Modeling the depreciation rate of construction machinery. An Ordinary Least-Squares approach and quantile regression.

David Postiguillo, Ana Blasco and Fco. Javier Ribal
[a]Department of Economics and Social Science, Universitat Politècnica de València, Valencia,Spain.

Abstract
The development of information and communication technologies has had an impact on the economic, political, social and cultural perspectives. After the world economic crisis and subsequent recession, several economic sectors have decreased their activity profoundly. In Spain, the construction industry has been the most affected by the economic crisis. As a consequence of the decrease in the public construction, part of the machinery used in that activity has been put on sale in the secondary market. Currently, a large amount of information is available on the internet, which allows studying the behavior of the price (endogenous variable) of these assets based on several variables (exogenous variable). This research uses ordinary least-squares regression from three perspectives, linear, exponential and power. The main goal is to determine the depreciation rate at which these assets are depreciated as a function of their age, that is, it relates the asking price in the secondary market with the machine age. Furthermore, this research shows the difference between each level of asking price and its depreciation rate for each group of assets. This relationship is the first basic parameter of the depreciation of a productive asset. Finally, these rates are contrasted with the minimum and maximum percentages proposed by the accounting regulations in Spain.

Keywords: *quantile regression, MAD, depreciation, machinery, construction.*

1. Introduction

The variety of construction machinery that is commercialized at the moment is extensive. In general terms, different asset families are established to carry out the analisys: machinery used for earthmoving, excavation and thrust, excavation and loading, loading and hauling, compaction and hoisting machinery.

The economic crisis has deeply affected the construction sector, and consequently public construction. This caused a downturn in the demand of this type of services, and led to an underutilization of the productive capacity of the sector. According to the Central Business Directory of Spain (CBDS) from 2008 to 2016 the construction sector has decreased by-34.63%. The cessation/stoppage of activity of a large part of the companies in the industry entailed the liquidation of their assets, and this caused a decrease of the market prices of public construction machinery. Its supply in the secondary market increased sharply while the demand was reduced or almost disappeared.

The mechanization of the construction industry has allowed gaining competitiveness, reducing production costs and increasingearnings. Labor costs have been gradually reduced, nevertheless, machinery costs have been increased, particularly due to the evolution of fuel prices, insurance, repairs, maintenance and depreciation. The depreciation methods legally established and accepted by the accounting principles are theoretical models. Nevertheless, these models do not assure the real imputation of the depreciation that the assets have suffered.

In the United States there are several studies that show this situation, as reflected by Peacock and Brake (1970), McNeil (1979), Leatham and Baker (1981), Reid and Bradfrod (1983), Perry et al. (1990), Hansen and Lee (1991), Cross and Perry (1995) and Unterschultz and Mumey (1996). Some of them used regression methods to estimate the residual value of the machinery taking into account variables such as age and technical characteristics. In Spain, some studies have also been developed, as shown by Fenollosa and Guadalajara (2007), in the case of the agricultural machinery industry.

The extensive number of machines in the market together with the growing data availability on the internet makes it possible to study the machinery depreciation with samples larger than ever. Therefore the main goal of the study is to determine empirical depreciation rates and models for construction machinery.

2. Methodology

2.1. Data Gathering

The information to carry out this study has been obtained by means of web-scraping techniques. Specifically, sale listings of used construction machinery in Spain where gathered from www.europa-mop.com on Agust, 2015.

For each machinery type the listings provided some descriptive information (brand and model of the asset, location and other secondary information), machine age, operation hours and sale price (asking price).

For this research the information of operating hours has been deemed insufficient since many of the sale references do not provide it. Furthermore the accounting systems implemented in Spanish Small and Mediums Enterprises (SMEs) do not track the number of operating hours of their machines. Thus, it is difficult to apply a depreciation coefficient as a function of the number of operating hours.

The research focuses on the analysis of the following groups of assets: *a) Bulldozers, b) Compactors, c) Track excavators, d) Wheel excavators, e) Mini excavators, f) Graders*

2.2. Regression models

This research focuses on analyzing the relationship between the age of the machines from several groups of assets and their market price. To do this a regression model, based on ordinary least squares, is proposed.

The general expression of a regression model for a total of k explanatory variables is:

$$Y = a + b_1 \cdot x_1 + b_2 \cdot x_2 + \cdots + b_n \cdot x_n + U \qquad [1]$$

Where 'Y' is the endogenous variable, 'x_i'are the exogenous variables, and the parameters 'b_i'are parameters that quantify the relationship between the endogenous variable and each exogenous variable, 'a' represents de interception in the regression model and 'U' is the model's error.

In this case, the model is based on relating the asking price (exogenous variable) with the age of the machine (endogenous variable). It is not a valuation model since is not used to value but to obtain the depreciation rate. Three diferents approaches have been developed in order to determine the depreciation rate following models from literature.

The model uses asking price as the endogenous variable since sale listings are the main data source. However, the goal of the research is to model depreciation which should be related with market value. Therefore the asking price is used as the best proxy of market value although some bargaining discounts can be expected, Peña (2000).

In some cases, a exponential relationship can be found between t (*age*) and V (*asking price*):

$$V = a \cdot e^{bt} \qquad [3]$$

By applying the neperian logarithm, equation [3] can be linearized:

$$Ln(V) = b \cdot t + \ln(a) \qquad [4]$$

Finally, he relation between t (*age*) and V (*asking price*) can be logarithmic.

$$V = a \cdot t^b \qquad [5]$$

it can be transformed into:

$$\log(V) = b \cdot \log(t) + \log(a) \qquad [6]$$

2.3. Quantile regression

Since the data sample are made of machine types each sample includes different brands and models which brand new price can be totally different. This fact raises the question whether expensive and economical machines should use the same depreciation rate. That is to say, is the depreciation behavior the same within each machinery group?

To answer this question quantile regression will be used. The quantile regression offers the possibility of creating different regression lines for different quantile levels for the dependent variables. For this research sample, the relationship between quantile machinery prices and age could be worked out. Koenker and Basset (1978) explain that quantile regression is suited for those cases of heteroscedasticy, presence of outliers or structural change.

In order to determine the coefficient of determination of each quantile the Pseudo-R or R_1 has been used (Koenker and Machado, 1999).

2.4. Outliers treatment. Median Absolute Deviation (MAD)

In a database obtained from public sale listings errors, mistakes and non-realistic values are bound to exist. Therefore an strategy to deal with outliers is needed. Considering the number of machine groups and the number of machines in each group an automated strategy has been applied.

Specifically, the median absolute deviation (MAD) has been used. The MAD relies on the use of the deviations around the median. The median (M) is, like the average, a measure of the central tendency but offers and advantage, it is less sensitive to the presence of outliers. An example of this lack of sensitivity would be the "breaking point" (Donoho & Huber, 1983). MAD would be defined, according to Huber (1981) as:

$$\mathrm{MAD} = \mathrm{b}\ \mathrm{M_i}\left(\left|\mathrm{x_i} - \mathrm{M_j}\left(\mathrm{x_j}\right)\right|\right) \qquad [7]$$

Where xj is the original number of observations and Mi is the median of the series. The parameter b = 1.4826 is usually a constant, assumed from the normality of the data, against the abnormality induced by the outliers (Rousseeuw&Croux, 1993). The MAD has been applied recursively to each machine group until no outlier is found.

3. Results

The R programming language has been used for processing and modeling. Table 1 summarizes the coefficients obtained by applying the least-squares regression models in their linear, exponential and potential approaches. The column 'n0' expresses the number of initial data for each group of assets. Nevertheless, when outlier data are detected, MAD technique is used to remove them. In this way, the variable 'n1' provides the information corresponding to the final data for each group.

Table 1. Summary of statistical parameters.

			OLS Linear Model (M1)		
Type of asset	**n0**	**n1**	**Coef. A**	**Coef. B**	**R^2**
Wheel excavators	451	407	52,413.43	-1,841.7224	0.5145

			OLS Exponential Model (M2)		
Type of asset	**n0**	**n1**	**Coef. A**	**Coef. B**	**R^2**
Wheel excavators	451	407	1,109.69	-0.0753	0.6163

			OLS Power Model (M3)		

Type of asset	n0	n1	Coef. A	Coef. B	R^2
Wheel excavators	451	407	1,235.30	-0.9044	0.5475

Among the three linear least squares regression models, Linear (Model 1), Exponential (Model 2) and Power (Model 3), Model 2 shows the higher R^2 coefficient for any type of productive assets. Compactors are the only exception, Model 2 offers an R^2 of 0.0181, while Model 3 equals 0.0322. Nevertheless, in both cases, this R^2 indicates that the model does not have a significant goodness-of-fit.

The R^2 explains how much of the variability of a factor can be caused or explained by its relationship to another factor, i.e. the quality of the model when calculating the value of the type of productive asset as a function of the explanatory variable (age). Compactors have a low R^2, in all of the three models proposed. This implies that the explanatory variable ‘age’ is not representative to determine the price of this type of assets.The closer to 1 is, the greater the adjustment, and therefore the less possibility that there are significant devaitions between the calculated value and the value that can be found in the market.

At this point it should be noted that the purpose of this research is not to establish a model to carry out the valuation of productive assets. On the other hand, the market depreciation rate is analyzed in order to determine the rates of depreciation according to the market behavior and to compare it with the coefficients established by official bodies (such as the Public Finance). Developing this study we can observe that Model 2, exponential regression, has the highest R^2, which belongs to the group of Wheel Excavators (R^2 = 61.63%).

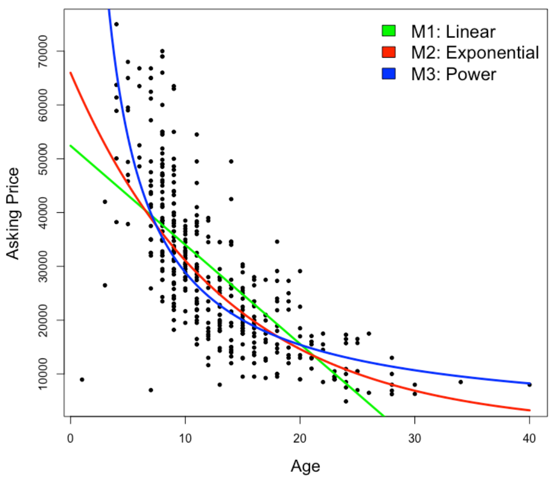

Figure 1. Regression models f(Price, Age) Wheel Excavators. R software.

The exponential model presents a path of productive assets subject to accelerated depreciation, greater depreciation in the initial stage of the asset’s useful life, and then a moderate depreciation rate. For the first years, the exponential model slope is less steeper than the potential model one (see Figure 1). The R^2 of Model 3 is 54.71%. Thus, we proceed with the calculation and presentation of the depreciation coefficients for each asset group based on the three models analyzed (Table 2).

Table 2. Summary of depreciation coefficients.

	Model 1. Linear	Model 2. Exponential	Model 3. Power
Wheel excavators	-0.035	0.927	-0.904

In Model 1, it can be seen that for all asset groups, the depreciation rate goes from 0.7% (compactors) to 3.8% (mini excavators) following a straight-line. Wheel Excavators would depreciate at 3.5% annual rate. That is, they would have a maximum useful life of approximately 28 years.

Through Model 2, it can be concluded that the assets with the highest depreciation coefficient are the ones corresponding to the excavators (track, wheels and mini excavators). Compactors would have a longer lifespan. In general, the exponential regression exhibits a higher depreciation in the first years; and a milder depreciation in the medium/long term. E.g., in the fifth year the Wheel Excavators have been depreciated by 31.38% of their market value. By age 28, the accumulated depreciation reaches 89.56%.

Finally, Model 3 shows the extremely fast depreciaton of the assets in the first years. Wheel Excavators value would deteriorate by almost 76.67% in five years of use.

According to the Spanish corporate tax regulation machinery should be depreciated by means of straight-line method with a depreciation rate within in the range 5.55% - 12%. The secondary market, on the other hand, implicitly recognizes that these productive assets have a longer life than the legal or accounting life. This extension of the useful life is determined by updates and maintenance, which improves and increases the state of conservation of the machinery. There are several variables from which regression analysis can be established (brand, model, hours of operation, etc.), however, the approach developed in this study aims to establish a basic depreciation rate, based on the age of the assets.

These coefficients would apply to all assets of the same typology, nevertheless, there may be a difference in the behavior of the depreciation rate as a function of the value of the assets.

Thus, by applying the quantile regression on the exponential model for the "Wheel excavator", the realized quantile partition is shown in Figure 2.

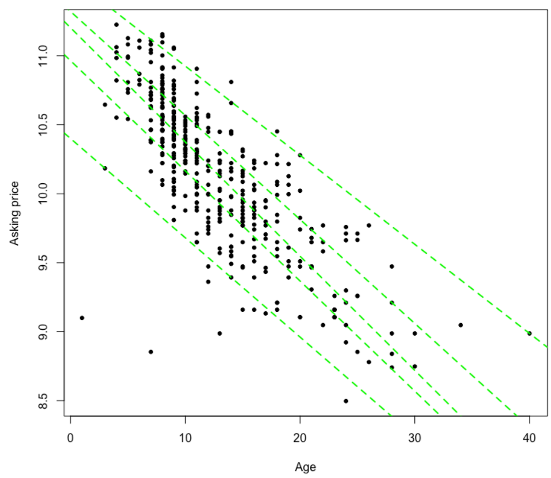

Figure 2. Quantile exponential regression model f(Price, Age) Wheel Excavators. R software.

Results show that the depreciation rate is in the range 0.92 – 0.94 for all the quantiles. This means that in 30 years the residual value would be in the 9 – 14.5 %.

In other words, the cheapest Wheel excavators have a slower rate of depreciation.

Table 3. Depreciation coefficients by quantile regression (Exponential model).

		tau= 0.025	tau= 0.25	tau= 0.50	tau= 0.75	tau= 0.975
Wheel excavators	Dep. rate	0.93058421	0.923259251	0.920539692	0.927396572	0.937452789
	Pseudo R2	9.95%	34.07%	43.08%	42.23%	37.62%

The same quantile analysis has been carried out for the rest of the machinery groups. In all of them the depreciation rates are not affected by the machine asking price.

4. Conclusions

This study allows two main conclusion to be drawn:

- The data availabitily in the machinery secondary market makes possible to determine that these machines do not follow a straight line depreciation. The best fit is reached by means of an exponential or semi-log relationship. This relationship implies that the depreciaton is higher in the early years.
- Economical machines do not depreciate differently than expensive machines.

This work makes up a good example of how the increasing Internet information can help to improve anlysis and decisions in business environments. It also highlights the differences between fiscal and accounting regulations, and market behavior.

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