealer advertising prices for tractors and headers	Age and total hours
Fenollosa and Guadalajara	2007	n.a.	MOMA (intermediary) buying and selling tractors	Horsepower
Al-Chalabi *et al.*	2014	n.a.	Maximum computerized maintenance management system (CMMS)	Corrective and preventive maintenance costs, repair time, and optimal replacement time

Table 1. *Body of literature.*

From table 1, we can conclude that most of these studies deal with agricultural machinery and that there are at least two elements which can influence market depreciation: age, and wear and tear.

In this context, the main goal of this study is to find out whether the growing available information can help us provide depreciation patterns linked to the market. With this purpose, we have undertaken a case study on building machinery (heavy equipment).

The paper is structured as follows: in the next section, we describe the methods; then we develop the case study, which is followed by the main results; and finally, we discuss our findings and offer some conclusions.

MATERIALS AND METHODS

DATA COLLECTION

The construction industry relies heavily on the use of machinery. Particularly public construction companies routinely use complex machinery. The economic crisis affected the building industry deeply, which caused a significant underutilization of its production capacity. According to the Spanish Company Directory (DIRCE, 2018), the number of building companies decreased by 35.23% between 2008 and 2017. Due to this fact, the supply of used construction machinery in the market has increased, as well as the volume of information about that market. This large amount of information also makes it possible to develop models that explain how the asking price relates to some explaining variables such as age, brand, model, state of repair, etc.

The data for this case study was collected in June 2015 (cross-section analysis) from a website that buys and sells used construction machinery, www.europa-mop.com. The data include information on brand, model, asking price, accumulated working hours, age, as well as other descriptive information. With this study, we aim to estimate the depreciation market rate for six types of machinery and equipment commonly used in the construction industry:

Código de campo cambiado

a) Bulldozers
b) Compactors
c) Track excavators
d) Wheel excavators
e) Mini excavators
f) Graders

METHODS: MODEL DEVELOPMENT

After the data gathering, observations deemed outliers were removed so as to obtain a clean database. For each machinery type, we applied three ordinary least squares models to the data in order to find the best fit. Additionally, we used two complementary techniques: on the one hand, cross-validation in order to check for overfitting and, on the other hand, a quantile regression together with a bootstrap test to determine whether asking prices do influence depreciation rates. Figure 1 sums up the whole procedure.

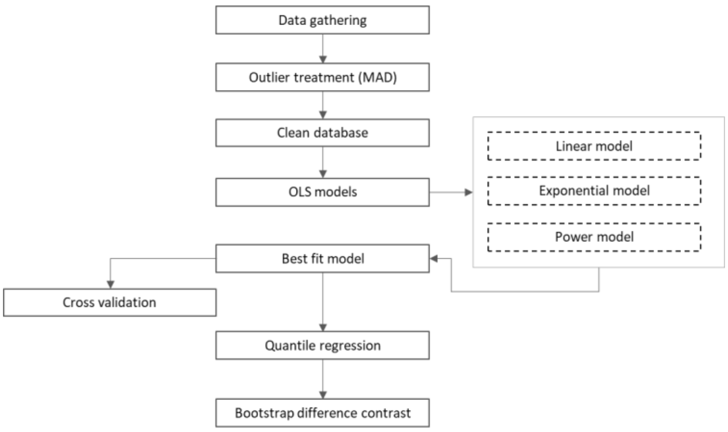

Figure 1. *Steps to obtain the depreciation coefficient.*

Outlier treatment

As McClelland (2000) stated, by means of exploratory data analysis, we can detect nasty and unruly data, which can be tamed by transforming it and deleting outliers. Failure to detect important assumption violations and outliers may mean that researchers report misleading conclusions about their data.

Hence, we applied an outlier detection technique to identify those machines with anomalous measurements. As Vakili and Schmitt (2014) pointed out, even a few outliers, if left unchecked, can exert a disproportionate pull on estimated parameters. In our analysis, the application of an automatic criterion for the purpose of detecting outliers and removing them has been deemed unavoidable. Researchers are quite used to detecting the presence of outliers by observing an interval spanning over the mean plus (minus) two or three standard deviations. However, Cosineau and Chartier (2010) and Leys *et al.* (2013) spotlighted the problems of using mean values as central tendency indicators: the first problem is that normality is assumed; the second one, that the mean and the standard deviation are greatly affected by outliers, and the third snag are some issues related to small samples.

As an alternative measure, we have used the absolute deviation around the median (MAD). This technique was (re-)discovered and popularized by Hampel (1974), who attributes the idea to Carl Friederich Gauss (1977-1855). Like the mean, the median (M) is a measure of central tendency but offers the advantage of hardly being affected by the presence of outliers.

Here, we calculated MAD by setting a threshold value of ± 3 times MAD, which is a conservative threshold, according to Miller (1991).

Ordinary Least Squares Models

As mentioned before, the use of regression models to study the behavior of variables explaining the value (asking price) is widely accepted, as well as for making predictions and estimations.

Depreciation patterns are mainly determined by both time and use (Perry *et al.,* 1990). In spite of this, most companies do not employ a depreciation system linked to the use of the asset but rather to its age. Moreover, tax regulations set limits on depreciation based on the asset's age. Because of this, we have chosen the age of the machine as the explaining variable for our model. We assume that the machine's age is a good proxy of the usage (accumulated working hours).

Thus, in this research, we do not analyze the potential impact of other variables used in the calculation of depreciation rates, such as brand, model, or other qualitative information,

First of all, we determine the endogenous variable *(V)* and the exogenous variables *(t)*. Our model is based on the relation of the asking price (exogenous variable) to the age of the machinery (endogenous variable). Therefore, it is not a valuation model since we do not use it to value an asset but rather to obtain the depreciation rate.

A linear regression model with one explanatory variable can be expressed as follows:

$$V = \alpha + \beta_1 \cdot t \quad (1)$$

With equation (1) we can obtain the model's coefficients (α and β) (De Carvalho *et al.*, 2017).

Furthermore, as Juen *et al.* (2014) indicate, in some cases, an exponential relationship can be found between *t* (age) and *V* (asking price):

$$\ln(V) = \beta \cdot t + \ln(\alpha) \qquad (2)$$

The predictive equation will be:

$$V = \alpha \cdot e^{\beta \cdot t} \qquad (3)$$

Other researchers like Pleijel (2004) use a logarithmic relationship:

$$V = \alpha \cdot t^{\beta} \quad (4)$$

Transforming (5), the following predictive equation may be obtained:

$$Ln\,(V) = Ln\,(\alpha) + \beta \cdot Ln\,(t) \quad (5)$$

In linear regressions, β is interpreted as an elasticity coefficient, and variations of 1% in *t* imply a change in *V* equal to β, whereas in exponential regressions, an increase in "t" of 1-unit will result in *V* being multiplied by e^{β}. Finally, power regressions can be interpreted as an expected percentage change in *V* when *t* increases by a certain percentage (Benoit, 2011).

Table 2 summarizes the valuation equations and the depreciation rates obtained.

Model	**Fitting equation**	**Transformed equation**	**Depreciation Rate**
Linear	$V = \alpha + \beta \cdot t$	$V = \alpha + \beta \cdot t$	$dr = \beta / \alpha$
Exponential (semilog)	$Ln\ V = Ln\ \alpha + \beta \cdot t$	$V = \alpha + e^{\beta \cdot t}$	$dr = e^{\beta}$
Power (log)	$Ln\ V = Ln\ \alpha + \beta \cdot Ln\ t$	$V = \alpha \cdot t^{\beta}$	$dr = \beta$

Table 2. *Depreciation models with their corresponding depreciation rates.*

Additionally, we have used two complementary techniques: cross-validation and quantile regression.

As the use of new data for model validation is frequently neither practical nor feasible, data splitting is regarded as an acceptable alternative, provided that the dataset is large enough (Kozak and Kozak, 2003). Cross-validation (CV) is a popular strategy for selecting an algorithm. The main idea behind CV is to split data, once or several times. Part of the data (the training sample) is used for training the model, while the remaining part (the testing sample) is used for validating the model (Arlot and Celisse, 2010).

On the other hand, quantile regression offers the possibility of creating different regression curves for different quantiles of the endogenous variable. In a valuation model, this technique can shed light on the effect of the asking price on the depreciation rate. That is to say, should we use the same depreciation rate for expensive machines than for cheap ones?

Quantile regression was initially proposed by Koenker and Bassett (1978). This regression approach shows two advantages over classic regression models by OLS. On the one hand, it allows us to obtain a more complete view of the effects of the exogenous variables *(t)* on the endogenous variable *(V)*. The parameters of the quantile regression capture the change that occurs in the endogenous variable as a consequence of a variation in one unit of the exogenous variable, for each quantile. According to Zhike and Ting (2016), quantile regression is more robust to non-normal errors and outliers than OLS regression is. To check the existence of statistical differences between the quantiles, we used a bootstrap approach. The concept of *bootstrap* was first proposed by Efron (1979, 1982), who called it a "resampling" procedure, which involves repeatedly drawing samples from a training set and refitting a model of interest for each sample. Giménez-Nadal *et al.* (2019) conclude that bootstrap techniques can be used for three purposes: (i) computing standard deviations of quantities of interest in difficult or complex situations; (ii) quantifying the uncertainty associated with a given estimator, and, related to this end, (iii) improving statistical learning methods (Efron and Gong 1983).

RESULTS

After using the MAD technique to be able to remove the outliers, the three main depreciation models have been applied to each machine type. Table 3 shows how the outlier cleaning reduces the sample size. The drop in the sample size is considerable, especially for graders and bulldozers, since these types of machinery are more heterogeneous, which leads to higher variability.

Machine type	**No. of initial observations**	**No. of observations after MAD**	**% final data / total data**
Bulldozers	1,010	727	71.98%
Compactors	678	523	77.14%
Crawler excavators	1,859	1,681	90.42%
Graders	332	209	62.95%
Mini excavators	885	795	89.83%
Wheel excavators	451	407	90.24%

Table 3. *Sample observations*

Tables 4, 5, and 6 present the main coefficients of the fitting for each model, together with the determination coefficient. As expected, all beta coefficients are negative, and most of them are statistically significant. This means that the variability in values may be partly due to the age of the machine.

	Linear Model (Model 1)			
Asset	**a**	**β**	**R^2**	**β Significance**
Bulldozer	54,978.10	-1,130.02	0.2118	***
Compactor	15,693.39	-107.95	0.0105	*
Crawler excavators	64,428.40	-2,210.86	0.2955	***
Graders	68,367.34	-1,110.17	0.2058	***
Mini excavators	24,065.64	-919.94	0.1956	***
Wheel excavators	52,413.43	-1,841.72	0.5145	***

Table 4. Linear regression coefficients (Model 1).

β significance [p-value] (0 < *** < 0.001 < ** < 0.01 < * < 0.05 < '.' < 0.1 < ' ' < 1) indicates the probability of rejecting the null hypothesis when it is true.

	Exponential Model (Model 2)			
Asset	**a**	**β**	**R^2**	**β Significance**
Bulldozer	10.92	-0.0329	0.2433	***
Compactor	9.50	-0.0098	0.0181	**
Crawler excavators	11.11	-0.0574	0.3182	***
Graders	11.12	-0.0281	0.1970	***
Mini excavators	10.08	-0.0552	0.2205	***
Wheel excavators	11.10	-0.0753	0.6163	***

Table 5. Exponential regression coefficients (Model 2).

β significance [p-value] (0 < *** < 0.001 < ** < 0.01 < * < 0.05 < ¨¨ < 0.1 < ¨ < 1) indicates the probability of rejecting the null hypothesis when it is true.

	Power Model (Model 3)			
Asset	**a**	**β**	**R^2**	**β Significance**
Bulldozer	11.30	-0.3338	0.1859	***
Compactor	9.82	-0.1876	0.0322	***
Crawler excavators	11.64	-0.5079	0.3179	***
Graders	11.30	-0.2525	0.1514	***
Mini excavators	10.29	-0.3299	0.2012	***
Wheel excavators	12.35	-0.9044	0.5475	***

Table 6. Power regression coefficients (Model 3).

β significance [p-value] (0 < *** < 0.001 < ** < 0.01 < * < 0.05 < ¨¨ < 0.1 < ¨ < 1) indicates the probability of rejecting the null hypothesis when it is true.

Almost all machinery types and models show a good β level of significance. Only compactors, in the linear and exponential model, reflect a β significance level between 0.01 and 0.05, and 0.001 and 0.01, respectively.

R^2 shows how well terms (data points) fit a curve or a line.

Next, we ranked the machine types and models according to their R^2 values and classified them as with three “+++”, two “++”, and one “+” signs.

Table 7 provides information about the determination coefficient for each model and machine type in a synthetic way. The exponential and power models obtain slightly higher R^2 scores than the linear one. As regards to the machine type, the variability in the values of wheel excavators can be explained by their age much better than with the rest of the machines. The explanation power of the models shows that there can be other important variables that have been left out in the analysis.

Machine type	M1	M2	M3
Bulldozer	++	+++	+
Compactor	+	++	+++
Crawler excavators	+	+++	++
Graders	+++	++	+
Mini excavators	+	+++	++
Wheel excavators	+	+++	++

Table 7. Comparison of R^2 values by model and machine type.

For each model and machine type, table 8 shows the depreciation rate, as defined in table 2.

Machine type	**Model 1**	**Model 2**	**Model 3**
Bulldozer	-0.0206	0.9677	-0.3338
Compactor	-0.0069	0.9903	-0.1876
Crawler excavators	-0.0343	0.9442	-0.5079
Graders	-0.0162	0.9723	-0.2525
Mini excavators	-0.0382	0.9463	-0.3299
Wheel excavators	-0.0351	0.9275	-0.9044

Table 8. Depreciation rate from OLS estimation.

The depreciation coefficients show the rate of capital consumption for each model. Machines that suffer from a higher wear and tear, such as excavators, have a higher depreciation rate and consequently, a shorter operating life. In the first years of a machine's life, values drop quickly with the exponential and power models. Later on, their curves soften, whereas the value decline of the linear model is constant. Figure 2 shows the graphical fitting of the models for each type of machine.

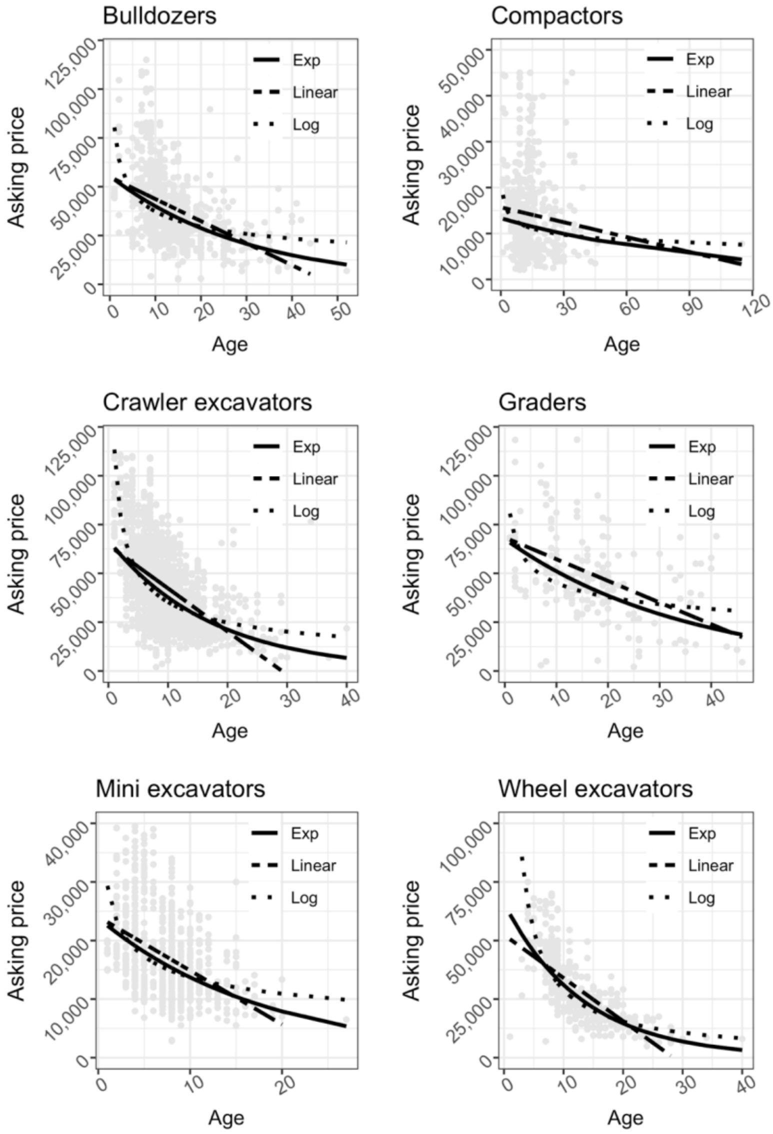

Figure 2. Graphical fitting by machine type and regression model.

The use of the regression models raises two questions concerning the robustness of the results. The first question is: Is there any sample selection bias that could influence the coefficients? And the second question is: Are depreciation rates influenced by the asking price? To answer these two questions, we considered observations from the wheel excavator market since the best predictive model (the exponential one) was obtained for that particular market.

To establish the existence of any bias in the sample selection, we applied cross-validation techniques. We split the clean sample into two subsamples, a training set, and a testing set. The size of the training set was fixed as a percentage of the total sample. This percentage varied from 10% to 90%, with 10%-increase steps in order to check the effect of the training set size on the results. For each subsample size combination (e.g., 10-90, 20-80, …), the depreciation rate was obtained 10,000 times for both sets, and the relative difference between the depreciation rates was computed and plotted (figure 3). As the null difference is always within the frequency distributions, no significant differences were found. This means that the model is not affected by the sample selection.

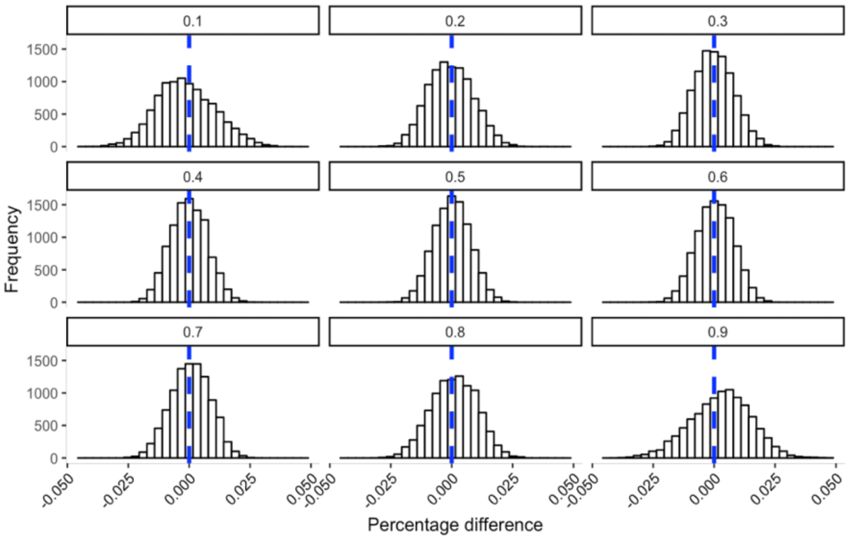

Figure 3. Distribution of the relative difference of the depreciation rate of the training and testing set as a function of the training set partition (0.1 – 0.9).

To answer the second question, we resort to quantile regression. With the help of this regression analysis, we can assess whether the depreciation rate can change as a function of the asking price level. Five quantiles of the asking price are used (τ = 0.2, 0.4, 0.5, 0.6, 0.8). When τ = 0.2, the wheel excavators with the lower asking price are considered, whereas if τ = 0.8, the analysis is carried out with the expensive ones.

Table 9 gathers the regression coefficients, the depreciation rate, and the coefficient of determination. The coefficient of determination is computed following Koenker and Machado's (1999) procedure, and it is termed "pseudo-R^2", as it is not a real R^2. Comparison between R^2 (from OLS) and pseudo-R^2 is not possible (Vicéns and Medina, 2011).

Variable	τ = 0.2	τ = 0.4	τ = 0.5	τ = 0.6	τ = 0.8
α	10,9097	11,1602	11,2029	11,2541	11,3124
β	-0,0785	-0,0855	-0,0828	-0,0810	-0,0693
Dep rate	**0.9245**	**0.9181**	**0.9205**	**0.9222**	**0.9330**
pseudo-R^2	**0,4275**	**0,4314**	**0,4223**	**0,4048**	**0,3752**

Table 9. Exponential quantile regression for wheel excavators. Coefficients

In figure 4, the exponential model is exhibited for each τ using the expression of the adjusted equation from table 2. In this way, we can test whether there are significant differences in the depreciation rate for each τ level. By using quantile regression with 10,000 bootstrap iterations for each τ level, the empirical distribution of the depreciation rate can be obtained (figure 5).

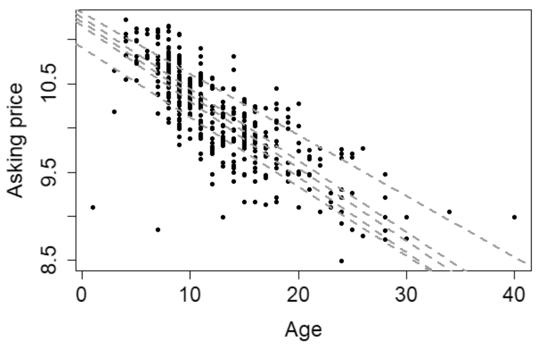

Figure 4. Quantile regression fitting for wheel excavators. τ = 0.2, 0.4, 0.5, 0.6, 0.8

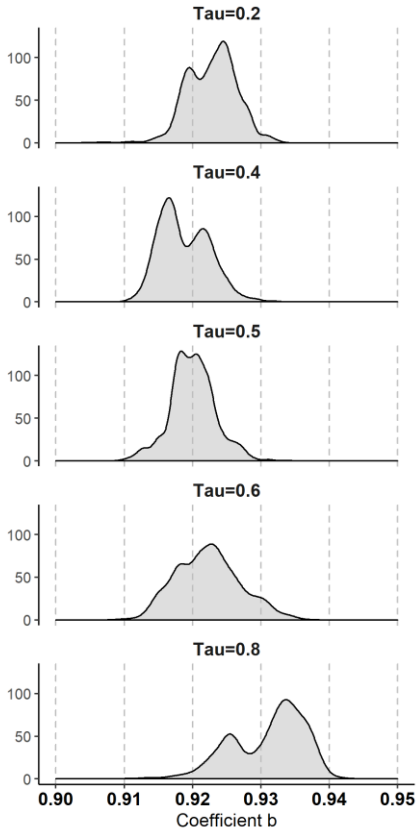

Figure 5. Density distribution of the depreciation rate for wheel excavators using the exponential model for different τ

A pair-wise comparison between τ levels is undertaken (figure 6) by subtracting the empirical distributions. By holding the difference in the beta coefficient constant at a value of zero, the existence of statistical significance can be checked. There is no significant difference between the depreciation rates for τ = 0.2, 0.4, 0.5, and 0.6. However, for τ = 0.8, significant differences at 0.05 level with τ = 0.4, 0.5 and 0.6 are found. This means that expensive machines show statistically different depreciation rates, whereas no differences are found among the rest of the asking price levels.

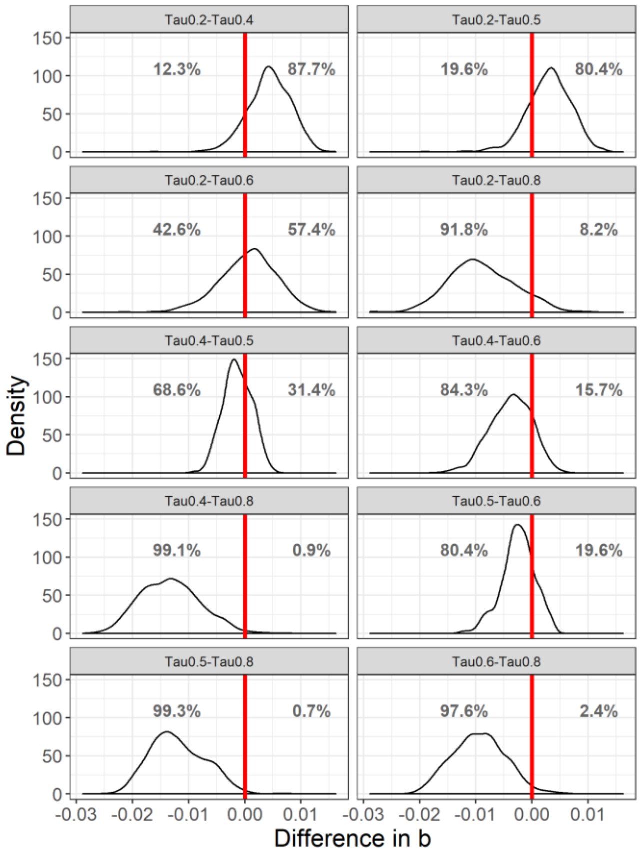

Figure 6. *Differences in the depreciation rate distributions for wheel excavators*

The interpretation of the difference in the depreciation rates for the τ levels is straightforward: quantiles 0.2 to 0.6 have a higher capital consumption rate than the expensive machines quantile (0.8), which means that expensive wheel excavators depreciate at a slower rate than the rest.

CONCLUSIONS

Greater data availability has allowed us to review the depreciation behavior of certain fixed assets. Our results on construction machinery show its depreciation pattern according to the market.

Since accounting depreciation methods are fundamentally based on age, we have used machine age as the main explanatory variable. The results show that diminishing balance methods fit market depreciation better than the straight-line method. However, although accounting standards consider diminishing balance methods more appropriate (such as the well-known declining balance method of depreciation, IAS 16 (2009), property, plant and equipment), companies usually rely on the straight-line method. With the diminishing balance types of method, the annual depreciation is higher at the beginning.

A quantile regression together with bootstrap sampling can improve knowledge of the rates of capital consumption for a given industry considering different price ranges (cheap equipment vs. expensive equipment). The results for wheel excavators show that expensive machines maintain their value for a longer period than those machines purchased at more economical prices.

This line of research can be further developed by extending the study framework, not only considering the machines' age, as in accounting, but adding other explanatory variables, such as brand or model. Furthermore, it can be extended to other industries or assets, and within the same industry, it could be repeated with a different cross-section, in order to check the stability of the results.

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