A Statistical Analysis and Model of the Residual Value of Different Types of Heavy Construction Equipment

by

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Abstract

Residual value is defined as the price for which a used piece of equipment can be sold in the market at a particular time. It is an important element of the owning costs of equipment and needs to be estimated by equipment managers for making investment decisions.

The purpose of this study is to gain insights into the residual value of selected groups of heavy construction equipment and to develop a mathematical model for its prediction. Auction sales data were collected from two online databases. Manufacturer publications and an online source provided size parameters and manufacturers suggested retail prices matching the auction records. Macroeconomic indicator values were collected from a variety of sources, including government agencies. The data were brought into the same electronic format and were matched by model name and calendar date, respectively.

Data from auctions in the U.S. and in Canada were considered for this study. Equipment from four principal manufacturers of up to 15 years of age at the time of sale was included. A total of 35,542 entries were grouped into 11 different equipment types and 28 categories by size as measured by horse power, standard operating weight, or bucket volume. Equipment types considered were track and wheel excavators, wheel and track loaders, backhoe loaders, integrated toolcarriers, rigid frame and articulated trucks, track dozers, motor graders, and wheel tractor scrapers.

Multiple linear regression analyses of the 28 datasets were carried out after outliers had been deleted. Explanatory variables for the regression model were age in years, the indicator variables manufacturer, condition rating, and geographic region, and selected macroeconomic indicators. The response variable was residual value percent, defined as auction price divided by manufacturers suggested retail price. Different first, second, and third-order polynomial models and exponential and logarithmic models of age were examined. A second-order polynomial was selected from these functional forms based on the adjusted coefficient of determination. Coefficients for the 28 models and related statistics were tabulated. A spreadsheet tool incorporating the final regression model and its coefficients was developed. It allows performing the residual value prediction in an interactive and intuitive manner.

For my family

and my friends

Disclaimer: Mention of trade names is solely to provide information for the reader and does not constitute endorsement of their products.

Engineering is the professional art of applying science to the optimum conversion of natural resources to the benefit of man.

—Ralph J. Smith
1962

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I am proud of having had the opportunity of being a student of Virginia Tech and experiencing the truly unique spirit and enthusiasm of this university.

—*Go Hokies!*

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Symbols and Units

C	= regression coefficient for condition rating indicator variable
C	= Mallow's C_p statistic
CY	= cubic yard
c	= condition rating indicator variable
d	= difference of the sample
E	= regression coefficient for economic indicators
e	= economic indicator
F	= F-test statistic
f	= inflation rate
gal	= gallon
H	= hypothesis
HP	= horse power
h	= hour
i	= interest rate
K	= adjustment factor for residual value
k	= number of explanatory variables
lbs	= pounds
M	= regression coefficient for manufacturer indicator variable
MB	= mega byte
m	= manufacturer indicator variable
n	= number of complete observations
p	= number of parameters estimated for regression model
p	= p-value
R	= Pearson coefficient of correlation of the sample
R	= regression coefficient for auction region indicator variable
R^2	= coefficient of determination of the sample
r	= auction region indicator variable
r	= studentized residual
S	= sum of squares
T	= time period
t	= Student's t-test statistic
t	= time
X	= matrix of explanatory (independent) variables
x	= explanatory (independent) variable
y	= response (dependent) variable
yr	= year
z	= Fisher's z-test statistic
α	= significance level, probability of Type I error
β	= regression coefficient

ε = error term, random noise
μ = mean of the population
θ = non-linear regression parameter
ρ = correlation coefficient of the population
σ = standard deviation of the population
σ^2 = variance of the population
0, 1 = binary variables (no, yes)
a* = transformed value
$\bar{a}$ = arithmetic mean value
$\hat{a}$ = estimated value
$\tilde{a}$ = vector
E(•) = expected value of
f(•) = function of

Subscripts

adj = adjusted
b = index of best model
corr = correlation
diff = difference
e = subscript of natural logarithm, Euler's number
err = error
full = full model
G = generation
i = index number
j = index of regression model
k = number of explanatory variables
mod = model
obs = observed, subscript of test statistic
p = subscript of Mallow's C_p statistic
red = reduced model
reg = regression
res = residual
t = index of trade journal model
tot = total
xx = index of corrected sum of squares for cross product of x and x
xy = index of corrected sum of squares for cross product of x and y
0 = index of null hypothesis
1 = index of alternative hypothesis
0, 1, 2 = time sequence, index number

Abbreviations

AGE = column heading for age

ANOVA	= analysis of variance
AP	= column heading for auction price
ART	= articulated trucks
BCI	= building cost index
BHL	= backhoe loaders
Bil.	= billion
CCI	= construction cost index
CI	= confidence interval
COND	= column heading for condition rating
CPI	= consumer price index
DATE	= column heading for auction date
DD	= days in a date
DESCR	= column heading for description
DOZ	= dozers
df	= degrees of freedom
ENR	= Engineering News Record
EROPS	= enclosed roll-over protective structure
FIRM	= column heading for auction firm
GDP	= gross domestic product
GRD	= motor graders
ITC	= integrated toolcarriers
LOC	= column heading for location
LP	= column heading for list price
MAKE	= column heading for manufacturer
Mil.	= million
MLR	= multiple linear regression
MM	= month in a date
MODEL	= column heading for model
MS	= mean square
MSE	= mean square error
MSRP	= manufacturers suggested retail price
N/A	= not applicable
NASDAQ	= National Association of Securities Dealers Automated Quotation System
NLR	= non-linear regression
NSA	= not seasonally adjusted
OOCC	= Owning and Operating Cost Calculator
OUTLIER	= column heading for outlier
PI	= prediction interval
PP	= purchase price
PPI	= producer price index
PRESS	= prediction error sum of squares
PRICE	= column heading for auction price
PTO	= power take off
p.a.	= per annum
REG	= column heading for region
RFT	= rigid frame trucks

RND	= column heading for random number
ROPS	= roll-over protective structure
RV	= residual value
RVC	= residual value calculator
RVP	= residual value percent
RVP	= column heading for residual value percent
RVP2	= column heading for newly estimated residual value percent
S&P	= Standard and Poor's
SA	= seasonally adjusted
SAAR	= seasonally adjusted annual rate
SCR	= wheel tractor scrapers
SERIAL	= column heading for serial number
SLR	= simple linear regression
SOURCE	= column heading for data source
SS	= sum of squares
STATE	= column heading for state
TRL	= track loaders
TRX	= track excavators
Ths.	= thousands
U.S.	= United States of America
VIF	= variance inflation factor
WHL	= wheel loaders
WHX	= wheel excavators
w/	= with
YEAR	= column heading for year of manufacture
YOM	= year of manufacture
YY	= years in a date, last two digits only
YYYY	= years in a date
ZIP	= zone improvement plan

Chapter 1 Introduction

Earthmoving operations are found in many construction projects. Heavy construction equipment is used particularly in the heavy and highway segment of the construction industry, but may also be employed in other areas, depending on the requirements of the particular project. If the volume of earthwork is high, the overall project costs can be significantly influenced by the equipment costs. Several different pieces of heavy construction equipment are usually required to perform the functions of cutting, loading, hauling, and disposing of the material on the project site. Owning and operating these machines is a major capital investment for construction contractors. Many machines are listed to cost in the range of six-digit dollar figures and create a variety of costs to the owner during their lifetime. Cost analysis of such assets therefore is an integral part of the business function for the owner and is vital for the success of the enterprise.

This chapter introduces the topic of this study. The research objectives, scope, and limitations are presented, the research hypothesis is formulated, the importance of the topic is underlined by performing a sensitivity analysis of an example, and an outline of the entire document is given.

1.1 Equipment Management

The work of equipment managers is related to all aspects of employing equipment in order to support construction operations. Equipment management covers a wide range of responsibilities. These include managing physical functions, such as repair and maintenance, operational planning, such as resource allocation, and financial control, such as investment decisions and cost accounting.

Financial analysis of construction equipment is concerned with the effective management of owning and operating costs throughout the life of construction equipment fleets and their individual units. It focuses on three stages during the economic life of a machine: Buying the right equipment, keeping and using it profitably, and selling it when it becomes advisable from an economic point of view.

Contractors have to properly account for the declining residual value of their equipment in order to develop accurate life cycle costs. Operating a piece of equipment has to generate revenue for the contractor that exceeds the total loss of its residual value plus the cost of capital for financing the equipment plus direct and indirect operating costs and taxes (Whittaker 1987). Accurate consideration of these costs in the decision making process can help contractors to maintain their competitive advantage in the marketplace.

1.2 Owning and Operating Costs

The costs associated with an individual piece of equipment are commonly broken down into the two categories of owning and operating costs. Individual cost elements as depicted in Figure 1.1 are assigned to one of the categories owning costs and operating costs. Owning costs are incurred simply by having ownership of a piece of equipment while operating costs are only incurred when it is actually utilized.

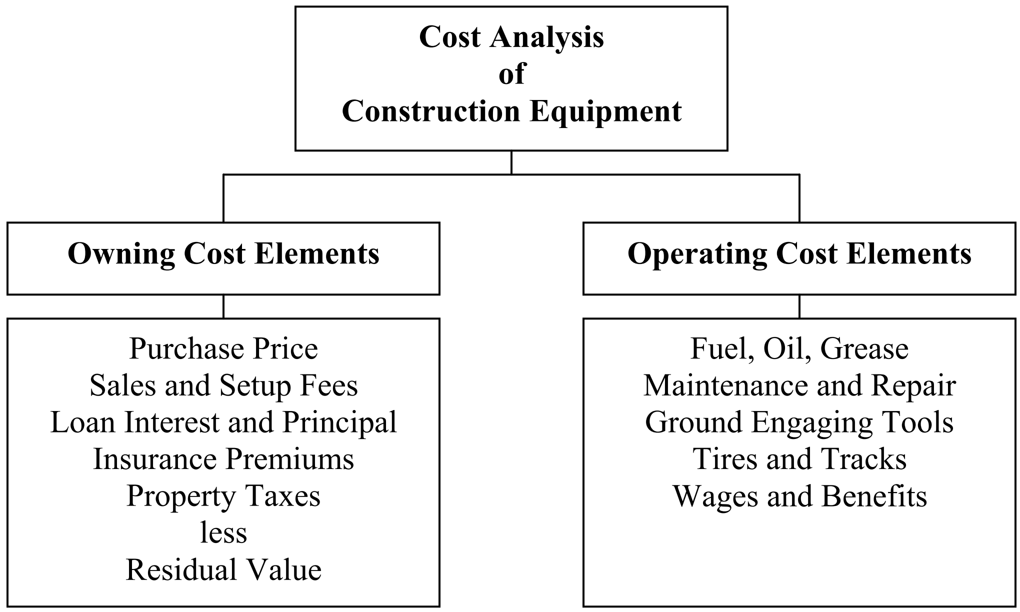


Figure 1.1: Owning and Operating Cost Elements

Owning costs consist of the initial purchase price plus any associated sales and setup fees minus the residual value that is recovered at the end of the owning period. Other owning cost elements are loan interest and principal payments from financing the investment, if applicable, as well as insurance premiums and property taxes (Cross and Perry 1996). Operating costs include consumables such as fuel, oil, and grease, ground engaging tools or replaceable parts thereof, maintenance and repair costs, as well as “tire [or track] replacement, wages, and fringe benefits” for the equipment operator (Tsimberdonis 1993, p54).

The costs for a machine will accumulate over time and lessen its value to its owner until it is finally more economically feasible to dispose of the piece of equipment than to retain it any longer. This optimum duration of ownership is also referred to as economic life or useful life and may be considerably shorter than the physically possible service life span of the machine. This actual life of the machine depends on the wear and tear from utilization and can be prolonged through proper maintenance and repair measures.

1.3 Residual Value

The following paragraphs provide an introduction to the terminology that is used throughout this document. The concept of economic value is introduced and residual value is defined.

The residual value of a piece of equipment is defined as “the amount of money that the machine could be sold for at a particular point in time” in the market (Mitchell 1998, p57). From an equipment appraisal point of view, this definition can be further detailed by adding information on the exact circumstances of the sales event, whether it is a regular sale between two equal parties, an auction, a liquidation, or a trade-in (Associated General Contractors of America 2001). Another important consideration is whether there is any difference in the knowledge about the object on sale that exists between the buyer and the seller or not. In an ideal situation, no information asymmetry would exist and the sales decision would be made fully informed and based solely on mutual benefits of the transaction. The following definition of residual value shall therefore be adopted for the purpose of this study:

> *Residual value “is the amount expressed in terms of money, as of a certain date, that may reasonably be expected to exchange between a willing buyer and a willing seller, with equity to both, neither under any compulsion to buy or sell, and both fully aware of all relevant facts.”* (`<http://www.eagi.com>`).

The importance of the residual value for equipment cost analysis becomes apparent when the process of cost calculation is reviewed. As outlined in Section 1.2, the difference between the residual value and the sum of the purchase price, sales fees, and setup fees has to be recovered by the owner. Adding the remaining owning costs and the projected operating costs to this amount gives the overall expenses that the owner expects to incur. The more reliable the residual value, the more accurate the assessment of expenses will be and better investment decisions can be made. Important questions that the equipment manager needs to answer are:

- What is the residual value of the machine now?
- How will the residual value of the machine develop?

- What factors influence the residual value?
- Which of these factors can be controlled and need to be controlled?

1.4 Terminology

The term value, which is central to this study, requires further explanation. Seven different "classes of value" exist according to Aristotle, "(1) economic, (2) moral, (3) aesthetic, (4) social, (5) political, (6) religious, and (7) judicial. Of these classes, only economic value can be measured in terms of (hopefully) objective monetary units" (DeGarmo et al. 1993, p573). Other definitions of the value of an object are "[w]orth, desirability or utility" (<`http://www.ask.com`>). In this document, the term value is used exclusively in its economic connotation. Expressed in terms of engineering economy, "[t]he value of a durable asset is the net present value of the stream of expected net returns over its remaining life" (Perry et al. 1990, p317).

Terminology in the reviewed literature, of which an overview is given in Chapter 2, varies widely. Among the different terms that are used for almost identical concepts, sometimes within the same study, are fair market value, junk value, recovery value, remaining value, resale value, residual value, salvage value, scrap value, terminal value, and trade-in value. Other possible terms are realized value and selling value. For the sake of clarity, the term residual value shall be used throughout this document.

Additional confusion is added when the term depreciation, meaning a lessening of the initial economic value, is used. Such value loss generates the residual value of the equipment. Depreciation can be related to the equipment itself (physical condition, age, deterioration or obsolescence) or to the economic situation (supply and demand for the equipment or its product) in which the value is assessed (Perry et al. 1990). This is different from the use of depreciation in the accounting or tax context, where it refers to the process of determining the book value of an asset for administrative and taxation purposes by regularly charging expenses to the initial capital investment. A brief description of depreciation is provided in Section 2.3.

1.5 Problem Statement

Equipment managers, who are charged with cost analysis for machines under their supervision, need to keep track of the cost elements and examine them carefully. The depth of knowledge about individual elements, however, is not equal. For projected operating costs the owner can consult manuals that the equipment manufacturers have published. Repair and maintenance costs have been examined statistically by Mitchell (1998), who also presented a methodology for data collection, preparation, and analysis and found that a second-order polynomial equation can be used to model these costs.

Among the owning cost elements the purchase price and related fees are known by the owner with certainty, loan interest and principal payments can be calculated easily, and insurance premiums and property tax liabilities may be forecasted from their annual percentage rates (Cross and Perry 1996, Caterpillar 2001a). The residual value occurs at the end of the owning period, yet it is an important element of the equipment cost calculation that, in part, offsets the other costs. If the residual value is plotted over time its curve is expected to slope down (Grinyer 1973). Often the residual value is assumed to slope down steeply at the beginning of the economic life while sloping less steeply later to reflect a quick value loss early in the life of the machine, as shown in Figure 1.2. As time passes and costs and hours worked for the machine accumulate, its productivity and condition will decline and the residual value accordingly will decline as well. External conditions, e.g. the rate of technological change mentioned by Grinyer (1973) also contribute to the continued loss of value.

Figure 1.2: Residual Value Percent over Age in Calendar Years

Estimates of the residual value are essential for making investment decisions, as emphasized by various authors (Reid and Bradford 1983, Perry et al. 1990, Cross and Perry 1995). “The salvage or residual value of a piece of equipment, whether at the end of its useful life or at some age before, will affect cash flows, rates of depreciation, maintenance and repair decisions, and new and used machine purchase decisions” (Cubbage et al. 1991, p16). It is, however, the most uncertain among the cost elements. Perry and Glyer (1990, p524) stated that even with “the importance and the amount of research conducted on depreciation, no clear consensus exists about the depreciation patterns followed by different types of capital goods.” The current state of knowledge about the residual value is presented in more detail in Chapter 2.

1.6 Research Hypothesis

The hypothesis that will be tested in this study has been formulated in analogy to the hypotheses put forward by Mitchell (1998) in his research on repair and maintenance costs.

> *It is possible to develop a statistically significant model for the residual value of heavy construction equipment using regression analysis of publicly accessible data, including data on the overall economic situation.*

1.7 Research Objectives

This study intends to perform a comprehensive statistical analysis of the residual value (the dependent variable) for different types of heavy construction equipment as determined by various influencing factors (the independent variables). The data shall describe the equipment and the economic situation under which its residual value is established. A methodology needs to be developed for collecting, preparing, and analyzing relevant data about the selected range of equipment types, manufacturers, and models. The following objectives need to be accomplished for this study:

1. Identification of the data necessary for this study and their properties and sources;
2. Collection of the data;
3. Preparation of the data for statistical analysis;
3. Statistical analysis of the data using regression;
4. Development of an implementation tool to assist equipment managers;
5. Presentation of the results and contributions of this study to the body of knowledge.

Expressed in different terms, this study aims at finding a better estimate of the future worth (in monetary terms or as a percentage of the initial price) of a piece of equipment after a certain time period of ownership.

1.8 Research Scope and Limitations

Due to the large number of different manufacturers and equipment models that exist in the Construction Industry, the study will have to make a clear selection of which types, manufacturers, and models of heavy construction equipment will be considered for analysis. Since the available databases of auction records for heavy construction equipment are rather extensive, the selection can be based on the applicability of its results to the equipment management practice. This study therefore focuses on the most common types of heavy construction equipment of the largest manufacturers and limits itself to the North American market only.

The central assumption for this study is that data from the past generation, *G-1*, can be used to predict the residual value for the present generation, *G*. In particular, the past list price LP_{G-1} and the past residual value RV_{G-1} can be used to forecast the future residual value RV_G based on the present list price LP_G. It is expected that the RV_{G-1} has been affected by inflation over the time *T*, which needs to be considered when deriving RV_G. Figure 1.3 illustrates this important concept.

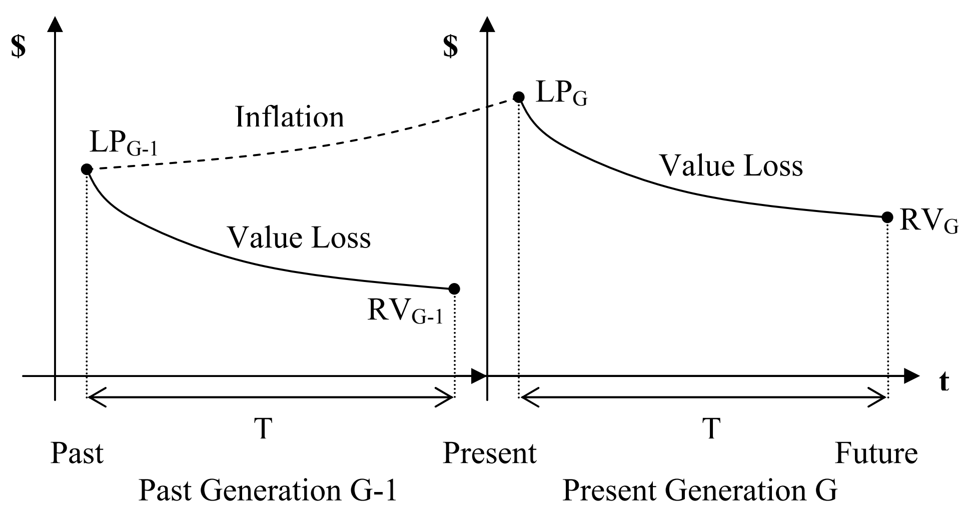


Figure 1.3: Prediction of Residual Value

Two practical applications of residual value prediction by equipment managers exist, as shown in Figure 1.4:

- Predicting the residual value at the present time;
- Predicting the residual value at a future time.

Both these applications are mathematically equivalent, as becomes apparent when examining Figure 1.4 and Equations 1.1 and 1.2. The only difference lies in the definitions of past and present, and of present and future, respectively. It therefore suffices to examine one generalized problem in this study that simply considers the time *T* without any fixed points in time. The difference in time between *LP* and *RV* requires an inflation correction.

$$RVP_{G-1} = \frac{RV_{G-1}}{LP_{G-1} \cdot (1+f)^T} . \qquad \textbf{Equation 1.1}$$

$$RVP_G = \frac{RV_G}{LP_G \cdot (1+f)^T} . \qquad \textbf{Equation 1.2}$$

where *RVP* is residual value percent, *RV* is the residual value is dollars, *LP* is the list price in dollar, *G-1* is the past generation and *G* is the present generation, *T* is the time, and *f* is the inflation rate in percent.

Estimates of all independent variables are necessary for predicting the dependent variable residual value. Uncertainty in the input variables will affect the quality of the residual value prediction. This study is an observational study using real data that were generated through transactions in the economy, as described further in Section 3.3.1. Predictions based on such observations will always contain a certain amount of error that can be attributed to the imperfect nature of occurring, observing, and recording of the data. Results from this study will be average expected residual values for typical machines, but individual future sales will differ from these means due to their inherent variability. An element of uncertainty – the spirit of the moment of a sales event – will remain in every transaction.

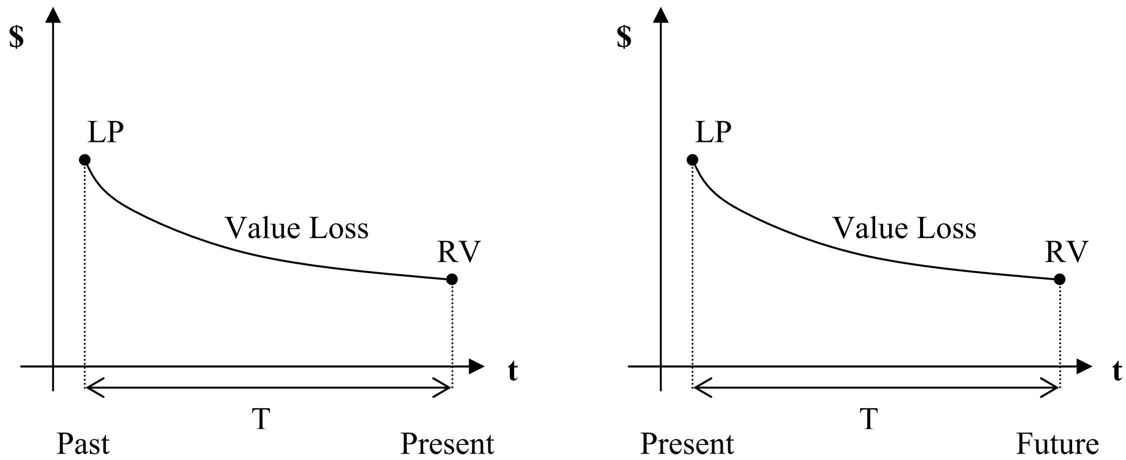


Figure 1.4: Applications of Residual Value Prediction

A clear methodology for the collection, preparation, and analysis will be presented. This methodology can be extended to other areas, e.g. the Mining Industry, and to other equipment types, manufacturers, and models when its assumptions and limitations are considered appropriately.

1.9 Influence of Residual Value

The potential influence of the residual value on the owning and operating cost calculation is examined in this section using an example. The Owning and Operating Cost Calculator (OOCC) developed by Kastens (2002) was used for the calculations. Following is a brief overview of this tool and how its results can be presented graphically.

1.9.1 Owning and Operating Cost Calculator

The OOCC consists of a series of EXCEL worksheets that contain the individual elements of owning and operating costs. The first worksheet provides input cells into which the user enters the information about the particular machine. The following worksheets each contain a matrix of cumulative hours of use over age in calendar years and calculate the costs for all possible combinations. Total hourly owning and operating costs are summed in the final worksheet and are displayed numerically and graphically.

Table 1.1 lists the sample input that was used throughout this section to examine the influence of residual value on the overall costs.

Table 1.1: Sample Input for Owning and Operating Cost Calculator

Item	Value	Item	Value
Purchase Price	\$280,000	Oil and Grease Costs	10% of fuel
Adjustment Factor K	varies 0.0 to 1.0	Attachment Hours per Set	1,000 h/set
Penalty Factor	0.8	Attachment Price per Set	\$600/set
Interest Rate i	10%	Tires or Tracks Hours per Set	2,500 h/set
Write-Off Period	5 yr	Tires or Tracks Price per Set	\$5,000/set
Write-Off Limit	20% of purchase price	Inspection and Maintenance Hours between Services	250 h
License Cost	1% of book value	Inspection and Maintenance Price per Service	\$500/service
Insurance Cost	1.5% of book value	Repair Cost Coefficient A (Mitchell 1998)	-0.01256
Property Tax	2% of book value	Repair Cost Coefficient B (Mitchell 1998)	0.007659
Fuel Consumption	7 gal/h	Age in Calendar Years	varies
Fuel Price	1.25 \$/gal	Cumulative Hours of Use	varies

In particular, Kastens (2002) used Equation 1.3 for calculating the residual value. The adjustment factor K is used to either consider the residual value in the sample calculation ($K = 1.0$) or to ignore it ($K = 0.0$).

$$RV = K \cdot PP \cdot \frac{1}{\sqrt{\frac{Cumulative\ Hours\ of\ Use}{1{,}000}}}. \qquad \textbf{Equation 1.3}$$

where *RV* is the residual value in dollars, *K* is the adjustment factor, and *PP* is the purchase price in dollars.

1.9.2 Cost Contour Diagrams

In the diagram of Figure 1.5 the x-axis represents the age in calendar years and the y-axis represents the cumulative hours of use. Total hourly owning and operating costs are represented along the z-axis with contour lines and colors in this bird's eye view of a cost landscape. Costs exceeding 150% of the overall minimum are not displayed for the sake of clarity.

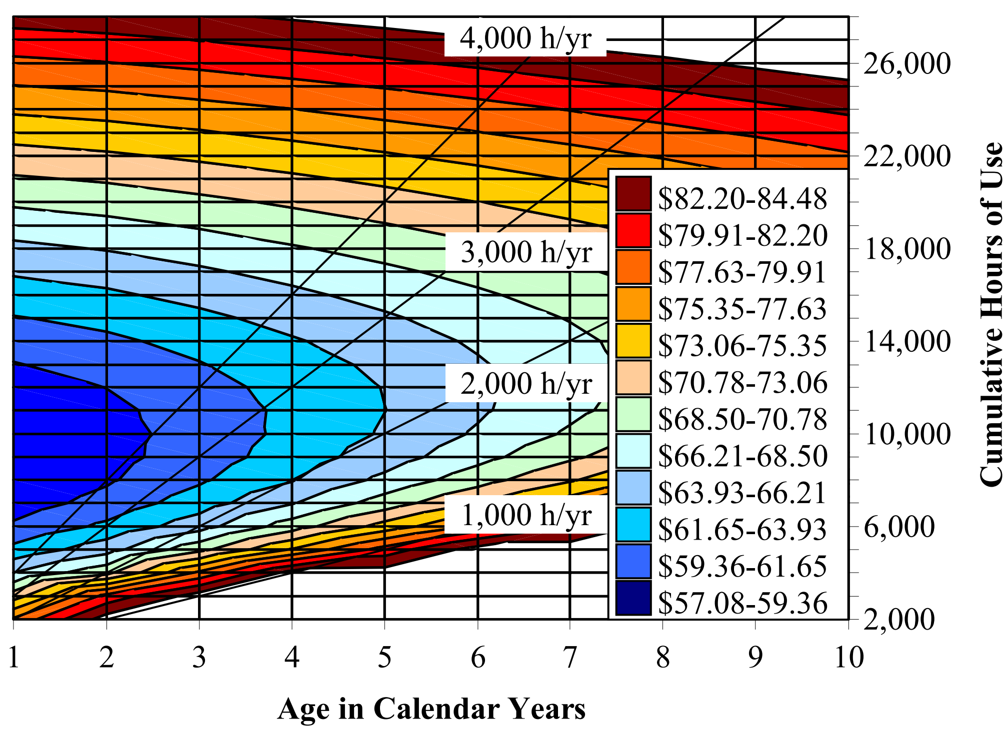


Figure 1.5: Cost Contour Diagram of Total Hourly Costs
[Generated with Owning and Operating Cost Calculator (Kastens 2002)]

This diagram was obtained from the OOCC using the input values from Table 1.1 and $K = 1.0$ to fully consider the residual value. The factor K is an adjustment factor between 0.0 and 1.0 that determines the percent of the residual value that is actually used in the calculation. It is calculated by subtracting the total deductions of Table 1.2 from 1.0 (Kastens 2002).

With the given graphical accuracy the total hourly costs would be e.g. about $66.21 for 5 years of age and 15,000 hours of use (equivalent to an annual utilization of 3,000 hours per year). Lines of constant utilization per year are added to the diagram for ease of use, in this case for 1,000, 2,000, 3,000, and 4,000 hours per year. The lowest point in the diagram represents the minimum costs that can possibly be achieved. The advantage of the cost contour diagram is the intuitive way of displaying the effect of changes in the cumulative hours of use or of keeping the machine until a higher age.

Table 1.2: Deductions for Adjustment Factor K

Item	Condition	Deduction
Equipment Type	Few Moving Parts	0.0
	Many Moving Parts	0.1
	Vibrates and Shakes	0.2
Manufacturer	Industry Leader	0.0
	Exotic	0.1
Equipment Model	Standard, Multi-Use	0.0
	Current	0.0
	Exotic, Special Use	0.1
	Discontinued	0.1
Condition Rating	Excellent	0.0
	Good	0.1
	Bad	0.2
Local Market Conditions	Strong	0.0
	Weak	0.1
	Poor	0.2

Additional helpful charts can be derived from the cost contour diagram in form of views along the x-axis, the y-axis, and other cross sections. Figure 1.6 is a view along the x-axis that shows the total hourly costs over the cumulative hours of use for a selected range of age. Each age is represented by one curve. Full curves in the diagram represent $K = 1.0$ and dashed curves represent $K = 0.0$. Curves for other values of *K* lie within the envelope of curves given by these extreme cases. Figure 1.7 shows cross sections diagonally through the cost surface along the lines of constant annual utilization. A view along the y-axis would result in a less readable diagram where both sides of the cost valley are displayed behind each other.

1.9.3 Sensitivity Analysis

A sensitivity analysis for the residual value is performed using the OOCC. The difference in total hourly costs is compared for the cases of fully considering the residual value in the owning and operating cost calculations versus ignoring it. Results for the sample input of Table 1.1 are discussed in the following. Other input values have also been used for verification. The repair cost coefficients *A* and *B* were obtained from Mitchell (1998) to be -0.01256 and 0.007659.

Figure 1.6 shows total hourly costs depending on age. Comparing the curve bundles for $K = 1.0$ and $K = 0.0$ for 2 through 5 years of age shows a significant difference. Minimum total hourly costs are higher and occur at higher cumulative hours of use when residual value is ignored. Figure 1.7 shows total hourly costs depending on annual utilization. The significant difference is also visible in this cross section. Numerical values for the selected range of results are listed in Tables 1.3 and 1.4, respectively.

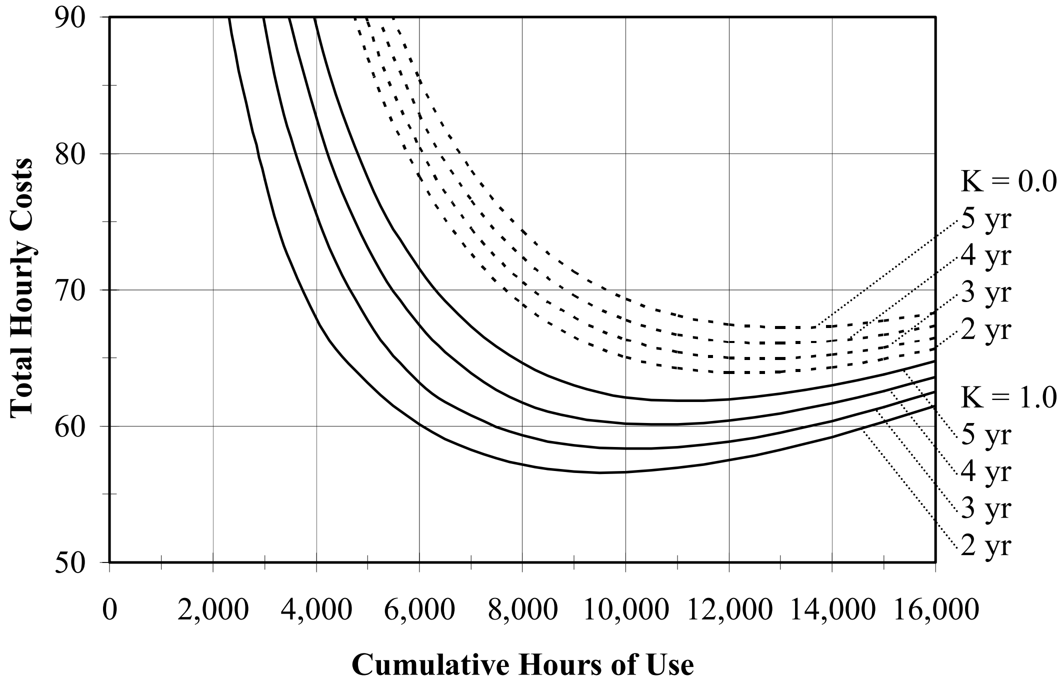


Figure 1.6: Cost Diagram for Age in Calendar Years

[Derived from Owning and Operating Cost Calculator (Kastens 2002)]

Table 1.3: Comparison of Total Hourly Costs for Different Age

K	Age	Cumulative Hours of Use							
		2,000 h	**4,000 h**	**6,000 h**	**8,000 h**	**10,000 h**	**12,000 h**	**14,000 h**	**16,000 h**
N/A	yr	$/h	$/h	$/h	$/h	$/h	$/h	$/h	$/h
1.0	2	98.99	67.89	60.12	57.15	56.62	57.47	59.19	61.49
	3	118.30	75.52	63.17	59.34	58.32	58.87	60.37	62.50
	4	134.90	82.61	67.43	61.71	60.17	60.38	61.64	63.60
	5	149.83	89.28	71.55	64.63	62.08	61.94	62.97	64.75
0.0	2	178.67	101.22	78.27	68.93	65.05	63.89	64.29	65.65
	3	185.18	104.48	80.44	70.56	66.35	64.97	65.21	66.47
	4	192.43	108.10	82.85	72.37	67.80	66.18	66.25	67.37
	5	200.11	111.94	85.41	74.29	69.34	67.46	67.35	68.33

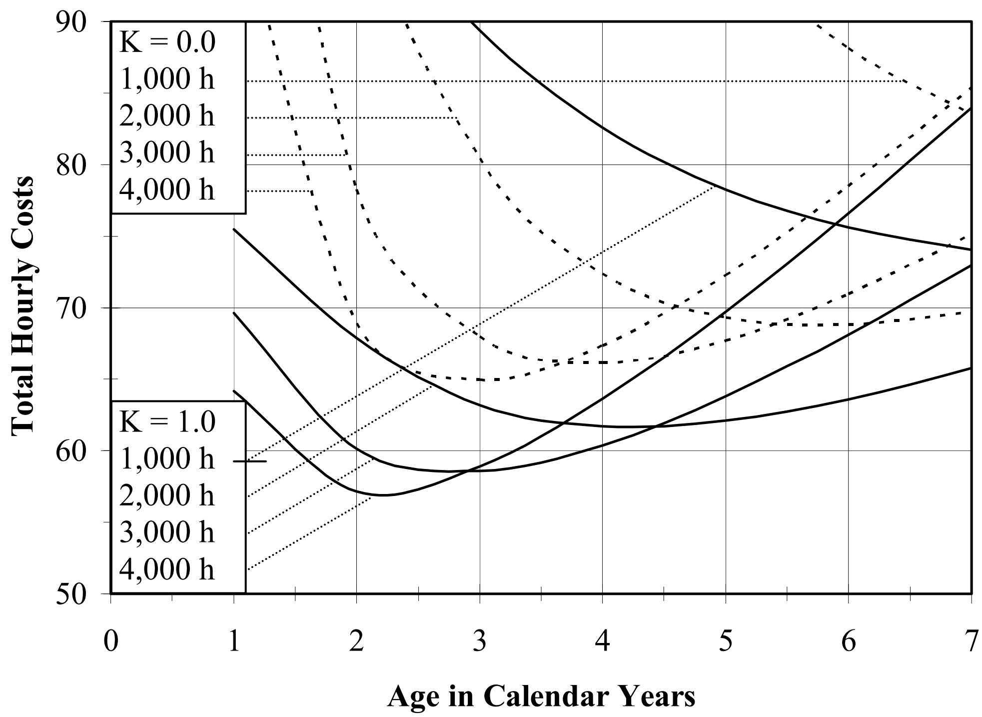


Figure 1.7: Cost Diagram for Annual Utilization

[Derived from Owning and Operating Cost Calculator (Kastens 2002)]

Table 1.4: Comparison of Total Hourly Costs for Different Annual Utilization

K	**Utilization**	**Age in Calendar Years**						
		1 yr	**2 yr**	**3 yr**	**4 yr**	**5 yr**	**6 yr**	**7 yr**
N/A	h/yr	$/h	$/h	$/h	$/h	$/h	$/h	$/h
1.0	1,000	94.99	98.99	89.39	82.61	78.26	75.61	74.06
	2,000	75.49	67.89	63.17	61.71	62.08	63.58	65.77
	3,000	69.65	60.12	58.58	60.38	63.78	68.11	72.98
	4,000	64.13	57.15	58.87	63.60	69.73	76.61	83.95
0.0	1,000	331.64	178.67	130.66	108.10	95.59	88.14	83.48
	2,000	174.49	101.22	80.44	72.37	69.34	68.82	69.71
	3,000	123.54	78.27	67.98	66.18	67.73	70.96	75.13
	4,000	99.13	68.93	64.97	67.37	72.29	78.47	85.35

Table 1.4 requires explanation of the unexpectedly smaller value 94.99 \$/h for 1,000 hours of annual utilization at 1 year of age. It is possible that negative repair costs are calculated when a coefficient such as A in this example is negative. The coefficients were obtained from a regression analysis of equipment fleet data. Mitchell (1998, p181) notes that while "it is not ideal to have negative repair costs predicted for any portion of a machine's life, the range of use affected by this problem is small and not critical. Many of the repairs that take place during that range are covered by warranty." Examination of the repair parts and labor costs showed that all values for 1,000 hours of annual utilization are negative. In Figure 1.7, the two curves for 1,000 hours of annual utilization are affected by this phenomenon.

Tables 1.5 and 1.6 list the percent influence of residual value for the curves of Figures 1.6 and 1.7. Percent differences between $K = 1.0$ and $K = 0.0$ were calculated for the minimum total hourly costs and for the age or annual utilization at which it occurs, respectively. Cumulative hours of use in both tables are calculated by multiplying age with annual utilization.

Table 1.5: Percent Influence of Residual Value on Minimum Costs for Different Age

K	Age	Minimum Total Hourly Costs	Percent Difference in Costs	Annual Utilization	Percent Difference in Utilization	Cumulative Hours of Use
N/A	yr	$/h	%	h/yr	%	h
1.0	2	56.59	12.86	4,803	28.54	9,606
	3	58.32	11.30	3,379	24.21	10,137
	4	60.09	9.92	2,664	20.65	10,656
	5	61.83	8.74	2,231	17.71	11,155
0.0	2	63.87	N/A	6,174	N/A	12,348
	3	64.91		4,197		12,591
	4	66.05		3,214		12,856
	5	67.23		2,626		13,130

Table 1.6 Percent Influence of Residual Value on Minimum Costs for Different Annual Utilization

K	Annual Utilization	Minimum Total Hourly Costs	Percent Difference in Costs	Age	Percent Difference in Age	Cumulative Hours of Use
N/A	h/yr	$/h	%	yr	%	h
1.0	1,000	73.05	6.26	8.978	24.50	8,978
	2,000	61.67	11.55	4.224	37.00	8,448
	3,000	58.54	13.03	2.832	37.99	8,496
	4,000	57.08	13.81	2.141	37.74	8,564
0.0	1,000	77.62	N/A	11.178	N/A	11,178
	2,000	68.79		5.787		11,574
	3,000	66.17		3.908		11,724
	4,000	64.96		2.949		11,796

The null hypothesis stating that the mean difference μ_{diff} of the population is equal to zero is tested with a paired t-test for dependent samples. In other words, it is tested whether there is a difference between considering the residual value in the calculation of total hourly costs or not.

$$H_0 : \mu_{diff} = 0 . \qquad \textbf{Equation 1.4}$$

$$H_1 : \mu_{diff} \neq 0 . \qquad \textbf{Equation 1.5}$$

$$t_{obs} = \sqrt{n} \cdot \frac{\bar{d}}{s_{diff}} . \qquad \textbf{Equation 1.6}$$

$$\text{If } |t_{obs}| \leq t_{1-\alpha/2,\, n-1} \text{ then fail to reject } H_0. \qquad \textbf{Equation 1.7}$$

$$\text{If } |t_{obs}| > t_{1-\alpha/2,\, n-1} \text{ then reject } H_0.$$

where H_0 is the null hypothesis, H_1 is the alternative hypothesis, μ_{diff} is the mean difference of the population, t_{obs} is the test statistic for the null hypothesis, n is the number of complete observations in the prediction dataset, $\bar{d}$ is the sample mean, s_{diff} is the sample standard deviation, and $t_{1-\alpha/2,n-1}$ is the cutoff value for the hypothesis test. The decision rule is provided in Equation 1.7. Using a significance level α of 0.1, it is found that for all datasets the null hypothesis is rejected, i.e. as expected μ_{diff} in all cases is significantly different from zero. Considering residual value in the calculation of total hourly costs makes a difference. Results for this t-test are listed in Table 1.7 for the comparison of minimum costs and annual utilization when age is varied and for the comparison of minimum costs and age when the annual utilization is varied.

Residual value therefore plays an important role in cost analysis for construction equipment. It can have a double-digit influence on the minimum costs and an even stronger influence on the annual utilization and age at which it occurs.

Table 1.7: t-Test Comparison Results

Variable Parameter	Comparison of Minimum Costs			Comparison of Utilization or Age		
	t_{obs}	$t_{0.95,3}$	p-Value	t_{obs}	$t_{0.95,3}$	p-Value
Age	12.0543	2.3534	0.00061	9.7426	2.3534	0.00115
Annual Utilization	6.5623	2.3534	0.00360	10.4752	2.3534	0.00093

1.10 Document Structure

This document consists of six chapters and several appendices. Following are brief descriptions of the contents of each chapter and appendix, respectively. Figure 1.8 shows the flow of the document.

- *Chapter 1 – Introduction* sets the stage for the research by introducing the concept of residual value and the problem that is examined in this study. The research objectives, scope, and limitations are presented, the research hypothesis is formulated, and the influence of the residual value is examined in a sensitivity analysis.

- *Chapter 2 – Literature Review* provides the framework of current knowledge. Related literature is reviewed and important studies from other disciplines and their methods are presented. Information from equipment manufacturers and the experience of equipment managers with respect to the residual value are reviewed.

- *Chapter 3 – Research Data* introduces the four families of data that are needed for this study. The sources, ranges, and properties of auction records, equipment parameters and list prices, and macroeconomic indicators are described. The procedure used to collect and prepare the data for statistical analysis is explained in detail.

- *Chapter 4 – Statistical Analysis* begins with general considerations that apply to the data and the regression analysis procedure, respectively. It further contains information about how an appropriate model with macroeconomic indicators was selected, and how outliers were identified. Results of the regression analyses are presented and are verified through cross-validation.

- *Chapter 5 – Residual Value Calculator* explains the implementation tool that was developed using spreadsheet software. The layout and functioning of the tool is explained, its input and numerical and graphical output is presented, and information on correct use and maintenance of the tool is provided.

- *Chapter 6 – Contributions* concludes the document with a review of the research hypothesis and how the study contributes to the body of knowledge, gives a summary of the research results and points out areas of further research. Among the key findings of this study is the central role of age as a factor influencing residual value and the importance of considering the economic situation for predicting the residual value. Further results describe for each equipment type and size class examined the influence of the factors manufacturer, condition rating, and auction region on the residual value.

- *Appendices* contain the computer code that was programmed for this study and tables with the coefficients and statistical parameters that were calculated. The code is provided for all spreadsheet macros and commands that were used for data preparation and in the tool. Descriptive values for the datasets and the coefficients and statistics that were calculated are tabulated. The code for analysis with the statistics software is listed. Box plots give graphical representations of the properties of all datasets.

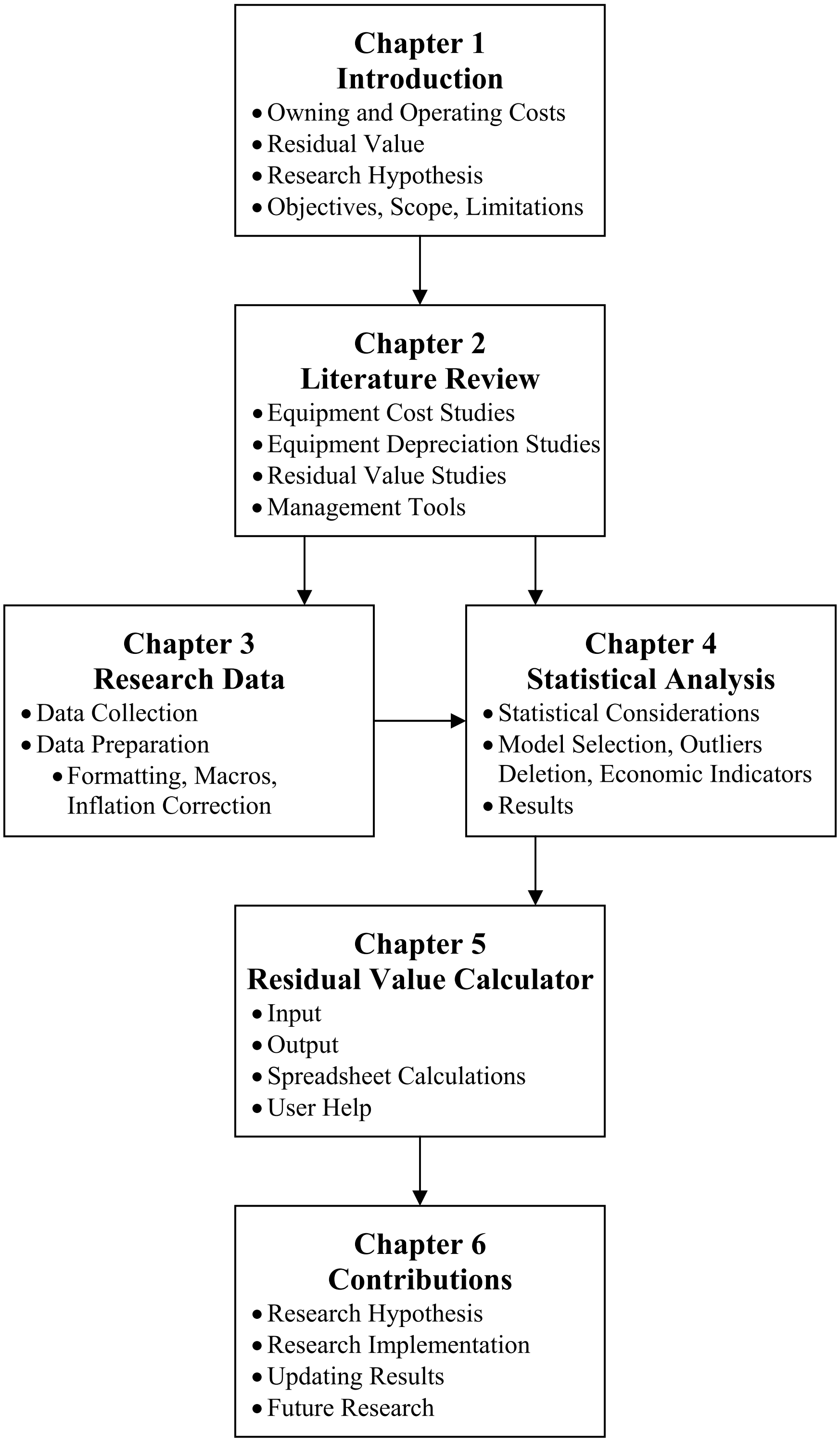


Figure 1.8: Document Structure

Chapter 2 Literature Review

2.1 Introduction

This chapter reviews the literature that exists on the residual value and on its role in equipment owning cost calculations. After studies examining the residual value have been reviewed, their approaches to data collection, preparation, and analysis are extracted and summarized.

2.2 Equipment Costs

A considerable range of literature exists in which the costs of equipment are analyzed (Watts and Helmers 1981, Powell 1988, Manatakis and Drakatos 1993, Cebesoy 1997). In general, equipment economics studies present models to minimize costs or to maximize profits (Douglas 1978, Collier and Jacques 1984, Wonsiewicz 1988). Mitchell (1998) in his study on maintenance and repair costs has provided a comprehensive overview of classic studies on economic replacement of construction equipment. Residual value is an important element among owning costs. It "helps determine a machine's economic depreciation, which is the amount of market value lost each year due to age, wear, and obsolescence (not to be confused with tax depreciation)" Kastens (1997, p6).

Published owning and operating cost calculations often make the assumption that the residual value (usually abbreviated RV, SV, or S for salvage value) of a machine is known (Sears and Clough 1981, Sprague and Whittaker 1985). In some cases, it is even set to 0%. This is highly unrealistic, as even a completely dysfunctional piece of equipment will have some value as scrap metal. There appears to be considerable uncertainty in estimating the residual value of equipment with sufficient accuracy. Referring to the loss in residual value as economic depreciation, Perry and Glyer (1990, p524) state that even considering "its importance and the amount of research conducted on depreciation, no clear consensus exists about the depreciation patterns followed by different types of capital goods."

Residual value may depend on various factors, such as e.g. on the current condition of the machine, the location and time of sale and the state of the economy and technology at that time. The spirit of the moment at the transaction may also influence the sales price. Assumptions of fixed residual values are therefore unrealistic (Grinyer 1973). It is much better to determine estimates of residual values using its realizations, i.e. "evidences of value" (Cowles and Elfar 1978, p141), in particular actual sales data.

2.3 Equipment Depreciation

Studies on equipment costs often include a discussion of the depreciation of a particular piece of equipment (Perry and Glyer 1989, Cross and Perry 1995, Unterschultz and Mumey 1996). Cross and Perry (1996, p547) note on the importance of depreciation:

> *Depreciation is an important component of tax policy analyses as well. The range of problems in which depreciation costs are recognized or required indicates the importance of obtaining accurate depreciation cost estimates. Also, the linkage between interest costs and machinery values further underscores the need to correctly estimate machinery values over time.*

The concept of depreciation derives from cost accounting, where it is used to account for a "loss of value of a piece of equipment over time" (Peurifoy et al. 1996, p52) that has been using to generate accounting revenue. Common depreciation methods include Straight Line Depreciation, Declining Balance Depreciation, Units-of-Production Depreciation, and Sum-of-the-Years

Depreciation. Choice of a particular method is determined by minimizing the tax liability of the company as permissible under the currently governing tax legislation. It needs to be noted that accounting depreciation is an estimate for tax purposes and yields rather fictitious results. Its cumulatively depreciated book value rarely matches the residual value of the equipment. Residual value is realized only upon sale in the market. It is influenced by “physical deterioration and obsolescence, … changes in market supply and demand for the asset” (Perry et al. 1990, p317), technological change, and by the state of the economy.

2.4 Residual Value

Previous studies have addressed the determination and analysis of the residual value of equipment in the area of agricultural farm equipment, as well as for logging equipment in forestry. The significance of estimating the residual value for investment decisions is frequently underlined in these studies (Werblow and Cubbage 1986, p11):

> *Residual value is important because it affects the amount of investment that must be recovered through usage. Equipment with large estimate resale values will have a lesser equipment cost recovery (depreciation) than equipment with small salvage values.*

Cross and Perry (1995, p194) mentioned “the need to estimate the market value of used equipment at one or more points in the equipment’s life” in equipment economic studies. They note on the role and nature of residual value (Cross and Perry 1996, p547):

> *In order to accurately assess interest costs over the life of a machine, the value of that machine over time must be known. Machinery values are determined in the marketplace based on transactions between willing buyers and sellers. The challenge (for budgeting purposes) is to value machinery without actually selling it. Agricultural machinery and equipment, like other non-real assets, typically*

> *decline in value over time. This decline in value is referred to as depreciation, which occurs because of age, use, and obsolescence of machinery.*

Unterschultz and Mumey (1996, p296) put the use of residual value for equipment investment decisions in perspective:

> *Reliable terminal value forecasts are required for any investment analysis based on expected cash flow analysis. The standard practice when forecasting terminal asset values is to base them on economic depreciation estimates. These estimates are then used in the machinery investment analysis. Improved terminal asset value forecasts reduce the risk in machinery investment by reducing the uncertainty surrounding the forecast.*

Several studies from agriculture and forestry are reviewed in the following sections. Their approaches, assumptions, and parameters are summarized, their analysis procedures for deriving the residual value estimates is described, and their conclusions are presented. Studies specifically on the calculation of the residual value of used heavy construction equipment were not identified.

2.4.1 Kelley Blue Book

A source of residual value information for the automobile industry is the Kelley Blue Book, which is described as "the most trusted automotive resource for consumers and the industry" (`<http://www.kbb.com>`). Available in printed and online versions, it allows users to obtain predictions of the residual value of their vehicles. This section provides a brief overview of a sensitivity analysis that was performed with the Kelley Blue Book.

Examining the predictions made with the Kelley Blue Book allows gaining insights into how a residual value model that is used in the business practice is composed. A selection of automobile models from different years and different manufacturers and with different equipment was examined and for each combination of input values the predicted residual value was recorded for further analysis. Input values for the online Kelley Blue Book were the type of transaction with the three options buying from a dealer, selling to a dealer, and buying to or selling from a private person, furthermore the model year, manufacturer, model name, and engine, transmission, and drivetrain types, if applicable. Additional inputs were the mileage of the vehicle, the geographic region is identified by the ZIP code, the condition rating ranging across excellent, good, fair, and poor, and last not least a variety of equipment options such as e.g. air conditioning, power steering, and AM/FM stereo radio.

Plotting the recorded data over mileage showed that Kelley Blue Book uses S-shaped stepped curves to model the residual value. The minimum step width was 1,000 miles. The curves were constructed such that very low and very high mileage yielded a constant dollar amount as the initial and final residual value. The mileage at which it occurred depended on the particular model year. Beginning at 80,000 miles the residual value for all model years is stepped in 10,000-mile intervals until it reaches a constant value.

It was found that the geographic region as well as the type of transaction also only had an additive effect. Three geographic regions could be identified wherein the residual values were constant. Residual value was lowest in the Eastern U.S., higher in the Central U.S. and the Caribbean, and reached the highest values in the Western U.S. including Alaska and Hawaii. Residual value was lowest when selling to a dealer, higher when buying from or selling to private person, and reached the highest values when buying from a dealer. The condition rating had simply had an additive effect on residual value that shifted the stepped curve up or down. Individual items of equipment also had an additive effect, with the exception of standard equipment that was always present in a vehicle.

It was found that Kelley Blue Book uses a default value of 15,000 miles per year of age and the standard equipment of the vehicle in case the user does not enter any specific input values. Information on the number of observations in the Kelley Blue Book database and the exact analysis procedure could not be established with this sensitivity analysis.

2.4.2 Agriculture and Forestry Studies

A considerable amount of work has been conducted on the residual value of agricultural equipment. The residual value of forestry equipment has also been examined.

2.4.2.1 Reid and Bradford (1983)

Reid and Bradford (1983) reviewed previous research and found that those models had only included age as an explanatory variable. In their study of optimal replacement of farm tractors they included age in calendar years, PTO (power take off) horse power (HP), and average net farm income. Two indicator variables were used to code three different manufacturers and two indicator variables captured time periods assumed to display different technological change. Residual value percent (RVP) was obtained by dividing the remaining market value by the list price after inflation-correcting both with the Wholesale Price Index, an earlier version of the Producer Price Index (PPI) that was introduced in 1978 (<http://www.bls.gov/bls/glossary.htm>). Data from 1954 to 1978 published by a distributor association were used for developing the model (Reid and Bradford 1983). The statistical model was applied to a replacement model and to evaluate the impact of tax regulations.

2.4.2.2 Perry and Glyer (1989)

Perry and Glyer (1989) examined the value loss rate of tractors using auction records from 1984 to 1988. They constructed price per horse power as the response variable based on the notion that the horse power "is a good measure of a tractor's productive capacity" (Perry and Glyer 1989, p526). It was additionally included as an explanatory variable. Other explanatory variables were age in calendar years, condition rating and auction region in form of indicator variables, and a new equipment index that was constructed from new equipment prices. Since age and cumulative hours of use were found to be highly correlated the new variable annual utilization was created.

Price per horse power was adjusted by a probability of survival and a scrap value that were derived from a regression analysis. The researchers noted that it is possible that equipment is retired without being sold and that equipment is sold earlier when it incurs high utilization. Adjusting for the probability of survival and including annual utilization were therefore seen as measures to make the data more representative of the actual marketplace. A statistical analysis using a Box-Cox flexible functional form was carried out. Values of the adjusted coefficient of determination R^2_{adj} of the final models ranged between 0.789 and 0.718 for different manufacturer.

2.4.2.3 Perry, Bayaner, and Nixon (1990)

Perry, Bayaner, and Nixon (1990) examined tractors using auction sales data from 1985 to 1988. List prices were adjusted for special options as far as known from the auction records. List prices and auction prices were adjusted to a common year using average price changes for tractors as reported by the U.S. Department of Agriculture and then were divided to obtain RVP. Explanatory variables were age in calendar years, annual utilization as cumulative hours of use divided by age, numerical condition rating ranging from 1 = excellent to 4 = poor, numerical HP, and the macroeconomic indicators real net farm income and real after tax interest rate. Indicator variables were used to represent manufacturer, auction type, and auction region. Interaction terms for HP and age, HP and utilization, manufacturer and age, and manufacturer and utilization were included in the model.

The hypotheses were made that a positive interaction exists between HP and age and that a negative interaction exists between HP and utilization. Using the Box-Cox transformation on the response, age, utilization, and HP the model yielded a value of 0.8032 for R^2_{adj}. The interaction of HP and age was found to be significant at the significance level α of 0.05 with a negative sign instead of the hypothesized positive sign.

2.4.2.4 Cross and Perry (1995 and 1996)

Cross and Perry (1995 and 1996) discussed shortcomings of earlier studies and the approach that the American Society of Agricultural Engineers (ASAE) had used. Original data for the ASAE equations were from 1965 and had only been updated in 1971. Sales prices published by a distributor association were used. Data additionally suffered from the assumption of a fixed rate of value loss, fixed reconditioning costs, and a fixed markup (Cross and Perry 1995).

In their own studies, Cross and Perry (1995 and 1996) analyzed monthly auction reports from 1984 to 1993 for different types of agricultural equipment. Explanatory variables extracted from the auction records were manufacturer, year of manufacture, annual utilization in hours, condition rating, size class (three groups of tractors by HP), special options, and auction type and region for each transaction. Age in years and hours of use were found to be highly correlated. Condition ratings had not been reported for all observations. Indicator variables were used to model the manufacturer, condition rating, auction type, special options, and nine geographic regions within the U.S. Real net farm income and the prime interest rate were included in the dataset as macroeconomic indicators. Auction prices were divided by list prices to calculate RVP. List prices and auction sales prices were inflation-corrected to a common year using the PPI. The researchers hypothesized that residual value would decrease with higher age or annual utilization and with lower condition rating.

Again the Box-Cox transformation was used to fit the statistical model. Apart from the original regression model the researchers also presented simpler models containing only age and annual utilization as explanatory variables. Values for the R^2_{adj} ranged between 0.705 and 0.546 for combines, swathers, conditioners, and balers (Cross and Perry 1995).

In a related study (Cross and Perry 1996) a regression model for the square root of RVP was developed containing the explanatory variables square root of age, annual utilization in hours, net farm income, and indicator variables for condition rating and auction type. Age was found to always be statistically significant, while annual utilization was significant for one equipment type. Statistically significant differences between different equipment types were found. Values for R^2_{adj} ranged between 0.632 and 0.079 for tractors, mowers, balers, combines, swathers, plows, disks, planters, manure spreaders, and skid steer loaders. The researchers also presented a mathematically simpler model containing only age, utilization, and real net farm income for practical application that they recommended for inclusion in ASAE standards (Cross and Perry 1996, Cross 1998).

2.4.2.5 Unterschultz and Mumey (1996)

Unterschultz and Mumey (1996) examined farm tractors and combines. Their model did not use the Box-Cox transformation, but considers the value of the asset adjusted for changes in technology and quality and for loss of economic value. Introduction of a new series for an equipment model was assumed to signify a technological change. Distributor sales prices from 1972 to 1992 were used. Reconditioning costs and a fixed markup percentage had been deducted in the semiannual cost reference guidebook to generate comparable prices. The Consumer Price Index (CPI) was used for inflation adjustment. RVP was calculated based on the sales price of one-year-old equipment. List prices were not used as they "are not observed transaction prices and confound depreciation estimates with the manufacturer's marketing methods" (Unterschultz and Mumey 1996, p298).

Data were separated into cohorts for each manufacturer, model series, and year of manufacture. Three indicator variables modeled the year of the observation, the age in half-year increments, and the equipment model series as a measure of technology. A time-series analysis was performed for each cohort and a constant annual value loss rate was found in most cases. A seasonal effect between spring and fall and differences in the value loss rates depending on manufacturer and model series were identified. Results of the statistical analysis were found to be significant for a significance level α of 0.05.

2.4.2.6 American Society of Agricultural Engineers (1998)

The American Society of Agricultural Engineers (ASAE) publishes Agricultural Machinery Management Data in ASAE D497.4 JAN98. This standard provides an equation for RVP that is based on the equation developed by Cross and Perry (1996) without the economic indicator net farm income. The equation considers the age in calendar years and the annual utilization in hours. Data from auction sales between 1984 and 1993 were used. Tabulated coefficients for 12 types of agricultural equipment, among them three sizes of farm tractors, are provided (ASAE 1998).

2.4.2.7 Cubbage et al. (1991)

Werblow and Cubbage (1986) published average operating costs per hour for various types and size classes of forestry equipment. They also included average residual value in U.S. dollars, average owning period in years, and average annual utilization for each size class. Residual value was assumed at 25% of the purchase price at the end of the owning period. Data for the year 1984 had been obtained from distributors and from cost reference guidebooks.

Cubbage et al. (1991) reviewed traditional rules-of-thumb and previous studies on the residual value, whose values “often range from 15 to 25 percent of the original sales value of the machine. The values represent a machine’s value at the end of its assumed useful life span, generally 3 to 6 years depending on the type of equipment” (Cubbage et al. 1991, p16). However, none to the reviewed studies had analyzed actual sales data. The researchers collected data on rubber tired feller bunchers, cable skidders, grapple skidders, and knuckle boom loaders of up to 10 years of age from annual auction reports and from an auction firm publication. The response variable RVP was calculated as auction price divided by original sales price. It is not clear whether original sales price refers to the list price or to the purchase price from a distributor. Explanatory variables were age, numerical condition rating ranging from 1 = poor to 5 = excellent, and indicator variables for the auction region. Adjustments for non-standard options (e.g. special attachments) were made to the original sales price using an average value for the respective option. In case of upgrades the adjustment was made to the auction price. The highest goodness-of-fit with an R^2 value of 0.49 was achieved with a model including the inverse of the square root of age. In some cases including the condition rating was seen as useful. The authors expressed the need to keep residual value analyses updated (Cubbage et al. 1991).

2.4.3 Manufacturer Performance Handbooks

RVP is used in two cost analysis examples in the Caterpillar Performance Handbook (Caterpillar 2001a). It is based on the original purchase price, not on the list price. Purchase price in turn consists of the gross selling price less commission costs, make-ready costs, and inflation during the owning period. To obtain accurate values for RVP the Caterpillar Performance Handbook recommends relying on the owner's experience, contacting distributors for information, using auction results, or "comparing the current used machine value to the current new machine value" (Caterpillar 2001a, p20-11). The Deere Performance Handbook assumes a certain dollar amount subtracted from the delivered price for residual value (Deere 2002).

2.4.4 Experience Rules

Conversations with construction equipment managers showed that empirical rules-of-thumb are often used in practice (Agoos 2003). They relate even values of RVP to a specific age in calendar years or to cumulative hours of use. This approach simplifies the actual nature of residual value because the equipment type, the manufacturer, the condition rating, and other parameters are not considered. Rules-of-thumb only express the relationships between one particular value of age or hours of use and its RVP and do not offer the flexible predictive capabilities that a mathematical function for such relationship would have.

2.4.5 Data Collection and Preparation

Agricultural and forestry equipment studies mostly used actual market data instead of distributor prices (Cross and Perry 1996). Using auction prices was seen as superior to using distributor prices, which may include distortions from marketing promotions, as well as from "the value of warranties, financing options, and trade-ins" (Perry et al. 1990, p318). The researchers found their auction prices in publications such as e.g. "annual summary books published by various equipment cost auction houses and data sources" (Cubbage et al. 1991, p17). Monthly auction price reports from professional data providers were also used (Cross and Perry 1995).

Fenton and Fairbanks (1954) are credited as being the first researchers to use the concept of RVP. They divided "current market price by initial purchase price and then average[d] these values across several different kinds of equipment. Subsequent work has used manufacturer's list price as a proxy for sale price" (Cross and Perry 1995, p195). Cross and Perry (1996, p547) write on their own use of list price that it "was used as a proxy for actual machinery sales price because original sales price was not available. List price was deemed the closest value available to represent sales price." Kastens (1997) concurs and stresses that list prices need to be brought to the same date as the auction price, possibly by inflation-correcting them. Cubbage et al. (1991, p20) note on dividing auction prices by list prices to obtain RVP:

> *The list price for new equipment was compared with the resale price from auction sales to calculate a percentage resale value by equipment age, condition, and region of sale. In practice, buyers may receive some discount from list, and auctioneers charge a fee for their services. These discounts are not consistent, so the stated original purchase and auction prices provide the best means for estimating resale percentage values. Since the discounts tend to reduce prices for both, they should have little effect on average resale percentages.*

Some studies made adjustments for non-standard options to their list prices and auction prices by adding or subtracting an average value for the respective option (Cubbage et al. 1991). Cross and Perry (1995, p195) stated that since "the sale of used equipment virtually never occurs during the original purchase year, the sale and list price must both be indexed to a common year." They used the PPI for inflation adjustment. Its earlier version, the Wholesale Price Index, was also used (Reid and Bradford 1983). Other researchers used the CPI, since it "is consistent with the general concept that investment is an exchange of consumption opportunities across time" (Unterschultz and Mumey 1996, p298). Inflation adjustment was also performed with an index of average price changes (Perry et al. 1990). RVP finally was calculated by dividing the inflation-corrected auction price by the inflation-corrected list price.

Table 2.1 lists the factors that were considered as explanatory variables and the response variable in the reviewed studies.

2.4.6 Statistical Analysis

For the statistical analysis of residual value for agricultural equipment the Box-Cox flexible functional form was used to calculate the coefficients that provided the highest goodness-of-fit with the data (Perry et al. 1990, Perry and Glyer 1990, Cross and Perry 1995, Cross and Perry 1996). The models developed with the Box-Cox Method were seen as an improvement over the functions estimating RVP as recommended by the American Society of Agricultural Engineers (ASAE) (Cross and Perry 1996). The transformed models developed by Cross and Perry (1995 and 1996) resemble the model presented by Mitchell (1998), citing Vorster (1995), who expresses the residual value for heavy construction equipment using an adjustment factor *K* as:

$$RV = K \cdot PP \cdot \frac{1}{\sqrt{\frac{Cumulative\ Hours\ of\ Use}{1{,}000}}}. \qquad \textbf{Equation 2.1}$$

where *RV* is the residual value in dollars, *K* is the adjustment factor, and *PP* is the purchase price in dollars. Similar to Equation 2.1, Cubbage et al. (1991) found that a function of the inverse square root of age best modeled the residual value for forestry equipment, with condition rating followed in significance. Age in calendar years has been found to be highly correlated with hours of use (Perry and Glyer 1989). However, Unterschultz and Mumey (1996) caution that estimation problems may result from applying the Box-Cox transformation to the data.

Table 2.1: Explanatory and Response Variables for Residual Value Studies

Explanatory and Response Variables	Variable Type	Variable Use
Manufacturer	Categorical indicator variable	Explanatory variable
Model series	Categorical indicator variable	Explanatory variable
Horse power	Numerical variable	Explanatory variable Denominator for RVP Size class
Age in calendar years	Numerical variable, difference of auction date and year of manufacture	Explanatory variable Denominator for annual utilization
Cumulative hours of use	Numerical variable	Explanatory variable Numerator for annual utilization
Average cost of special options, upgrades, etc.	Numerical variable	Adjustment to auction price Adjustment to list price
Special options	Categorical indicator variable	Explanatory variable
Condition rating	Numerical variable Categorical indicator variable	Explanatory variable
Auction type	Categorical indicator variable	Explanatory variable
Auction region	Categorical indicator variable	Explanatory variable
Auction time period	Categorical indicator variable	Explanatory variable
Auction price	Numerical variable, inflation-corrected	Numerator for RVP
List price	Numerical variable, inflation-corrected	Denominator for RVP
Purchase price from distributor	Numerical variable	Denominator for RVP
Macroeconomic indicator, e.g. real net farm income, real after tax interest rate, prime interest rate	Numerical variable	Explanatory variable
New equipment index	Numerical variable	Explanatory variable

Sources: Reid and Bradford 1983, Perry and Glyer 1990, Cubbage et al. 1991, Cross and Perry 1995, Cross and Perry 1996, Unterschultz and Mumey 1996.

2.5 Conclusion

This chapter has reviewed the Kelley Blue Book and various studies from the areas of agriculture and forestry. Their approaches to data collection, preparation, and analysis were summarized to assist in developing the methodology for the work performed in this study.

Chapter 3 Research Data

3.1 Introduction

This chapter describes the four data families that have been identified for use in this study. It outlines the date collection including the sources, ranges, and properties of each of the four data families, and for each explanatory variable explain the exact steps that have been performed for data preparation.

3.2 Data Families

A variety of different data needed to be collected to accomplish the objectives of this study. Central questions that had to be addressed with respect to the data collection were:

- What different kinds of data are needed?
- Which ranges should these data cover?
- Who collects and can supply these data?

After the data had been collected, they needed to be prepared for the statistical analysis. Central questions that had to be addressed with respect to the data preparation were:

- How should the data be formatted and sorted?
- How can errors in the data be detected and corrected?

- How should the data be assembled into datasets?

This chapter provides answers to these questions and lays the foundation for Chapter 4. Figure 3.1 provides a flowchart of all data collection and preparation steps that are explained in this chapter.

The response variable, or dependent variable, RVP is going to be predicted using several explanatory variables, or independent variables. Prior to the statistical analysis it is unknown which of the possible explanatory variables will contribute to the final regression model in a statistically significant way. Therefore, the range of explanatory variables for which data were collected was kept wide initially. Selection of the actually important explanatory variables is done as part of the statistical analysis. All explanatory variables had to be expressed in numerical terms to be usable in a statistical analysis. Variables that had a different form needed to be transformed appropriately. The numerical data not necessarily had to be continuous but could be discrete, e.g. to describe different categories of a parameter.

Data for this study were measured on several levels that span from the individual machine to the economy at large. The complete dataset for this study was composed of the following four data families:

- Auction records captured the transactions of individual machines;
- Size parameters described the characteristics of machine models;
- Manufacturers Suggested Retail Prices, or list prices;
- Macroeconomic indicators described the overall economic situation.

Each data family is described in more detail in the following four sections. Data from the four data families had to fulfill the following conditions:

- Be available;
- Be current and be updated regularly;
- Be complete and reliable.

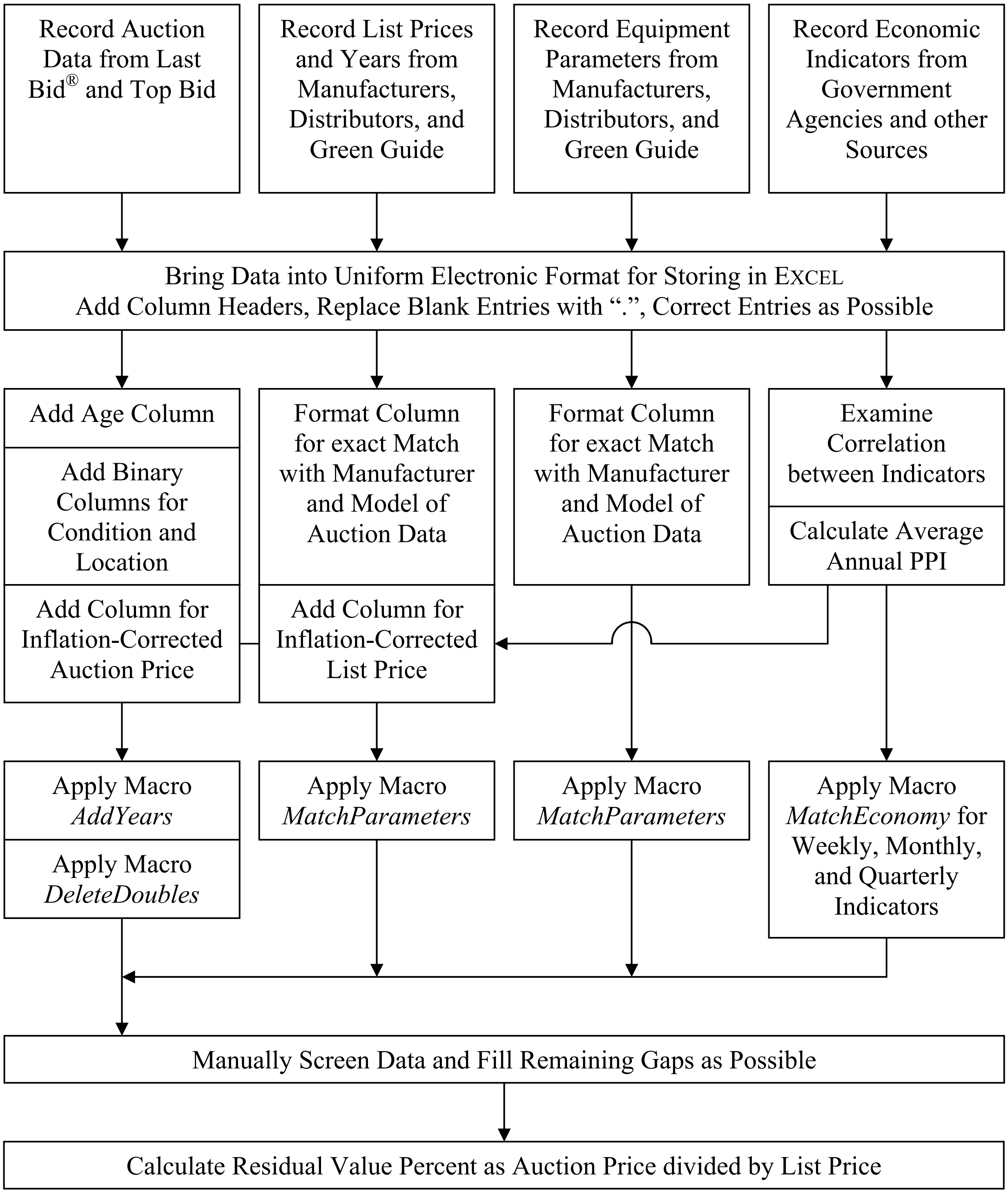


Figure 3.1: Flowchart of Data Collection and Preparation

Data for individual equipment transactions should also fulfill the additional conditions:

- Contain a sufficient number of data points for different types, manufacturers, and models;
- Contain a sufficient number of data points over time;
- Contain detailed information on the circumstances of each auction.

For each of the four data families the following sections describe the sources of the data, their range, and their specific properties. Figure 3.2 depicts the elements of each of the data families. Figure 3.3 lists the sources for the data families. Since size parameters and list prices are closely related information, they are depicted together. Publicly available data were used whenever possible so that future users can easily collect new data using this research methodology. All data were stored in tabular form in EXCEL.

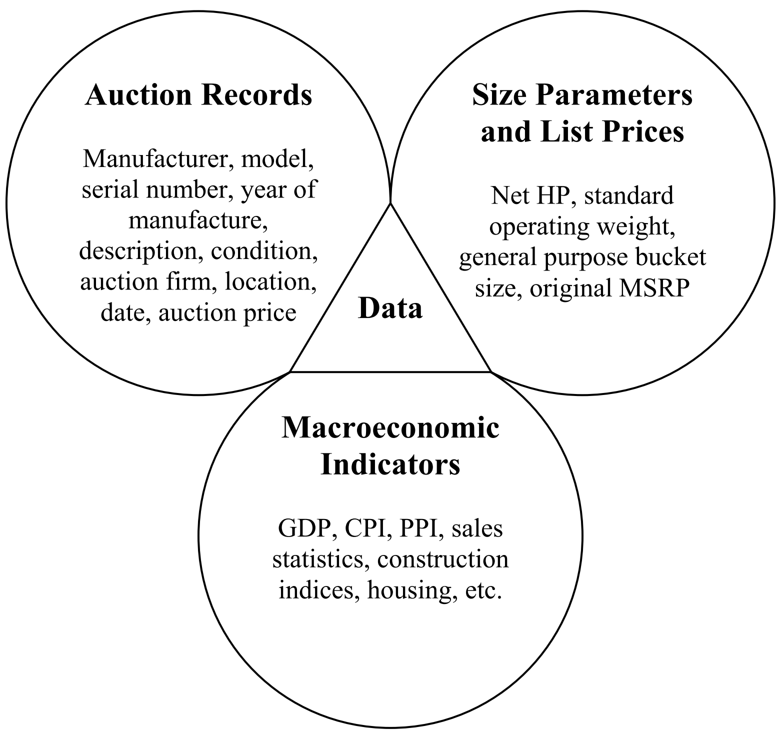


Figure 3.2: Elements of Data Families

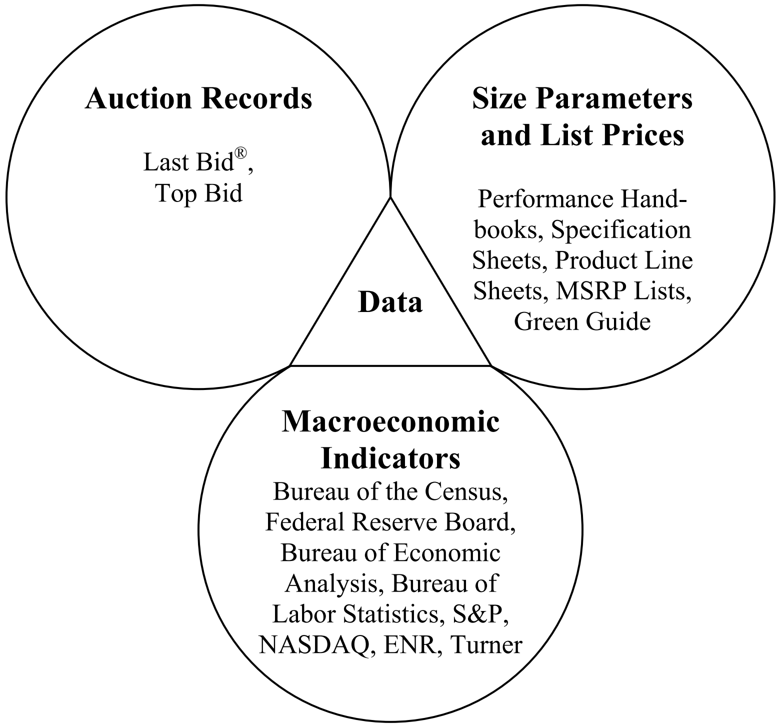


Figure 3.3: Sources for Data Families

3.3 Auction Records

It has been outlined in Section 2.4.5 that records from public auctions were considered to be the best realizations of economic value. Sales offers do not reflect values that were realized between a buyer and a seller but rather only the expectation of a seller. Data for the residual value of machines therefore were collected from construction equipment auctions. Data from sales offers, which were listed in many online market places for used heavy construction equipment, were not used. It was anticipated that sufficient data would be available from the databases of auction results.

3.3.1 Data Collection

Auction records are generated at public sales events that are held by equipment auction firms. They usually publish a catalog of the equipment to be auctioned off, which interested bidders use to prepare for and follow the ongoing auction. Auction firms sometimes post their track record after their auctions, in particular the auction prices that were achieved. Specialized data providers exist that collect and publish auction records.

Elements of this data family are:

- Type, manufacturer, model;
- Serial number;
- Year of manufacture;
- Description of tires and tracks, body and attachments, setup and special options;
- Condition rating;
- Auction firm;
- Auction location;
- Auction date;
- Auction price;
- Other information (if applicable).

Auction price was the most important piece of information within this data family, as it is used to determine the residual value of the equipment. Other pieces of information in the auction records described the circumstances of the respective auction (auction firm, location, date). Information about the machine were its unique identifiers (manufacturer, model, serial number, year of manufacture), while condition rating is an aggregate measure for the use and care received by the machine, and possibly a verbal description of the condition, accumulated use, and features of the machine. Condition rating is an aggregate value that represented a summary of the wear and tear that the machine had undergone and the maintenance and repairs that it had received.

3.3.1.1 Data Sources

Two data sources were identified to provide the auction records for this study. Obtaining auction records from two sources allowed verification by comparing the two entries for the same auction event via unique identifiers such as the serial number. Subscriptions for the online databases of Last Bid® (`<http://www.ironmax.com>`, formerly Green Guide Auction Report™) and Top Bid (`<http://www.equipmentworld.com>`) were purchased for one and three months, respectively. Both data sources gave written permission to use their data for the research purposes of this study. Tables 3.1 and 3.2 show the layout of the output screens of Last Bid® and Top Bid containing fictitious auction records for illustration purposes.

Table 3.1: Artificial Data from Last Bid®

Equipment Category:	CRAWLER TRACTORS	**Maximum Price:**	$340,000.00 (U.S. Dollars)
Equipment Type:	STANDARD CRAWLER DOZERS	**Minimum Price:**	$27,636.00 (U.S. Dollars)
Manufacturer:	CATERPILLAR	**Average Price:**	$204,475.35 (U.S. Dollars)
Model:	D8R		
Number of Matches:	179		Export Results
Expand your results,	Compare Similar Models	Note: All prices are listed in US Dollars.	
Narrow this list using a	Detailed Search	Prices from sales held in local currencies	
Start a New Search		have been converted to US Dollars at the	
View Auctions Recorded		sale day exchange rate.	

Results Navigation – navigate results by clicking the range group links

1-20 21-40 41-60 61-80 81-100 101-120 121-140 141-160 161-179

Range 1-20 Next 20 results

Underlined headings can be sorted

Manufacturer	Model	Serial#	Year	Description	Cond	Auctioneer	Verified	Location	Date	Price
CATERPILLAR	D8R	7XM8389	1996	w/8SU dozer w/tilt canopy	Good	Ritchie Bros. Auctioneers (Amer) Inc.	V	Lakeville, MN	12/15/1998	160,395
CATERPILLAR	D8R	7XM6022	2000	w/ROPS semi-U blade	Good	Alex Lyon & Son	V	Charlotte, NC	3/7/2002	180,000
CATERPILLAR	D8R	7XM7469	1998	w/SU dozer EROPS AC w/good u/c	-	Yoder & Frey Auctions Inc.	V	Riverside, CA	12/3/1999	197,640

Table 3.2: Artificial Data from Top Bid

Auction Dates From: Dec 2001 To: Dec 2002 Location: All Locations

NOTE: If a dropdown box is empty, it means no records match your Date/Location criteria

Selection Criteria: ○ **by Make/Model:** ⊙ **by Equipment Type:** ○ **by Auction:**

Equipment: Crawler Tractors CATERPILLAR D8R

Go To Auction Summaries **Reset** **GO**

TopBid Auction Results for: **Crawler Tractors – CATERPILLAR – D8R**

Low: 48,000 Average: 170,230 High: 248,000 for 46 results Spreadsheet Print

YOM	Make	Model	Serial No	Price	Condition	Auction Date	Auctioneer	Location
1996	CATERPILLAR	D8R	7XM6526	USD 155782	Good	4 Feb 2002	RITCHIE BROS.	PHILADELPHIA MS 39350
SU-BLADE W/TILT, CANOPY								
1998	CATERPILLAR	D8R	7XM1680	USD 167500		20 Mar 2002	ALEX LYON & SON	KISSIMMEE FL 34741
8SU-BLADE W/TILT, CAB W/AIR								
1998	CATERPILLAR	D8R	7XM7614	USD 210000	Very Good	15 Oct 2002	RITCHIE BROS.	FORT WORTH TX 76135
8SU-BLADE W/TILT, M/S RIPPER, GOOD U/C								

Both data sources reported that they had collected their data through their own staff or through subcontracted agents who had attended and observed equipment auctions. According to the printed edition of the Green Guide Auction Report™, they also relied on auction firm catalogs for some of their information (Primedia 1999, pviii):

> *For each transaction, any pertinent information relating to machine condition that is included in the auctioneer's catalog will also be included in our machine description, but we cannot verify the accuracy of those statements. The information is included only for the reader's interpretation.*

These two databases covered most construction equipment auctions that were held in the North American market. Putting their records together allowed verification of entries by comparing data from both sources via the serial number and other unique identifiers (provided they did not rely on the same agents at an auction) and also slightly increased the overall number of auctions that were covered.

Both Last Bid® and Top Bid offered search functions for their data to find equipment of particular types, from particular manufacturers, or of particular models. A selected range of data could be downloaded in spreadsheets form from their Web sites. One spreadsheet was downloaded for each equipment model. Individual spreadsheets were compiled into larger spreadsheets that contained all entries for one particular equipment type.

3.3.1.2 Data Ranges

The range of earthmoving equipment types examined for this study covered common types of heavy construction equipment to ensure broad applicability and usefulness of the results. The equipment types studies are hydraulic excavators (track-type, wheel-type), loaders (wheel-type, track-type, backhoes, integrated toolcarriers), rear-dump haulers (rigid frame, articulated), track dozers, motor graders, and wheel tractor scrapers. Rare or specialty types of equipment like e.g. cranes, rollers, and trenching and boring machines were not considered.

The range of manufacturers studied covered large manufacturers of heavy construction equipment in the U.S. and Canadian market, as determined by overall sales volume and market share. Manufacturers that were included are Caterpillar, Inc., Deere & Company, Komatsu America International Company, and Volvo Construction Equipment North America, Inc. This selection was checked against the numbers of available data points in the Last Bid® and Top Bid databases to ensure that a sufficient number of data points was available.

Only auction records for equipment of up to 15 years of age at the time of sale were included. The equipment age is easily determined as the difference between the year of manufacture and the auction date. Going back in time more than fifteen years would not be useful for practical application, as construction equipment of such age is rare and data are limited.

3.3.1.3 Data Properties

The auction records contained entries with different formats as shown in Tables 3.1 and 3.2. Verbal information was found in the columns containing manufacturer and condition. Various abbreviated keywords were found under the description column. The model name and the individual serial numbers were combinations of letters and digits. Names of the auction firm and location were several words long and included two-letter abbreviations of U.S. states and Canadian provinces and territories, respectively. The auction date was given in DD-MM-YY or in DD-Month-YYYY formats, respectively. Only the column containing the auction price in U.S. dollars could be used directly. Auction prices for all pieces of equipment sold at auctions in countries other than the U.S. had been converted by Last Bid® and Top Bid to U.S. dollars at the daily official exchange rate, thus eliminating the need to perform any conversion.

3.3.2 Data Preparation

The first and most important data family for this study is auction records. After they had been collected from the two data sources, they were prepared for the statistical analysis as described in detail in the following sections.

3.3.2.1 General Formatting

Once the EXCEL worksheets had been assembled from newly downloaded datasets, they were given clear labels as to the type of equipment that they contained. Data from both Last Bid® and Top Bid were stored in the same worksheet to form a single dataset. They were, however, still kept distinguishable visually by using two different font colors and by creating an indicator column SOURCE with “0” denoting Last Bid® entries and “1” denoting Top Bid entries for possible future sorting.

Columns in the worksheets of newly downloaded datasets were given clear headings for future reference. The self-explanatory headings were MAKE (manufacturer), MODEL, SERIAL (serial number), YEAR (year of manufacture), DESCR (description), COND (condition rating), FIRM (auction firm), LOC (location), DATE (auction date), and PRICE (auction price). Columns were formatted either as text, numbers, dates, or prices according to the type of data that they contained. The rows in the worksheets were then sorted in the hierarchical order of model, serial number, and auction date for clarity, unless other sorting was required for a particular preparation step.

Each row of the worksheets contained the entry from one auction event, i.e. one piece of equipment being sold at a particular auction. If the same machine was sold several times at different auctions it would create several entries. This could be identified by the serial number that appeared in several consecutive rows. The assumption was made that these entries could be treated as independent events. The entry in one particular row is also referred to as a data point in the remainder of this document.

In the next step, the data points in each worksheet were sorted consecutively by each column to find empty cells. Blank spaces that might have been part of numeric entries (e.g. "__$29,000__") were deleted. Empty cells and cells containing "-" were filled with the SAS® designation for a missing observation "." It was attempted to fill some of these gaps using adjacent information in the preparation step described in Section 3.3.2.13. All datasets were sorted by different columns and were checked for unusually large or small numerical entries, which may have resulted from erroneously adding or omitting digits to the number. In case such entries could not be corrected they were deleted.

3.3.2.2 Manufacturer

Data points were sorted by the MAKE column with its verbal categories of Caterpillar, Deere, Komatsu, and Volvo. They were converted to numbers from 1 to 4 in an intermediate column, which in turn were converted to three binary numbers in three new indicator columns m_1, m_2, and m_3 as listed in Table 3.3. The EXCEL code for this conversion is shown in Table 3.4. Using indicator variables in the statistical analysis is explained in Section 4.2.5.

Table 3.3: Conversion of Manufacturer to Binary Numbers

Manufacturer	Number	Binary Number		
		m_1	m_2	m_3
Caterpillar	1	0	0	1
Deere	2	0	1	0
Komatsu	3	0	1	1
Volvo	4	1	0	0

Table 3.4: EXCEL Code for Conversion of Manufacturer to Binary Numbers

Digit of Binary Number	Conversion to Binary Number
First Digit	`=IF(K3=4,1,0)`
Second Digit	`=IF(OR(K3=3,K3=2),1,0)`
Third Digit	`=IF(OR(K3=3,K3=1),1,0)`

3.3.2.3 Model Name

In a number of cases the model name of a piece of equipment was abbreviated or its spelling varied in the datasets. Examples of typical incorrect entries are listed in the following:

- Incomplete model name: Excavator PC300 instead of PC300HD-5;
- Incomplete series name: Excavator PC100 II instead of PC100C Series II;
- Missing hyphen: Excavator PW301 instead of PW30-1.

The correction was performed by sorting the data points by the SERIAL column and completing abbreviated or misspelled model names using information from more complete adjacent cells in the MODEL column. For clarity all blank spaces in the model column were deleted afterwards.

It is noted that less machines from newer series of a model had been auctioned than machines whose series had already been established for a longer time.

3.3.2.4 Serial Number

Different ways of recording the serial number were found in the datasets after they had been sorted by the SERIAL column. Model names were deleted in case they had been included in the serial number (e.g. “L120-V60401ASH” instead of “V60401ASH”). Since serial numbers had been given to machines in chronological order as they had left the manufacturer’s plant, it was possible to derive some corrections from this order. In some cases strings of zeros in the serial number (e.g. “2147” instead of “0002147”) had not been recorded, which was accounted for in the sorting and correcting. Typographical errors for individual letters or digits were detected in the SERIAL column in several cases and were corrected manually as far as possible by using other columns for comparisons. Since these errors always occurred between similar looking letters and digits, respectively, they probably resulted from the incorrect transcription of handwritten records into electronic files after the auction. Examples of typical incorrect entries are listed in the following:

- Letter or digit switches: 7XM instead of 7MX within a serial number;
- Letter or digit changes: 1=I, 2=Z, 3=6=8=B=S, 7=F=T.

3.3.2.5 Year of Manufacture

In some cases a difference of one year was found in the YEAR column between the records from Last Bid® and Top Bid for the same auction event as identified by the SERIAL and DATE columns. Correction of entries was possible when within a list of machines with consecutive serial numbers and identical year of manufacture one machine showed a sudden different entry in the YEAR column. Last Bid® gave the information that their records had been checked by serial number to verify the year of manufacture. It was also observed that Last Bid® entries tended to be more complete. Last Bid® entries therefore superseded Top Bid entries in case a pair of entries differed and required correction.

3.3.2.6 Description

Used equipment that was sold at auctions not necessarily had the same setup as when it had left the plant. Tires and track may have been replaced, attachments different from the original ones may have been sold together with the machine, or the machine may have been sold without any attachments whatsoever. Such machines would necessarily yield auction prices that are not typical for machine of standard setup and therefore needed to be deleted from the datasets. The DESCR column was searched for the words “no” and “not” and for “inoperable” machines. Conditional formatting was employed to achieve this task. All entries indicating missing parts like blades, buckets, cab, canopy, differential, dozer, engine, forks, moldboard, ripper, tires, ROPS, or EROPS, respectively, were deleted. The DESCR column was also skimmed for other unusual entries. Only one entry with missing tires was found in the datasets.

It was not possible to correct for wheels or tracks differing from the standard setup, as the DESCR column did not contain such information. Most entries lacked sufficiently detailed data in the DESCR column that would have allowed making adjustments to the auction price. It was still possible that data points with differing but unknown setup remained in the datasets. This slightly decreased the consistency between data points of the same manufacturer and model. However, it was attempted to identify such outliers with unusually high or low auction prices in the statistical analysis using studentized residuals, as explained further in Section 4.3.2.

The description “4X4” or “6X6” indicating the total number of wheels and the number of wheels driven was used to correctly group the trucks and assign their different list prices in the next step.

3.3.2.7 Condition Rating

The condition rating for a piece of equipment is a somewhat subjective proxy for the result of physical influences on that machine. It is commonly assessed by equipment appraisers who examine different parts of the machine, such as e.g. tires and tracks, undercarriage, and engine, record their observations in mostly standardized checklists, and determine a summarizing verbal condition rating. Wear and tear from use negatively affect the condition while care, i.e. maintenance and repair, attempt to improve or at least maintain the current condition (Perry et al. 1990). The owner of a machine may choose a philosophy of use that is located anywhere on the spectrum between perfect care and no care whatsoever.

Data points were sorted by the COND column with its verbal categories of new, excellent, very good, good, fair, poor, or "-" (missing entry). Table 3.5 lists the definitions that the data sources give for these categories. They were converted to numbers from 6 to 1 and "." in an intermediate column, which in turn were converted to three binary numbers in three new indicator columns c_1, c_2, and c_3 as listed in Table 3.6. The EXCEL code for this conversion is shown in Table 3.7.

In case the year of manufacture for a new machine was unknown, the assumption was made that the condition rating "new" concurred with zero years of age. Again it was found that Last Bid® entries tended to be more complete and thus superseded Top Bid entries. A number of auction records had been verified by Last Bid® staff with respect to their manufacturer, model, serial number, and condition. For other auction records is was not clear who had determined the condition rating – the auction firm, an independent appraiser, or the data source. The assumption was made that the condition rating for all auction records had been obtained in a consistent way. How much explanatory power the condition rating can actually contribute to the regression model will be established during the statistical analysis.

Table 3.5: Definitions of Condition Ratings

Condition Rating	Green Guide™ Auction Reports	Last Bid®	Top Bid
New	N/A	New unit	low or no hour machine
Excellent	Has seen very little or limited use.	Some use, but almost new mechanically	low hours, very little use
Very Good	Above average condition; may have been overhauled or may or may not have had enough use to require overhaul.	In above average mechanical condition; low hours or recently overhauled	above-average condition
Good	Average condition, with no known defects except as noted; in operating condition, but may need some repair or parts replacement soon.	In average mechanical condition; may need minor repairs or replacement of worn parts soon	an average piece of equipment, may need minor repairs
Fair	Has seen considerable service and may require repair or replacement of worn parts.	In below average mechanical condition; high hours or older unit	has been in service for a considerable time, may need repairs
Poor	Has seen hard service; needs repairs to be reliable, and may not be operational.	Needs major repairs	has undergone extensive service, may need repair, or be inoperative
Verified	N/A	Verified. Auction attended by EquipmentWatch field agent who verifies Make, Model, Serial Number and Condition.	N/A
(-)	N/A	(dash) Non-Verified. Data provided by Auctioneer. Erroneous transactions are corrected or omitted from database.	N/A

Sources: Primedia 1999, pviii, <http://www.ironmax.com>, <http://www.equipmentworld.com>.

Table 3.6: Conversion of Condition Rating to Binary Numbers

Condition Rating	Number	Binary Number		
		c_1	c_2	c_3
New	6	1	1	0
Excellent	5	1	0	1
Very Good	4	1	0	0
Good	3	0	1	1
Fair	2	0	1	0
Poor	1	0	0	1
-	.	.	.	.

Table 3.7: EXCEL Code for Conversion of Condition Rating to Binary Numbers

Digit of Binary Number	Conversion to Binary Number
First Digit	`=IF(OR(K3=6,K3=5,K3=4),1,0)`
Second Digit	`=IF(OR(K3=6,K3=3,K3=2),1,0)`
Third Digit	`=IF(OR(K3=5,K3=3,K3=1),1,0)`

3.3.2.8 Auction Firm

Data on the auction firms that performed the auctions were more complete than entries in the YEAR, COND, and DESCR columns. Only for a few cases the comparison of the auction firms, dates, and locations in the datasets with a list of auctions provided by Last Bid® showed that the names of two auction firms holding auctions in Florida apparently had been switched. Otherwise no corrections were necessary. Auction firm was not used as an explanatory variable in the statistical analysis. The assumption was made that all auction firms performed equally open and fair auctions to arrive at their auction prices.

3.3.2.9 Auction Region

The descriptive column LOC in the datasets included the cities and states, provinces, or territories, respectively, for each auction event. Top Bid entries provided the ZIP code of the city. Names of foreign countries were given in abbreviated form. Foreign countries for which auction records were available included Australia, England, Germany, Indonesia, Mexico, the Netherlands, Northern Ireland, the Philippines, Singapore, Spain, Thailand, Turkey, and the United Arab Emirates. Their identifiers were extracted into a new column and all entries from auctions that took place outside the North American market were deleted. The North American market in this study is defined was the U.S. and Canada. Records from auctions conducted via the Internet were also discarded for lack of a real geographic location.

A new column STATE was created into which the two-letter abbreviations of U.S. states and of Canadian provinces or territories were extracted from the LOC column. The abbreviations for Canadian provinces and territories had to be extracted with a slightly different EXCEL code, as the Canadian ZIP code system consists of six alternating letters and digits and not of five digits as in the U.S. Geographic regions were created for the statistical analysis. *Engineering News Record* was contacted whether any particular geographical division of the U.S. is commonly used for the Construction Industry. No such division was found and therefore the regions as defined by the Bureau of the Census were used. The five regions are Northeast, South, Midwest, and West, and Canada as an own region are listed in Table 3.9 with their individual states and provinces or territories, respectively. It should be noted that not all Canadian provinces and territories had entries.

The region of each entry was extracted into five new columns REG1, REG2, REG3, REG4, and REG5 in an intermediate step using the EXCEL code of Table 3.8. A “1” denoted that the auction took place in that region and “0” denoted it did not take place in that region. A control column summing up the “1” and “0” values was created to ensure that each entry had been assigned exactly to one region. It was then possible to convert the number of the region to three binary numbers in three new indicator columns r_1, r_2, and r_3 as listed in Table 3.9. The EXCEL code for this conversion is shown in Table 3.10.

Table 3.8: EXCEL Code for Conversion of State to Region

Region	Conversion from State or Province or Territory to Region
Northeast	`=IF(OR(K5="CT",K5="MA",K5="ME",K5="NH",K5="NJ", K5="NY",K5="PA",K5="RI",K5="VT"),1,0)`
South	`=IF(OR(K5="AL",K5="AR",K5="DC",K5="DE",K5="FL", K5="GA",K5="KY",K5="LA",K5="MD",K5="MS",K5="NC", K5="OK",K5="SC",K5="TN",K5="TX",K5="VA",K5="WV"),1,0)`
Midwest	`=IF(OR(K5="IA",K5="IL",K5="IN",K5="KS",K5="MI", K5="MN",K5="MO",K5="ND",K5="NE",K5="OH",K5="SD", K5="WI"),1,0)`
West	`=IF(OR(K5="AK",K5="AZ",K5="CA",K5="CO",K5="HI", K5="ID",K5="MT",K5="NV",K5="NM",K5="OR",K5="UT", K5="WA",K5="WY"),1,0)`
Canada	`=IF(OR(K5="AB",K5="BC",K5="MB",K5="NB",K5="NL", K5="NT",K5="NS",K5="NU",K5="ON",K5="PE",K5="PQ", K5="SK",K5="YT",),1,0)`

Table 3.9: Conversion of State to Binary Numbers

Census Region and Canada	Number	States	Binary Number		
			r_1	r_2	r_3
Northeast	1	CT, MA, ME, NH, NJ, NY, PA, RI, VT	0	0	1
South	2	AL, AR, DC, DE, FL, GA, KY, LA, MD, MS, NC, OK, SC, TN, TX, VA, WV	0	1	0
Midwest	3	IA, IL, IN, KS, MI, MN, MO, ND, NE, OH, SD, WI	0	1	1
West	4	AK, AZ, CA, CO, HI, ID, MT, NM, NV, OR, UT, WA, WY	1	0	0
Canada	5	All Provinces and Territories	1	0	1

Table 3.10: EXCEL Code for Conversion of Region to Binary Numbers

Digit of Binary Number	Conversion to Binary Number
First Digit	`=IF(OR(AH5=1,AI5=1),1,0)`
Second Digit	`=IF(OR(AF5=1,AG5=1),1,0)`
Third Digit	`=IF(OR(AE5=1,AG5=1,AI5=1),1,0)`

3.3.2.10 Auction Date

In many cases the auction date recorded by Last Bid® lagged behind the auction date recorded by Top Bid by one or two days for the same auction event as identified by the serial number. Possibly the two data sources used a different date of reference for their records. Equipment auctions may last several days and the auction date could be the beginning day, the closing day, or the day on which a particular machine was actually sold. This deviation was not critical for the analysis because age was calculated in calendar years only and the smallest frequency of economic indicator values was one week. Comparing auction dates from the datasets with a list of auctions provided by Last Bid® showed more agreement with entries in Last Bid®. They were chosen to supersede Top Bid entries in case the auction dates for the same auction event differed. This is consistent with the previous treatment of differing pairs of entries. Incomplete entries in the DATE column were corrected if possible by comparing them with auctions at the same location and with the list of auctions provided by Last Bid®.

A new column AGE containing the age in calendar years was created. Age was calculated as the difference of the year from the auction date and the year of manufacture. The datasets were then sorted by the AGE column and all entries with unreasonable ages, such as negative values (from e.g. "199_ - 1996") or very large values (from e.g. "2002 – 199_") were corrected if possible or deleted.

3.3.2.11 Auction Price

Comparing the pairs of entries from Last Bid® and Top Bid by their serial number in a few cases showed missing "0" digits in the auction price, which were corrected accordingly. A few entries showed a difference of $1,000 or higher between the auction price recorded by Last Bid® and Top Bid, which may be attributable to taxes and sales fees or attachments that were sold separately but were included in the auction price of the machine. Moreover, it was found that the auction prices reported by the two data sources for Canadian auctions did not match exactly but differed by about ± 6%, which may be attributable to converting Canadian dollars to U.S. dollars based on slightly different auction dates, as described in Section 3.3.2.10. To keep the datasets consistent, entries from Last Bid® were again chosen to supersede Top Bid entries in case the auction prices for the same auction event differed. It needs to be noted that most auction prices were multiples of $1,000 and fewer were multiples of $500.

3.3.2.12 Meter Hours and Mileage

Meter hours are measured by electronic meters that are activated by a pressure switch on the hydraulic system of the machine and record the time that the engine of the machine is running (Agoos 2003). It is possible that the machine is not working productively even when meter hours are being recorded. Meter hours thus are only a proxy for the actual hours of use of a machine. Contractors usually compare them with the operating and idle hours and with the available time and downtime as recorded in the daily logs that the job site superintendent fills in and submits to the equipment manager (Agoos 2003). Mileage is measured by the odometer of the machine to give a record of the distance traveled by that machine. However, not all miles recorded on the odometer may have been caused by working productively. Another indicator that could be used to measure equipment use is the fuel consumption, which depends on the intensity and duration of work. It can be measured accurately when a machine if fueled from a tank vehicle (Agoos 2003).

Neither meter hours nor mileage were available from the databases of Last Bid® or Top Bid because these data were not recorded at the auctions by their representatives (Corso 2002, Miller 2002). Information was provided that these two measures are generally considered unreliable by auction firms for several reasons: Electronic hour meters may fail even while being more reliable than older mechanical hour meters, they may have been replaced during major repairs and overhauls, they may have been tampered with, and due to these discrepancies are not representative of the actual hours worked. It was therefore not possible to include meter hours or mileage, respectively, as explanatory variables in this study.

3.3.2.13 Macro AddYears

It was attempted to fill gaps in the sorted datasets by systematically examining neighboring entries. Two approaches were used to fill the gaps. They could be filled by comparing the pair of entries from Last Bid® and Top Bid for the same auction event. Data were also reconstructed using adjacent data of similar kind. A missing year of manufacture could be inferred from a group of machines of the same model with nearby serial numbers. Gaps in the COND could only be filled by comparing the Last Bid® and Top Bid pairs of entries, since the condition rating was unique to every machine.

A macro was programmed in Microsoft® Visual Basic® for Applications 6.3 and was applied to the EXCEL worksheets of all datasets to fill gaps in an automated manner. The code for the macro *AddYears* can be found in Appendix A.1. It first requested several input columns to be entered by the user. The columns YEAR, DATE, SERIAL, and STATE were used in the comparison. For each entry with an empty cell in the YEAR column the macro compared the contents of the cells in the DATE, SERIAL, and STATE columns with their predecessors and successors. If a match was found, the content of the adjacent YEAR cell was copied into the empty cell. Appendix A.2 provides a flowchart for this macro.

The macro was also used to fill gaps in the DESCR and COND columns by comparing Last Bid® and Top Bid pairs of entries, with the modification that commands of the type

`CDate(Cells(i,m))` in the code were replaced by `Cells(i,m)` to reflect that text and not a date was copied. After the macro *AddYears* had been applied, the entire dataset was skimmed visually and remaining apparent errors were corrected, e.g. sudden different entries in the YEAR column for machines of the same model with consecutive serial numbers. However, even with this reconstruction some gaps remained in the datasets.

3.3.2.14 Macro DeleteDoubles

Once gaps had been filled as described in the previous section, any double entries that had resulted from consolidating the data from Last Bid® and Top Bid into the same datasets had to be identified and deleted. All datasets were sorted by model, serial number, and auction date for this purpose. Any possible redundant entries would thus appear consecutively in the dataset. The macro *DeleteDoubles* was programmed and was applied to the EXCEL worksheets. The code for this macro can be found in Appendix A.3. It first requested the user to enter the PRICE, AGE, SERIAL, STATE, and REG5 columns. The DATE column was not used for comparison, as pairs of entries from Last Bid® and Top Bid had slightly different auction dates for the same auction event. Column REG5 was used to determine if the auction had taken place in Canada. In this case the macro allowed for ± 6% difference between the auction prices in the pairs of entries. This range allowed comparing entries even with slightly different currency conversion from Canadian dollars to U.S. dollars. When a match was found the macro deleted the first entry of a pair. Last Bid® entries were retained since they usually reported a slightly later auction date than Top Bid entries and thus came second in a pair of entries. Appendix A.4 provides a flowchart for this macro. The entire dataset was again skimmed visually after the macro had been applied.

3.4 Size Parameters

Auction records identify every machine by manufacturer and model. Serial number and year of manufacture are provided as additional identifiers for most machines in the auction records. Based on these identifiers it is possible to gather additional data that were not contained in the auction records. Data on the rated performance and capacity of the machines were collected to create size classes by which equipment was grouped. These specifications will be referred to as size parameters in the remainder of this document. Commonly used descriptors were selected for every equipment type. Each size class contained only machines of the similar size. This yielded smaller but more consistent datasets and was expected to improve the goodness-of-fit of the regression models with their data.

3.4.1 Data Collection

Size parameters form the second data family. They described physical features or performance measures of machines, respectively, and were used to group the data into smaller datasets.

3.4.1.1 Data Sources

Classification of the data points by equipment size required one characterizing size parameter for all manufacturers and models for which data points had been obtained from Last Bid® and Top Bid. A spreadsheet with a catalog of size parameters was prepared from a variety of sources. Performance handbooks published by equipment manufacturers were assumed to have the highest accuracy and reliability and superseded other sources in case information differed. Further sources are listed in order of decreasing assumed reliability:

- Caterpillar Performance Handbook (especially the former models section);
- Deere Performance Handbook (especially the former models sections);
- Volvo Articulated Haulers Performance Manual;
- Folders and electronic files with Manufacturers Suggested Retail Prices and specifications kindly made available by manufacturers and distributors;
- Specification sheets from manufacturers' Web sites;
- Product line documents from manufacturers' Web sites;
- Interactive current model listings on manufacturer's Web sites;

- Green Guide™ and SpecFinder listings available from the Last Bid® Web site;
- Specifications Guide available from the *Construction Equipment* Web site
- X-Specs available from the SpecCheck Web site;
- Auction listings on the Internet to fill remaining gaps.

Some inconsistencies between different sources, e.g. conversions and rounding between U.S. and metric units, were resolved using the aforementioned hierarchy of sources. An excerpt of the size parameter catalog is shown in Table 3.11. Size parameters were be added to the each data point once the catalog had been assembled.

Table 3.11: Excerpt of Size Parameter Catalog

Equipment Type	Manufacturer	Model	Standard Operating Weight [lbs]	General Purpose Bucket Size [CY]	Net Horse Power [HP] (Flywheel)
…	…	…	…	…	…
Wheel Loader	Caterpillar	416	13,574	1.00	62
Wheel Loader	Caterpillar	426	14,626	1.25	70
Wheel Loader	Caterpillar	428	15,350	1.35	70
Wheel Loader	Caterpillar	436	15,062	1.38	77
Wheel Loader	Caterpillar	446	19,603	1.50	95
…	…	…	…	…	…

3.4.1.2 Data Ranges

The range of size parameters ideally was identical to the range of manufacturers and models for which data points had been obtained from the databases of auction records. In case size parameters were not available from any of the aforementioned sources, the affected data points were deleted from the worksheet. This ensures that only data points with complete information for all four data families entered the statistical analysis. Table 3.12 lists the size parameters that have been selected as being characteristic for the different types of equipment.

Table 3.12: Equipment Types and Size Parameters

Equipment Type	Size Parameter
Track Excavators	Standard Operating Weight
Wheel Excavators	Standard Operating Weight
Wheel Loaders	General Purpose Bucket Size
Track Loaders	General Purpose Bucket Size
Backhoe Loaders	General Purpose Bucket Size (of backhoe)
Integrated Toolcarriers	Net Horse Power (flywheel)
Rigid-Frame Trucks	Standard Operating Weight (empty)
Articulated Trucks	Standard Operating Weight (empty)
Track Dozers	Net Horse Power (flywheel)
Motor Graders	Net Horse Power (flywheel)
Wheel Tractor Scrapers	Standard Operating Weight (empty)

3.4.1.3 Data Properties

Manufacturers offer a variety of setup options for most equipment models. However, due to the brevity of the description column in the auction records, it was not possible to exactly identify the set of size parameters for each machine. In some cases different sources gave slightly different values for the same size parameter of a particular model.

For these reasons every data point of a particular model was matched with a set of size parameters for a standard machine of this model. Among different buckets the smallest general purpose bucket was selected as a standard value. If a specification sheet described the setup for measuring the standard operating weight, that bucket size was used. For backhoe loaders the size of the backhoe bucket was used. If available, enclosed roll-over protective structures (EROPS) were assumed. Track-type equipment was assumed to have normal width tracks. Net horse power (HP) at the flywheel was used as power rating of the machines. The standard operating weight for trucks in unloaded condition was used.

3.4.2 Data Preparation

The following sections explain how the auction records were matched with their size parameters and how size classes were formed.

3.4.2.1 Macro MatchParameters

All datasets were sorted by the model name to match the auction records with their size parameters. The macro *MatchParameters* was programmed and was applied to the EXCEL worksheets. The size parameter catalog was copied into the same worksheet as the auction records with sufficient space between the two blocks of cells left to be filled by the macro. The code for this macro can be found in Appendix A.5. It first requested the user to enter the range of cells containing auction records and the MODEL column within this range. It also requested the range of cells containing the size parameter catalog and the MODEL column within that range. For each entry in the auction records the macro went through all rows of the size parameter catalog and compared the model names. When a match was found between both ranges the macro copied the size parameter entry next to the auction records and proceeded to the next entry in the auction records. Appendix A.6 provides a flowchart for this macro.

3.4.2.2 Size Classes

Once the auction records had been matched with their respective size parameters they were divided into 28 size classes. Care was taken to create size classes for each equipment type that spanned equal ranges of the size parameter and still contained sufficiently large numbers of data points. In the case of wheel excavators and integrated toolcarriers the number of available data points did not allow creating size classes. The complete list of size classes is shown in Table 3.13. A detailed summary of the size classes and their data points can be found in Table 3.14 and in Appendix F. Cells containing zero observations are shaded. The statistical analysis was performed on these 28 datasets.

Table 3.13: List of Size Classes

Equipment Type	Number	Size from	Size to	Unit	Size Parameter
Track Excavators	1	0	24,999	lbs	Standard Operating Weight
	2	25,000	49,999		
	3	50,000	74,999		
	4	75,000	99,999		
	5	100,000	Open		
Wheel Excavators	6	All	All	lbs	Standard Operating Weight
Wheel Loaders	7	0	1.9	CY	General Purpose Bucket Size
	8	2	3.9		
	9	4	5.9		
	10	6	Open		
Track Loaders	11	0	1.9	CY	General Purpose Bucket Size
	12	2	Open		
Backhoe Loaders	13	0	0.9	CY	General Purpose Bucket Size (of backhoe)
	14	1	Open		
Integrated Toolcarriers	15	All	All	HP	Net HP (flywheel)
Rigid Frame Trucks	16	0	99,999	lbs	Standard Operating Weight (empty)
	17	100,000	Open		
Articulated Trucks	18	0	49,999	lbs	Standard Operating Weight (empty)
	19	50,000	Open		
Track Dozers	20	0	99	HP	Net HP (flywheel)
	21	100	199		
	22	200	299		
	23	300	399		
	24	400	Open		
Motor Graders	25	0	149	HP	Net HP (flywheel)
	26	150	Open		
Wheel Tractor Scrapers	27	0	74,999	lbs	Standard Operating Weight (empty)
	28	75,000	Open		

Table 3.14: List of Datasets with Outliers

Equipment Type	Number	Size from	Size to	Unit	Size Parameter	Entries from each Manufacturer				Total
						Caterpillar	Deere	Komatsu	Volvo	
Track Excavators	1	0	24,999	lbs	Standard Operating Weight	77	8	22	0	107
	2	25,000	49,999			590	218	1093	0	1901
	3	50,000	74,999			289	87	55	0	431
	4	75,000	99,999			398	28	44	0	470
	5	100,000	Open			0	5	58	0	63
Wheel Excavators	6	All	All	lbs	Standard Operating Weight	114	129	25	0	268
Wheel Loaders	7	0	1.9	CY	General Purpose Bucket Size	68	240	132	55	495
	8	2	3.9			236	2211	1002	444	3893
	9	4	5.9			372	106	1021	219	1718
	10	6	Open			214	0	142	88	444
Track Loaders	11	0	1.9	CY	General Purpose Bucket Size	45	461	62	0	568
	12	2	Open			138	251	270	0	659
Backhoe Loaders	13	0	0.9	CY	General Purpose Bucket Size (of backhoe)	0	230	0	0	230
	14	1	Open			186	7359	45	0	7590
Integrated Toolcarriers	15	All	All	HP	Net HP (flywheel)	289	48	0	0	337
Rigid Frame Trucks	16	0	99,999	lbs	Standard Operating Weight (empty)	332	0	21	0	353
	17	100,000	Open			105	0	2	0	107
Articulated Trucks	18	0	49,999	lbs	Standard Operating Weight (empty)	652	0	69	947	1668
	19	50,000	Open			404	0	0	573	977
Track Dozers	20	0	99	HP	Net HP (flywheel)	0	3652	1723	0	5375
	21	100	199			1904	1259	1491	0	4654
	22	200	299			52	0	240	0	292
	23	300	399			235	0	130	0	365
	24	400	Open			49	0	77	0	126
Motor Graders	25	0	149	HP	Net HP (flywheel)	333	367	0	0	700
	26	150	Open			321	478	0	0	799
Wheel Tractor Scrapers	27	0	74,999	lbs	Standard Operating Weight (empty)	623	164	0	0	787
	28	75,000	Open			165	0	0	0	165
Sum	N/A	N/A	N/A	N/A	N/A	8191	17301	7724	2326	35542

3.5 List Prices

Residual value is commonly standardized as percent of a base price to achieve better comparability between different scenarios. Possible denominators of this ratio are the original list price and the original purchase price. They are reviewed in the following paragraphs.

The term list price refers to the price lists used by manufacturers and their distributors to assemble information on the pricing of the equipment and its accessories. It is also called Manufacturers Suggested Retail Price (MSRP) and is defined as the retail price for a product as recommended and published by its manufacturer. Both terms are used interchangeably in this document. Since it is a recommendation without an actual transaction taking place, the MSRP only gives an indication of the dimension of the economic value. It should not be taken as absolute, but mostly serves as an artificial point of reference for a customer who receives an individual purchase discount. In essence, the MSRP can be considered idealized and is most likely overstating the actual market value of the machine due to ubiquitous discounts.

Discounts that are given from the published MSRP may depend on a variety of factors. Such factors can be a good business relationship with a particular customer, the volume of past transactions and the size of the current order, special sales events and promotions, the offered financing and payment options, the situation of the economy in the geographic region where the distributor is located, and overall state of the economy. The actual discount structure is kept confidential between a manufacturer and its distributors, and the individual discounts are kept confidential between the distributors and their customers.

Obtaining the current MSRP from a manufacturer or its distributors is generally possible. Obtaining a past MSRP may prove to be more difficult, as manufacturers and distributors may not have past records of list prices available indefinitely. Published list prices on the Web site of the Original Equipment Manufacturer may simply be overwritten when a new price list becomes effective.

The purchase price is the actual price for which the owner obtained a piece of equipment from the manufacturer or its distributor, respectively. As mentioned before, it is lower than the list price due to discounts given. Part of the purchase price may be sales and setup fees, e.g. the cost of transporting the machine from the distributor to its new owner. Using the original purchase price as a denominator to calculate RVP initially appears reasonable but may not be the most feasible option. Two arguments speak against its use. First, the aforementioned proprietary nature of the data could prevent obtaining a sufficient number of data points. Second, purchase prices are not directly comparable between different construction companies, each of which may receive different discounts. Using purchase prices would thus yield results of limited quality which could not be generalized to the Construction Industry at large.

For aforementioned reasons, the standardization – or rather normalization – was performed based on original MSRP. Discount structures on the other hand were too unique to the individual manufacturer to reasonably compare purchase prices with each other, the proprietary nature of these prices notwithstanding. This is in agreement with the approach that Cross and Perry (1995) presented. Statistical issues arising from the normalization itself are discussed in Section 4.2.6 of this document.

3.5.1 Data Collection

List prices form the third data family. They were published by manufacturers and their distributors and were used to establish a measure of the initial value of each machine for determining its RVP.

3.5.1.1 Data Sources

It was necessary to collect data on the original list prices for calculating the RVP as the ratio of the inflation-corrected auction price to the inflation-corrected list price. A spreadsheet with a catalog of list prices was prepared from a variety of sources, again in order of decreasing assumed reliability:

- Folders and electronic files with Manufacturers Suggested Retail Prices (MSRP) and some specifications kindly made available by manufacturers and distributors;
- Interactive current model listings on manufacturer's Web sites;
- Green Guide™ listings available from the Last Bid® Web site.

Since some manufacturers may consider their list prices to be proprietary information, no excerpts from the list price catalog are shown.

3.5.1.2 Data Ranges

The range of list prices was determined in analogy to the previously discussed size parameters. It covered all manufacturers and models for which data points had been obtained. In case list prices were not available from any of the aforementioned sources, the affected data points were deleted from the worksheet.

3.5.1.3 Data Properties

In case the obtained literature gave detailed list prices for different setup options of the same model, the standard machine as described in the Section 3.4.1.3 was chosen to calculate a total list price. If list prices were available only for a limited range of years but a machine had a year of manufacture outside this range, the assumption was made that list prices increase proportionally to the inflation rate as measured by the PPI. The missing list prices were extrapolated in the worksheet using the average annual PPI. Calculation of the average annual PPI is described in more detail in Section 3.6.2.5. It is acknowledged that this assumption may understate the actual increases in list prices as manufacturers over time may introduce small improvements in machines of the same model and may increase list prices accordingly. List prices may also change when a manufacturer adopts a new marketing strategy.

3.5.2 Data Preparation

The macro *MatchParameters* was used again to match the auction records (including their size parameters) with their list prices. The list price catalog was copied into the worksheet and the macro was applied. After all list prices had been added to the auction records they were sorted by the YEAR column. Only the list price for the actual year of manufacture was retained, all others were deleted. This approach allowed keeping the macro simple. Otherwise both the model name and the year of manufacture would have been necessary for comparison, which would have required exponentially more computation time. After the macro had been applied, the entire dataset was again skimmed visually.

3.6 Macroeconomic Indicators

It is expected that the situation of the Construction Industry and of the economy as a whole influence the residual value of a piece of equipment. A variety of numeric indicators was therefore included in the data to capture the macroeconomic situation at the times when auctions took place. Macroeconomic indicators will be referred to as economic indicators in the remainder of this document for brevity. These indicators were selected based on their general acceptance as measures of the state of the economy and their applicability for the Construction Industry, their public availability from official sources, and their frequency. One selected economic indicator was also used for inflation correction of the list prices and auction prices. Data series contained economic indicator values that occurred with weekly, monthly, or quarterly frequencies.

3.6.1 Data Collection

Economic indicators are used in the financial and political world in an attempt to capture a numerical measure of a selected aspect of the overall economy to give information about its state or health. At a macroeconomic level, the global, international, or national economy can be observed. On a smaller scale, industry and firm analysis can be performed, e.g. for the Construction Industry and its segments, e.g. construction equipment manufacturing and used equipment sales. The term economy in the following shall mean the market at the macroeconomic level.

Obviously, there cannot be a single measure for the state of the economy but rather a wide range of possible measures for different characteristics exists. Publicly available sources of economic information indeed contain a large range of very diverse data series. Often an economic calendar or release schedule (Bodie et al. 2002) is published to inform when new indicator values are made available to the general public. An important consideration for selecting an economic indicator is its acceptance in the economic and financial communities as being an accurate and reliable measure of one aspect of the state of the economy. In their aggregate these measures give an impression about the current situation and about development trends of the economy (Bodie et al. 2002).

3.6.1.1 Data Sources

Several different sources provided the economic indicator values to include the situation of the economy and the Construction Industry in the statistical analysis. Sources of economic indicators were government agencies, independent research organizations, regular corporate publications, and financial news services. Government publications had the advantage that they were in most cases available free of charge.

Compilations of economic data series were found on the Web sites of various government agencies and economic information services, such as `<http://www.economy.com>`.

Industry publications, such as the trade magazine *Engineering News Record* supplied data that are dealing more specifically with the situation of the Construction Industry. Series of stock prices for construction equipment manufacturers that are traded in secondary markets were obtained from financial news services.

3.6.1.2 Data Ranges

The range of values for every economic indicator depended on the auction records. These were sorted by auction date to determine the span of time during which auctions had been recorded and for which economic indicator values needed to be collected. Every auction date was matched with its specific set of values. An economic indicator catalog that assembles these values in a spreadsheet therefore was created. The assumption was made that the value of an economic indicator remained constant until the subsequent value was reported.

Three different types of major economic indicators – also referred to as business cycle indicators – are distinguished in macroeconomics and are commonly used as key indicators to describe the state of the economy – leading, coincident, and lagging indices. They are believed to give indications of economic trends, as implied in their names. This classification can be traced back to earlier work of the National Bureau of Economic Research (Bodie et al. 2002). The independent research organizations The Conference Board and the Economic Cycle Research Institute collect and maintain proprietary business cycle indicators such as listed in Table 3.15, some of which are available to the public free of charge.

Many of the components of these indicators or similar economic indicators have been included in this study. A comprehensive list of the economic indicators is provided in Appendix D, including their name, frequency, original source, and unit, if any. From the overwhelming number of available economic indicators the selected ones were considered to bear potential for predicting the residual value. It is expected that several of the selected economic indicators will contribute rather little to the regression model. Only in the statistical analysis it will be determined which economic indicators contribute significantly to the predictive power of the regression model.

Table 3.15: Components of Business Cycle Indicators

Index Name	Number	Component	Standardization Factor
Leading Index	1	Average weekly hours, manufacturing	0.1946
	2	Average weekly initial claims for unemployment insurance	0.0268
	3	Manufacturers' new orders, consumer goods and materials	0.0504
	4	Vendor performance, slower deliveries diffusion index	0.0296
	5	Manufacturers' new orders, nondefense capital goods	0.0139
	6	Building permits, new private housing units	0.0205
	7	Stock prices, 500 common stocks	0.0309
	8	Money supply, M2	0.2775
	9	Interest rate spread, 10-year Treasury bonds less federal funds	0.3364
	10	Index of consumer expectations	0.0193
Coincident Index	1	Employees on nonagricultural payrolls	0.5186
	2	Personal income less transfer payments	0.2173
	3	Industrial production	0.1470
	4	Manufacturing and trade sales	0.1170
Lagging Index	1	Average duration of unemployment	0.0368
	2	Inventories to sales ratio, manufacturing and trade	0.1206
	3	Labor cost per unit of output, manufacturing	0.0693
	4	Average prime rate [charged by banks]	0.2692
	5	Commercial and industrial loans [outstanding]	0.1204
	6	Consumer installment credit outstanding to personal income ratio	0.1951
	7	Consumer price index for services	0.1886

Source: <http://www.globalindicators.org>, comments added.

3.6.1.3 Data Properties

While economic indicators all attempt to measure a certain aspect of the health of the economy, it is quite possible that in reality they are significantly correlated with each other (Perry et al. 1990). In other words, the phenomena in the real world are created through a complex network of interactions between all economic participants. Measuring them can produce some similarity and overlap in showing upswings and downswings of the economy, regardless of which particular aspect is examined. Cyclical industries, such as e.g. durable and capital goods manufacturers, which are more sensitive to the business cycle, are commonly distinguished from defensive industries, such as e.g. food and utility producers (Bodie et al. 2002). The correlation between the selected economic indicators is examined in Section 3.6.2.1. Seasonally adjusted economic indicators have been used as far as possible to exclude seasonal effects from the analysis. How seasonal adjustment is performed is explained in Section 3.6.2.3.

3.6.2 Data Preparation

A variety of economic indicators as listed in Appendix D were obtained to create the economic indicator catalog, which was divided into indicators with weekly, monthly, and quarterly frequency. Entries that had an auction date of later than September 31, 2002 were deleted, as no later economic indicator values were available at the time of the work. A few recent economic indicator values had not yet been revised and re-released by their sources. As revised values differ only marginally from the first release, this is expected to have little effect.

Economic time series usually are available in form of two columns (date and indicator value) or in form of a block with 12 monthly indicator values in each row. Editing the latter form of economic indicators values required WORD codes as shown in Table 3.16.

3.6.2.1 Correlation of Macroeconomic Indicators

In this section the correlation between all economic indicators is examined. Correlation analysis follows the same principle as a simple linear regression (SLR) analysis. Two variables are compared with respect to their linearity, i.e. how close to a straight line the data points yield if one variable is plotted on the x-axis and the other on the y-axis. The pair that is compared in correlation analysis is not an explanatory variable and the response variable, but rather two explanatory variables.

Table 3.16: WORD Code for Editing Macroeconomic Indicators

Editing	Menu	Commands
Changing blank spaces in text block with monthly indicator values into tab stops	Edit / Replace	1) Click on "More" 2) Check "Use wildcards" 3) Find what: `([.0-9]@)([ ]@)([.0-9]@)` or `((p))([ ]@)((p))` 4) Replace with: `\1^t\3`
Converting text block with monthly indicator values to single column	Edit / Replace	1) Click on "More" 2) Check "Use wildcards" 3) Find what: `^t` 4) Replace with: `^p`

Ideally, among the selected economic indicators pairs with very low correlation as measured by the Pearson correlation coefficient R_{corr} should exist. This ensures that a broad range of economic indicators is available for the selection of explanatory variables in the regression analysis. The quality of the regression model can be improved by offering a variety of different explanatory variables, each of them displaying a somewhat different behavior under the same economic situation.

It was necessary to prepare the economic indicator catalog for correlation analysis by matching economic indicators of different frequency with each other. Two ways are theoretically possible to match weekly, monthly, and quarterly indicators. On the one hand, only one entry from the monthly and weekly series could be used per each quarter, possibly close to or on the date of the quarterly indicator. This procedure would ignore a considerable number of actual economic indicator values. On the other hand, the aforementioned assumption that all economic indicator values remain constant until the subsequent value is reported can be used. Values from monthly and quarterly series could be repeated and matched with the economic indicators of weekly frequency. This could cause the correlation coefficient to decrease slightly but would include all measured economic indicator values. It was therefore chosen over the first method. Table 3.17 shows how this matching would be performed for fictitious values of economic indicators with weekly, monthly, and quarterly frequency.

Table 3.17: Matching Macroeconomic Indicators of Different Frequencies

Weekly Macroeconomic Indicator Values	Monthly Macroeconomic Indicator Values	Quarterly Macroeconomic Indicator Values
…	…	…
63.97	17.52	50.87
65.57	17.52	50.87
65.06	17.52	50.87
64.57	17.52	50.87
64.95	18.98	50.87
61.93	18.98	50.87
60.64	18.98	50.87
66.25	18.98	50.87
67.18	20.73	50.87
66.98	20.73	50.87
61.60	20.73	50.87
60.79	20.73	50.87
…	…	…

The SAS® code of Appendix C.1 was used for the correlation analysis. Appendix E contains the SAS® output for all possible pairs of economic indicators. Since the correlation of a variable with itself is always equal to one, the first column and the last row of the table have been omitted. It was found that their correlation coefficients ranged from near 1.0 (almost perfectly correlation) to near 0.0 (almost perfectly uncorrelated). Table 3.18 lists the 20 pairs with the highest R_{corr} values and Table 3.19 lists the 20 pairs with the smallest R_{corr} values. Economic indicators of similar nature were highly correlated, e.g. the construction cost index (CCI) and building cost index (BCI) by *Engineering News Record* and the inflation measures CPI and PPI. It is therefore expected that both economic indicators from such pairs will not be selected for the regression model. Other economic indicators, e.g. ATSLS and INDPRD, were correlated very little and described the economic situation from very different points of view. While the correlation analysis has confirmed the potential of the economic indicator catalog, it cannot be said at this stage which economic indicators will be part of the regression model.

This test examined whether there exists any relationship at all between the two economic indicators as measured by R_{corr}. If such relationship exists the pair of economic indicators should not be used together in the regression model as they would contribute redundant information. The null hypothesis stating that the correlation coefficient of the population ρ is equal to zero was tested for all pairs of economic indicators.

$$H_0 : \rho = 0 . \qquad \textbf{Equation 3.1}$$

$$H_1 : \rho \neq 0 . \qquad \textbf{Equation 3.2}$$

$$t_{obs} = R_{corr} \cdot \sqrt{\frac{n-2}{1-R^2_{corr}}} . \qquad \textbf{Equation 3.3}$$

$$\textit{If } |t_{obs}| \leq t_{1-\alpha/2,\, n-2} \textit{ then fail to reject } H_0. \qquad \textbf{Equation 3.4}$$

$$\textit{If } |t_{obs}| > t_{1-\alpha/2,\, n-2} \textit{ then reject } H_0.$$

where H_0 is the null hypothesis, H_1 is the alternative hypothesis, ρ is the correlation coefficient of the population, t_{obs} is the test statistic for the null hypothesis, R_{corr} is the Pearson coefficient of correlation of the sample, n is the number of complete observations in the dataset, and $t_{1-\alpha/2,\, n-2}$ is the cutoff value for the hypothesis test. Using a significance level α of 0.1, it was found that the null hypothesis was not rejected for all pairs of Table 3.19 and several other pairs of economic indicators, i.e. their correlation coefficient was not significantly different from zero. Many economic indicators are highly correlated and selecting them to the regression model should be done carefully. The economic indicators that will be selected as explanatory variables for the final regression models will be checked against the list of economic indicators pairs for which the null hypothesis was not rejected.

Table 3.18: Macroeconomic Indicator Pairs with High Correlation Coefficients

Macroeconomic Indicator e_1	Macroeconomic Indicator e_2	Correlation Coefficient R_{corr}
BCI	CCI	0.99849
ECICOMP	PPIMIN	0.99677
GDP	RTLSLS	0.99665
CPI	PPIME	0.99645
CCI	ECICOMP	0.99552
ECICOMP	GDP	0.99539
PPIMIN	RTLSLS	0.99503
CCI	PPIMIN	0.99497
CPI	RTLSLS	0.99495
GDP	TNR	0.99488
CPI	ECICOMP	0.99482
GDP	OUTHR	0.99423
RTLSLS	TNR	0.99415
PPIMIN	TNR	0.99404
CCI	CPI	0.99361
GDP	PPIMIN	0.99300
EMPLY	GDP	0.99259
CPI	PPI	0.99219
GDSTRD	TTLTRD	0.99183
CPI	PPIMIN	0.99166

3.6.2.2 Matching with Canadian Auction Records

This study examines records of equipment auctions from the North American market, which was defined as consisting of the U.S. and Canada. Auction prices for all Canadian records had been converted to U.S. dollars at the applicable exchange rate by the data sources. The auction region of all observations was coded using indicator variables as described in Section 3.3.2.9.

Using auction records from Canada made it necessary to match them with economic indicators to create the dataset for statistical analysis. The assumption was made that the U.S. economic indicators can be applied to all observations from the North American market in order to predict the residual value of heavy construction equipment. This assumption refers solely to the statistical analysis of the data. It should be noted that it does not mean that any measures of the

U.S. and Canadian economies were assumed to be correlated or that the two economies were set equal, the large volume of trade between the two countries notwithstanding.

Table 3.19: Macroeconomic Indicator Pairs with Low Correlation Coefficients

Macroeconomic Indicator e_1	Macroeconomic Indicator e_2	Correlation Coefficient R_{corr}
CPI	South	0.02246
INTRST	South	0.01997
CHCK	STLPRD	0.01895
CNSCR	CNSCRNF	0.01672
CHCK	EMPLC	0.01597
CHCK	OUTHR	0.0158
CNSCRNF	TNR	0.01135
CHCK	TTLINV	0.00788
CHCK	PPIME	0.00534
ATSLS	CNSCRNF	0.00521
ATSLS	SVGS2	0.00337
ATSLS	INDPRD	-0.00091
South	TTLCNST	-0.00232
HWY	South	-0.0029
ATSLS	HWY	-0.0072
HMSTS	PPIME	-0.00761
PPI	South	-0.01144
CNSCR	South	-0.014
CNSCRNF	SWR	-0.01462
CHCK	SVGS2	-0.01629

3.6.2.3 Seasonal Adjustment

Many economic indicators have datasets that are seasonally adjusted or that are available both in seasonally adjusted and unadjusted forms. The purpose of seasonal adjustment is to allow better distinction of actual economic trends from underlying patterns that are recurring in the same manner every year. The Bureau of the Census provides more detailed information on how seasonal adjustment is performed on datasets. During this process, data are split into components as listed in Table 3.20.

Table 3.20: Components of Seasonal Adjustment

Component	Definition
Trend Cycle	Level estimate for each month (quarter) derived from the surrounding year-or-two of observations.
Seasonal Effects	Effects that stable in terms of annual timing, direction, and magnitude. Possible causes include natural factors (the weather), administrative measures (starting and ending dates of the school year), and social/cultural/religious traditions (fixed holidays such as Christmas). Effects associated with the dates of moving holidays like Easter are not seasonal in this sense, because they occur in different calendar months depending on the date of the holiday.
Irregular Component	Anything not included in the trend-cycle or the seasonal effects (or in estimated trading day or holiday effects). Its values are unpredictable as regards timing, impact, and duration. It can arise from sampling error, non-sampling error, unseasonable weather, natural disasters, strikes, etc.

Source: `<http://www.census.gov/ftp/pub/const/www/faq2.html>`.

The seasonally adjusted annual rate (SAAR) of a monthly value is calculated by dividing the monthly value by an adjustment factor to remove seasonal effects and multiplying it with 12. It assumes that no seasonal effect exists and that the particular monthly value would be representative throughout the entire year. While the SAAR does not constitute any measurable value in the actual economy, it allows direct comparisons between monthly, quarterly, and annual values. Seasonally adjusted (SA) economic indicator values were used in this study whenever possible instead of not seasonally adjusted (NSA) economic indicator values.

3.6.2.4 Macro MatchEconomy

The auction records including their size parameters and list prices still needed to be matched with their economic indicator values. All datasets were sorted by the auction date for this purpose. The macro *MatchEconomy* was programmed and was applied to the EXCEL worksheets. It is closely related to the macro *MatchParameters*. It was used to match the auction records with the economic indicator catalog that had been compiled. The economic indicator catalog with its three parts of weekly, monthly, and quarterly economic indicator values was copied into the same worksheet as the auction records with sufficient space between the two blocks of cells left for the macro to fill. The macro was applied three times, once for each part of the economic indicator catalog. The code for this macro can be found in Appendix A.7. It first requested the user to enter the range of cells containing auction records and the DATE column within this range. It also requested the range of cells containing the economic indicator catalog and the DATE column within that range. For each entry in the auction records the macro went through all rows of the economic indicator catalog and compared the auction date with the release date of the economic indicators. A release date equal to or directly following the auction date was considered a match. When a match was found between both ranges the macro copied the economic indicator values next to the auction records and proceeded to the next entry in the auction records. Appendix A.8 provides a flowchart for this macro. Following the matching all datasets were sorted in the hierarchical order of columns REG1, REG2, REG3, and REG4 to separate them into the different regions. Values for the number of housing starts (seasonally adjusted annual rate) as an additional economic indicator were obtained from the Bureau of the Census and from Statistics Canada. The macro was applied five more times to match the regionally sorted auction records with the respective regional time series. After the macro had been applied, the entire dataset was again skimmed visually.

3.6.2.5 Inflation Correction

The auction prices and the list prices that were obtained for the datasets were all recorded on a particular date under a particular economic situation. In order to legitimately divide them by each other to obtain RVP, all prices had to be corrected for inflation. Inflation is defined as the phenomenon of rising prices and sinking buying power of money due to an imbalanced demand and supply for goods and services (Bodie et al. 2002).

Mitchell (1998) presented a composite index for inflation correction based on Douglas (1975a). It was constructed from different economic indicators by applying appropriate weighting factors. These factors were based on an estimated percentage of influence of these economic areas on the cost components for the equipment. However, their estimation was difficult and therefore a singular measure of inflation was used in this study. The most widely accepted inflation indicators are the CPI and the PPI. They are both published in monthly intervals by Bureau of Labor Statistics.

Some criticism has been voiced over the CPI being a suitable measure for inflation. An extensive study of the CPI and its potential problems with this measure was carried out by the Boskin Commission (named after its chairperson), which in 1996 submitted a report titled "Toward A More Accurate Measure Of The Cost Of Living" to the Committee on Finance of the U.S. Senate. In an Economic Letter titled "A Better CPI" from 1999, the Federal Reserve Bank of San Francisco described the "types of biases that cause the CPI to overstate inflation, BLS [Bureau of Labor Statistics] actions to remove these biases, and possible implications for monetary policy" (<http://www.frbsf.org/econrsrch/wklyltr/wklyltr99/el99-05.html>).

For this study the PPI with its focus on manufactured goods was more appropriate for the inflation adjustment. It has been by other researchers to adjust the residual value of farm equipment for inflation (Cross and Perry 1995, Cross and Perry 1996, Kastens 1997). The time series of the PPI for finished goods was used for inflation correction in this study. Specialized PPI series exist for different industries, commodities, and stages of processing. Two of these PPI series that are related to construction have been included in the economic indicator catalog as potential explanatory variables.

The auction records provided the year of manufacture of every machine in calendar years without giving a month or day of manufacture. Equipment age as the difference between the auction date and the year of manufacture therefore could only be determined to an accuracy of whole years. Moreover, all list prices for a particular year of manufacture had to be adjusted by the same inflation correction. Kastens (1997) describes how an average annual PPI was calculated as the simple arithmetic average of 12 monthly values. Table 3.21 provides values for the average annual PPI as calculated for this study. The assumption was made that these values remained constant throughout the respective year.

Table 3.21: History of Average Annual Producer Price Index Values

Year	Average Annual PPI Value	Year	Average Annual PPI Value (continued)
1947	26.93*	1975	59.07
1948	28.47	1976	61.58
1949	27.43	1977	65.82
1950	29.04	1978	71.54
1951	30.84	1979	80.10
1952	30.51	1980	90.31
1953	30.38	1981	97.43
1954	30.40	1982	100.55
1955	30.58	1983	102.21
1956	31.66	1984	103.91
1957	32.78	1985	104.66
1958	33.19	1986	103.30
1959	33.16	1987	105.89
1960	33.53	1988	109.33
1961	33.39	1989	115.00
1962	33.48	1990	120.21
1963	33.43	1991	121.79
1964	33.58	1992	123.82
1965	34.43	1993	124.80
1966	35.30	1994	126.08
1967	35.84	1995	128.63
1968	36.93	1996	131.98
1969	38.45	1997	131.27
1970	39.57	1998	130.88
1971	40.78	1999	134.25
1972	42.37	2000	139.34
1973	47.07	2001	139.87
1974	54.33	2002	139.05**

Notes: * Calculated as Average of 9 Months
** Calculated as Average of 11 Months

List prices were adjusted from the year of manufacture to the current date using the average annual PPI and were stored in the newly created LP column. Auction prices were adjusted from the auction date to the current date using the monthly PPI and were stored in the newly created AP column. While any date would have worked equally well, the time when this work was carried out, November 31, 2002, was defined as the current date. Equation 3.5 gives the generic formula for adjusting prices from date 1 to date 2 using index values.

$$Price_2 = Price_1 \cdot \frac{PPI_2}{PPI_1}. \qquad \textbf{Equation 3.5}$$

where *Price* is any price in U.S. dollars and PPI is the producer price index for finished goods.

Once the average annual PPI has been used for inflation correction, it should not be used as an explanatory variable anymore. Otherwise, the regression could suffer from multicollinearity, which would make obtaining a unique closed-form solution for the regression model impossible. Multicollinearity is defined as "near-linear dependence among the regressors" (Montgomery et al. 2001, p117). PPIME and PPIMIN were therefore used as potential explanatory variables.

3.6.2.6 Residual Value Percent

Once the preparations described above had been completed, the RVP column was created for all datasets. RVP was calculated as the inflation-corrected auction price divided by the inflation-corrected list price. This normalization of the residual value allowed direct comparison for different scenarios. Calculation of RVP completed the preparations for the statistical analysis.

3.7 Conclusion

This chapter has documented the first half of the methodology of this study. It described how data from four data families that are necessary for this study have been identified, collected, and prepared. Preparations included filling missing values within the datasets as far as possible, checking them for apparent inconsistencies, matching the four data families with each other, performing an inflation adjustment on auction prices and list prices, and calculating the values that will actually be used in the statistical analysis. The individual steps were displayed in Figure 3.1.

At this stage the data are ready for being analyzed statistically. Explanatory variables have been extracted from the auction records and economic indicator catalog. Size parameters have been used to create 28 separate datasets for more detailed analysis of individual equipment size classes. List prices have been used to normalize the auction price to RVP, which has been inflation-corrected for comparability and consistency. Table 3.14 and Appendix F.1 summarize the numbers of data points for the different size classes prior to eliminating outliers from the datasets.

Chapter 4 Statistical Analysis

4.1 Introduction

This chapter describes the statistical analysis of the previously prepared data in detail. It covers statistical considerations relating to the type of study, characteristics and preparation of the data, and the analysis methodology that is employed. The process of selecting a statistical model that best predicts the response variable is described. Following that is the identification and deletion of outliers among the data and the selection of economic indicators to contribute to the regression model. Results of the regression analysis are presented for three models that were developed and are examined by manufacturer, condition rating, and auction region. The chapter concludes with a description of the validation procedure that was used to confirm the stability of the predictions.

4.2 Statistical Considerations

Several considerations have to be addressed prior to the actual statistical analysis. They relate to the restriction that is imposed by the type of study, the number of samples necessary, characteristics of the data, and to the assumptions and methods of regression analysis. Issues that arose during data preparation are addressed and the calculation of the adjusted confidence and prediction intervals, respectively, is discussed.

4.2.1 Study Type

The type of a research study influences what information its data can actually provide. In experimental studies all explanatory variables can be controlled under laboratory conditions by the researcher and can be set to predetermined values to provide a response. The order of experimentation can be randomized.

Observational studies differ from experimental studies in that they do not allow that explanatory variables are set to values that are determined by the researcher. Their values are realized without control and can only be observed. The most important drawback for interpretation of such studies is that no cause-effect relationships can be derived from their results (Montgomery et al. 2001). Only the association of certain values of explanatory variables and a particular response can be measured through their concurrence. A distinction can further be made between retrospective studies that use historically observed data and observational studies that use newly observed data (Montgomery et al. 2001). The consequences for this particular study remain the same, as in both cases the values of data cannot be influenced.

For lack of a large number of pieces of equipment that could be sold under controlled circumstances, this research can only be carried out as an observational study. It uses data that are generated in the construction equipment market and in the economy at large. Data originate from transactions between buyers and sellers of equipment that establish the economic value of a piece of equipment.

4.2.2 Sample Size

It is necessary to examine that a sufficient number of complete observations n is available for the regression analysis. The statistical literature commonly gives recommendations for the minimum recommended sample size for hypothesis tests. It can be calculated based on the confidence level and precision desired. The width of the confidence interval (CI) and prediction interval (PI) depends on the number of observations and thus for a given confidence level the formula can be solved for n.

For a regression analysis, consideration has to be given to the number of explanatory variables k in the model (or the number of estimated parameters $p = k + 1$, respectively) and the number of different levels that that a categorical variable can take on. Sample size is related to the population variance, the desired significance level, and the power of hypothesis tests (Hicks and Turner 1999). Different formulas and values of minimum recommended sample sizes for regression analysis and the associated hypothesis tests have been published as guidelines in the literature. Stevens (1995) provides a value of $n \geq 15 \cdot k$ for multiple linear regression. Green (1991) provides a value of $n \geq 50 + 8 \cdot k$ for multiple correlation and $n \geq 104 + k$ for testing explanatory variables. Datasets that would be considered small using such criteria are Dataset 5 with under 100 observations and Datasets 1, 17, 24, and 28 with under 200 observations, as listed in Appendix F. However, this study is not a planned experiment but an observational study. The principle holds that the number of data points should be as large as possible for creating and testing a satisfactory regression model. Aforementioned datasets will be examined closer. A final decision whether the number of observations has been sufficient will be made through the goodness-of-fit of the final regression models.

4.2.3 Regression Analysis

Regression analysis is a statistical method that aims at describing the relationship between one or more explanatory variables and a response variable with a mathematical equation that is derived from the data. Statistical literature provides comprehensive introductions into regression analysis, e.g. Montgomery et al. (2001). The following sections cover three major types of regression analysis, Simple Linear Regression, Multiple Linear Regression, and Non-Linear Regression.

4.2.3.1 *Simple Linear Regression*

Simple Linear Regression (SLR) uses the values of one explanatory variable x to predict the response variable y. In mathematical form the basic SLR model is shown in Equation 4.1:

$$y = \beta_0 + \beta_1 \cdot x + \varepsilon \, . \qquad \textbf{Equation 4.1}$$

where y is the response variable, β_0 and β_1 are regression coefficients (β_0 being the intercept and β_1 being the slope), x is the explanatory variable, and ε is an error term. SLR can be used whenever it is considered sufficient to use one explanatory variable to predict a response. For many applications this method can already provide good models, but for the more complex analysis of this study it is too simple a model.

4.2.3.2 *Multiple Linear Regression*

Multiple Linear Regression (MLR) is the extension of SLR to a general form. It uses the values of several explanatory variables x_1 to x_k to predict the response variable y. In mathematical form the basic MLR model is shown in Equation 4.2:

$$y = \beta_0 + \beta_1 \cdot x_1 + \ldots + \beta_k \cdot x_k + \varepsilon \, . \qquad \textbf{Equation 4.2}$$

where y is the response variable, β_0 to β_k are regression coefficients, x_1 to x_k are the explanatory variables, k is the number of explanatory variables (equal to the number of parameters p estimated for the model minus one), and ε is an error term. Linear in this context does not mean that a model necessarily can only work with terms of the first order, but refers to the linear additive nature of the terms in the basic MLR model. Individual terms can certainly contain terms of higher orders as well as exponential, logarithmic, and other expressions of the respective explanatory variables. These mathematical functions $f_i(\bullet)$ of the explanatory variables x_1 to x_k are expressed in Equation 4.3. The vector form of the MLR model is presented in Equation 4.4.

$$y = \beta_0 + \beta_1 \cdot f_1(x_1) + \ldots + \beta_k \cdot f_k(x_k) + \varepsilon \,. \qquad \textbf{Equation 4.3}$$

$$\tilde{y} = X \cdot \tilde{\beta} + \tilde{\varepsilon} \,. \qquad \textbf{Equation 4.4}$$

where $\tilde{y}$ is the vector of the response variable, X is the matrix of the explanatory variables, $\tilde{\beta}$ is the vector of regression coefficients, and $\tilde{\varepsilon}$ is the vector of error terms. The study by Mitchell (1998) modeled the repair costs of heavy construction equipment using a variety of multiple linear models. It also used several non-linear models that were transformed back into linear models using logarithms. Non-linear models are introduced in the following section.

4.2.3.3 Non-Linear Regression

Non-linear regression (NLR) models have a more general form than MLR models as shown by a comparison of the vector form of their general models (Montgomery et al. 2001) in Equations 4.4 and 4.5:

$$\tilde{y} = f\left(X, \tilde{\theta}\right) + \tilde{\varepsilon} \,. \qquad \textbf{Equation 4.5}$$

where $\tilde{y}$ is the vector of the response variable, X is the matrix of the explanatory variables, $\tilde{\varepsilon}$ is the vector of error terms, $f(\bullet)$ is the expectation function, and $\tilde{\theta}$ is the vector of NLR parameters. As can be seen, the MLR model of Equation 4.4 is linear with respect to its regression coefficients β_i whereas the NLR model of Equation 4.5 is not linear with respect its NLR parameters θ_i. A NLR model is defined as a model where "at least one of the derivatives of the expectation function with respect to the parameters depends on at least one of the parameters" (Montgomery et al. 2001, p416), where parameters refers to the regression coefficients β_i. "The distinction between linear and nonlinear models is often obstructed by references to graphs of the predicted values. If a graph of the predicted values appears to have curvature, the underlying statistical model may still be linear" (Schabenberger and Pierce 2002, p27).

NLR models have the advantage of their more flexible mathematical form than MLR and SLR models. They are often used when theoretical knowledge exists about the actual nature of the process under examination, in particular for growth models (Montgomery et al. 2001). However, they also have the disadvantage that “no simple closed-form solution” exists for estimating the parameters that could be determined analytically (Montgomery et al. 2001, p418). Rather, the regression coefficients β_i have to be determined through iteration using the estimated least squares. It is therefore often sought to transform non-linear models back into a linear form, e.g. using logarithms. A NLR is called intrinsically linear if it can be transformed into a MLR or SLR model. However, transformation will also affect the error structure of the model, potentially making it multiplicative or even more complex and thus less interpretable. More information on regression assumptions and transformations is provided in Section 4.2.4 and information on the error structure is provided in Section 4.2.6.

Another disadvantage of NLR models is that on the one hand they are often sensitive to outliers while on the other hand there are fewer methods available for these models to detect the outliers (`<http://www.itl.nist.gov/div898/handbook>`). A major drawback of NLR models is that hypothesis testing is no longer exact. Calculation of the CI and PI, which are discussed in Section 4.2.7, also is no longer exact (Montgomery et al. 2001, pp434f., emphasis omitted):

> *In a linear regression model when the errors are normally and independently distributed, exact statistical tests and confidence intervals based on the t and F distributions are available, and the parameter estimates have useful and attractive statistical properties. However, this is not the case in nonlinear regression, even when the errors are normally and independently distributed. That is, in nonlinear regression the least squares (or maximum likelihood) estimates of the model parameters do not enjoy any of the attractive properties that their counterparts do in linear regression, such as unbiasedness, minimum variance, or normal sampling distributions. Statistical inference in nonlinear regression depends on large-sample or asymptotic results. The large-sample theory generally applies for both normally and nonnormally distributed errors.*

(...) Consequently, statistical inference for nonlinear regression when the sample size is large is carried out exactly as it is for linear regression. The statistical tests and confidence intervals are only approximate procedures.

Because of the drawbacks associated with NLR models, MLR models will be the used initially for the statistical analysis. NLR could be used if a need for greater model flexibility would become apparent during the analysis. The linear forms of an exponential and a logarithmic model are also examined in analogy to the models used by Mitchell (1998).

4.2.4 Regression Assumptions

Fitting MLR models with the method of least squares is based on a set of basic assumptions that need to be fulfilled for the regression analysis to yield valid results The regression assumption are (Montgomery et al. 2001, p131, emphasis omitted):

> 1. *The relationship between the response y and the regressors is linear, at least approximately.*
> 2. *The error term ε has zero mean.*
> 3. *The error term ε has constant variance σ^2.*
> 4. *The errors are uncorrelated.*
> 5. *The errors are normally distributed.*
>
> *Taken together, assumptions 4 and 5 imply that the errors are independent random variables. Assumption 5 is required for hypothesis testing and interval estimation.*

The five assumptions were examined for all datasets to ensure that these did not violate the assumptions. Phrased differently, Assumption 1 means that the selected regression model is adequate for the data. Assumption 2 means that the average observation should lie on the curve of the regression model. Assumption 3 is the homoscedasticity assumption and means that all observations are measured with the same precision. Assumptions 4 and 5 mean that the errors occur at random without any pattern and thus indicate that all structure of the data has been included in the explanatory variable terms of the regression model. Hypothesis testing and the calculation of the CI and PI require normality of the data as per Assumption 5.

All datasets were examined in several ways. Plotting the values of all pairwise combinations of the explanatory variables among each other and with the response variable yielded an initial impression of the properties of the data. These scatterplots were examined for any obvious patterns. No interaction between explanatory variables could be detected in the scatterplots. The pattern of a curve sloping down monotonically was found in the scatterplots of RVP over age in calendar years. Box plots of this relationship are presented in Appendix H. Their box shows the median and the 25th and 75th percentiles of the data, while the whiskers show the extent of data within 1.5 times the interquartile range. Data outside this range are possible outliers.

Based on the experience of construction equipment managers (Agoos 2003) it is hypothesized that larger equipment loses its residual value slower than smaller equipment due to its more solid build. For the categorical variable condition rating it is expected that a lower condition rating will be correlated with a lower residual value. Results on the influence of manufacturer, condition rating, and auction region will be obtained from performing a sensitivity analysis on the final regression model.

Further examination of the assumptions of the model requires that a particular regression model has already been selected, as described in Section 4.3.1. Plots of the different residuals for the predicted response can be used to confirm that Assumptions 1, 2, and 3 are not violated. Assumption 4 is more difficult to examine because it relates to the data collection method. Finally, a normal probability plot that displays residuals over the percentiles of a Gaussian distribution can be generated to examine Assumption 5. The SAS® code of Appendix C.3 was used to identify outliers and to generate scatterplots, residual plots, and normal probability plots.

Plots of the residuals can be used to indicate that a regression assumption has been violated and that the model can possibly be improved. A curve or cyclical pattern in the plot of the residuals over a particular explanatory variable would signal that not all structure in the data has been captured by the regression model. In this case additional terms would be added to the model. A rounded shape or a funnel shape of residuals plotted over the predicted response values or over a particular explanatory variable would signal an instable variance. In this case a transformation of the response variable or of explanatory variables would be performed. It would also be possible to consider a non-linear model. “However, the issue often revolves around the error structure, namely, do the standard assumptions on the error structure apply to the original nonlinear model or to the linearized one? This is sometimes not an easy question to answer” (Montgomery et al. 2001, pp420f.). Choice of a suitable transformation ideally is supported by theoretical knowledge about the actual process that is analyzed. Table 4.1 lists common variance-stabilizing transformations with $E(\bullet)$ being the expected value of the response variable.

Table 4.1: Common Variance-Stabilizing Transformations

Pattern in Residual Plot	Variance Behavior	Transformation
Residuals are distributed in rounded shape	σ^2 proportional to $E(y) \cdot [1 - E(y)]$	$y^* = \sin^{-1}(\sqrt{y})$ (arcsin, binomial, $0 \leq y_i \leq 1$)
Residuals are distributed in even band	σ^2 constant	$y^* = y$ (no transformation)
Slight funnel shape, residuals are fanning out	σ^2 proportional to $E(y)^1$	$y^* = y^{1/2} = \sqrt{y}$ (square root)
Medium funnel shape, residuals are fanning out	σ^2 proportional to $E(y)^2$	$y^* = \log_e(y)$ or $\log_{10}(y)$ (logarithm)
Strong funnel shape, residuals are fanning out	σ^2 proportional to $E(y)^3$	$y^* = y^{-1/2} = 1/\sqrt{y}$ (inverse square root)
Very strong funnel shape, residuals are fanning out	σ^2 proportional to $E(y)^4$	$y^* = y^{-1}$ (inverse)

Source: Montgomery et al. 2001.

Plots of the scaled r-studentized residuals obtained with the plain model explained in Section 4.3.3 did not show any undesired curve patterns or cyclical patterns for the datasets. Few apparent outliers were observed in the residual plots. In general, the observations formed an even band of random points around the mean zero. In some cases the residual plots versus the predicted response showed a slight tendency to a rounded shape which may have been caused by fewer observations of extreme residual values in the datasets. Dataset 13 showed a cluster of observations in its residual plot for the predicted response. This dataset contains very few observations of eight years of age or younger and several ages for which observations are missing completely. Datasets 12, 22, 23, and 24 showed to slight clusters of observations in this plot. Almost all of these datasets do not contain observations for zero years of age, have a high variance at low ages, and contain few observations for higher ages. Results for these datasets need to be interpreted carefully. Due to the general lack of systematic patterns in the residual plots it was decided that no additional terms were necessary in the regression model.

The normal probability plots generally showed the expected straight line without significant deviations that might indicate skewed or non-Gaussian distributed data. Only the plots for datasets 17, 22, 24, and 28 deviated slightly from the straight line. Almost all of these datasets contain less than 200 observations. Results from these datasets need to be interpreted carefully.

In summary, it was found that the regression assumptions were adequately satisfied by the datasets for this research study. The plain model of Section 4.3.3 was used to obtain residuals. Transformations of variables or addition of explanatory terms to the regression model are not necessary. Some datasets will require more cautious interpretation due to their low number and uneven distribution of observations.

4.2.5 Indicator Variables

Indicator variables are used for explanatory variables that are not continuous but categorical, i.e. whose values are qualitative, not quantitative (Montgomery et al. 2001). Explanatory variables in this study that have verbal descriptors as values are the manufacturer, the condition rating, and the auction region. They need to be transformed into numerical values to be usable in the statistical analysis. This numerical form of the categorical explanatory variables is called an indicator variable or dummy variable (Montgomery et al. 2001). It is possible to create indicator variables by assuming quantitative measures for the different categories of the qualitative variable. However, this method is not recommended because it cannot be used for explanatory variables without clear hierarchy and it leads to a lower coefficient of determination R^2 (Montgomery et al. 2001).

The standard method to create indicator variables is to give each category except for one within a given factor its own indicator variable. The indicator variable is a binary number, i.e. it can take on the value "1" meaning that an observation is within that category or "0" meaning that an observation is not within its category. The last category does not require its own indicator variable but is defined as the case when all other indicator variables have "0" as their value. The number of indicator variables for an explanatory variable therefore is equal to the number of categories of the explanatory variable minus one (Montgomery et al. 2001). Such binary indicator variables have been used in various studies (Reid and Bradford 1983, Cross and Perry 1995, Cross and Perry 1996, Unterschultz and Mumey 1996).

In this study, however, indicator variables are created and used in a slightly different way. As explained in Sections 3.3.2.2, 3.3.2.7, and 3.3.2.9, the categories of an explanatory variable are numbered and these integer numbers are transformed into binary form. Each digit of the binary number then is one indicator variable that can take on either "0" or "1" as its value. It should be noted that indicator variables are used to distinguish between different categories, not to label all of them. This method allows using fewer indicator variables for an explanatory variable. Manufacturer has four categories, condition rating has six, and auction region has five categories. It suffices to use three binary indicator variables for each of these explanatory variables.

The advantage of this method is improved efficiency because fewer degrees of freedom (df) are used for each of the explanatory variables in the regression model. Having more independent pieces of information available is advantageous especially for the smaller datasets. The disadvantage is a loss in interpretability of the individual indicator variables. Taking the example of indicator variable r_3 of Table 3.9, the value "1" means that the observation is either located in the Northeast, or in the Midwest, or in Canada. Only the complete triplet of indicator variables allows determining the actual auction region. The second disadvantage is that information about the hierarchy of condition ratings is lost when the indicator variables are transformed. However, the associated decrease of explanatory power is expected to be smaller than for omitting the condition rating from the regression analysis or for assuming quantitative measures for each of its categories.

Interpretation of the regression results requires the inverse transformation. For each different category, the values of the regression coefficients in a triplet are multiplied with the value "0" or "1" of their respective indicator variable and are summed up. Comparisons between different categories for the explanatory variable are then possible and are provided in Section 4.4.

A special case occurs when a dataset does not contain data points from all four manufacturers. For three or less manufacturer it is not necessary to have a triplet of binary indicator variables. Two or one indicator variables are sufficient to distinguish between the different categories. Retaining the triplet would cause multicollinearity in the dataset. A correction to the indicator variables is necessary because of various model stability problems that are caused by multicollinearity. SAS® automatically sets the values of one or more of the indicator variables to zero in case they are not needed. Comparing Table 4.2 with Table 3.3 shows how one or two indicator variables are ignored and the different manufacturers can be correctly distinguished using the remaining ones. Cells containing zero observation or "0" as a value have been shaded for clarity. For condition rating and auction region the correction works analogously.

4.2.6 Normalization of Residual Value

The residual value of a piece of equipment can be reported either in dollar terms or as percent of its base value, the list price. RVP is the commonly used form in the literature (Cubbage et al. 1991, Reid and Bradford 1983, Perry et al. 1990, Cross and Perry 1996). Table 4.3 compares MLR models without and with normalization of the response variable. In Table 4.3, y is the response variable prior to the normalization, β_0 to β_k are regression coefficients, x_1 to x_k are the explanatory variables with x_k being the list price in dollars, k is the number of explanatory variables prior to the normalization, and ε is an error term.

Table 4.2: Correction in Binary Explanatory Variables

Number	Entries from each Manufacturer				Indicator Variable Values		
	Caterpillar	Deere	Komatsu	Volvo	M_1	M_2	M_3
1	76	8	22	0	0	…	…
2	584	216	1088	0	0	…	…
3	286	87	54	0	0	…	…
4	395	28	42	0	0	…	…
5	0	5	58	0	0	0	…
6	114	129	25	0	0	…	…
7	68	238	131	53	…	…	…
8	233	2195	996	433	…	…	…
9	364	104	1009	218	…	…	…
10	210	0	142	88	…	…	0
11	44	456	62	0	0	…	…
12	130	245	270	0	0	…	…
13	0	226	0	0	0	0	0
14	176	7311	43	0	0	…	…
15	286	47	0	0	0	…	0
16	329	0	21	0	0	…	0
17	104	0	2	0	0	…	0
18	648	0	69	941	…	…	0
19	403	0	0	567	…	0	0
20	0	3610	1710	0	0	0	…
21	1868	1250	1476	0	0	…	…
22	51	0	239	0	0	…	0
23	233	0	130	0	0	…	0
24	48	0	77	0	0	…	0
25	333	364	0	0	0	…	0
26	317	473	0	0	0	…	0
27	618	163	0	0	0	…	0
28	163	0	0	0	0	0	0

Performing the normalization somewhat reduces the richness of information contained in the dataset as the list price x_k becomes part of the response variable. The number of explanatory variables k in the regression model thus decreases by one.

Table 4.3: Effect of Normalization of Response on Model

Multiple Linear Regression Model	Effect of Model
$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_{k-1} x_{k-1} + \beta_k x_k + \varepsilon$	Without Normalization: List price is an explanatory variable, the response variable is measured in dollars
$\frac{y}{x_k} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_{k-1} x_{k-1} + \varepsilon$	With Normalization: List price is part of the response variable, which is measured in percent, the regression model contains one less explanatory variable

Performing the normalization shifts one df in the analysis of variance (ANOVA) table from the model source to the error source, as shown in Table 4.4. In Table 4.4, $k = p - 1$ is the number of explanatory variables, n is the number of complete observations, and p is the number of parameters estimated for the regression model. The $n - 1$ total df remain unaffected by this normalization. The regression coefficients β_i naturally will differ between the models without and with normalization. The reason to perform this normalization is not simply to redistribute one df within the ANOVA table, but much more importantly in the better comparability between different scenarios. Without the normalization a comparison would be made between different dollar amounts of residual value, not between the residual value percent values.

Table 4.4: Effect of Normalization of Response on ANOVA Table

Source of Variability	Degrees of Freedom	Sum of Squares	Mean Squares	F-Test Statistic
Model	k becomes $k-1$	SS_{mod} (also: SS_{reg})	$MS_{\text{mod}} = \frac{SS_{\text{mod}}}{k}$	$F_{obs} = \frac{MS_{\text{mod}}}{MS_{err}} \sim F_{k,\, n-p}$
Error	$n - p$ becomes $n - p + 1$	SS_{err} (also: SS_{res})	$MS_{err} = \frac{SS_{err}}{n - p}$	N/A
Total	$n - 1$	$SS_{tot} = SS_{\text{mod}} + SS_{err}$	N/A	N/A

Other statistics are also be impacted by this change in the internal distribution of the df. The coefficient of determination R^2 does not change. It is calculated by dividing the model sum of squares by the total sum of squares as per Equation 4.6. However, the adjusted coefficient of determination R^2_{adj}, which includes a correction to penalize for too many explanatory variables, is influenced because of its term $n - p$, as shown in Equation 4.7.

$$R^2 = \frac{SS_{\text{mod}}}{SS_{tot}} = 1 - \frac{SS_{err}}{SS_{tot}}. \qquad \textbf{Equation 4.6}$$

$$R^2{}_{adj} = 1 - \frac{\frac{SS_{err}}{n-p}}{\frac{SS_{tot}}{n-1}} < R^2. \qquad \textbf{Equation 4.7}$$

The mean square error MS_{err}, also abbreviated *MSE*, which provides the estimate for the variance $\hat{\sigma}^2$ also changes. The estimate for the variance $\hat{\sigma}^2$ is used for calculating the test statistic t_{obs}, for the CI and PI, and in Mallow's C_p statistic, which may be used for variable selection.

While normalization changes the characteristics of the regression model and the hypothesis testing for it, the sample sizes for the datasets that are examined in Section 4.2.2 are large enough to expect the reduction of one df in the model source to have only a minute effect.

4.2.7 Confidence and Prediction Intervals

The prediction of a single response value for a given combination of explanatory variable values is incomplete insofar as this point on the regression curve only gives the mean response without any measure of the natural variability around this value. Information on the variability of the original data is captured in the coefficient of determination R^2 and in the adjusted coefficient of determination R^2_{adj}, which includes a correction for the number of explanatory variables contributing to the regression model. They express the fraction of variability of the original response that is explained by the regression model.

Variability can also be expressed by the CI and PI. The CI provides limits within which one would be 100 $(1-\alpha)\%$, typically 95%, statistically confident that the actual RVP is within these limits. The value α is the probability of a Type-I error. Accordingly, 100 $(1-\alpha)\%$ is the level of confidence in percent (Benjamin and Cornell 1970). On the other hand, the PI provides limits within which a future observation would fall with a certain level of confidence. By definition it is larger than the CI, because it includes "both the error from the fitted model and the error associated with future observations" (Montgomery et al. 2001, p38). CI and PI generally are narrowest at the mean of the explanatory variables, and are wider for more extreme values of the explanatory variable. It is possible to encounter the problem of fewer data points at the boundaries of the dataset. However, for the purpose of this study the most interesting data points and predictions are for the middle range of the explanatory variables.

Equations 4.8 and 4.9 give the standard formulas for the CI and PI, respectively, for SLR models. These formulas apply when there is only one explanatory variable in the model. Upper and lower limits of the respective interval are calculated by following either the plus or the minus sign after the estimated residual value on the right hand side of the equations.

$$CI = \hat{y}_0 \pm t_{\alpha/2,n-2} \cdot \sqrt{MS_{res} \cdot \left(\frac{1}{n} + \frac{(x_0 - \bar{x})^2}{S_{xx}} \right)}. \qquad \textbf{Equation 4.8}$$

$$PI = \hat{y}_0 \pm t_{\alpha/2,n-2} \cdot \sqrt{MS_{res} \cdot \left(1 + \frac{1}{n} + \frac{(x_0 - \bar{x})^2}{S_{xx}} \right)}. \qquad \textbf{Equation 4.9}$$

where CI and PI are the confidence and prediction intervals, respectively, $\hat{y}_0$ is the point estimate of the RVP at the particular value x_0 of age, $t_{\alpha/2,n-2}$ is the t-test statistic value for significance level α and n complete observations from a t-distribution, MS_{res} is the mean square residuals, $\bar{x}$ is the mean age (for the entire dataset), and S_{xx} is the sum of squares of the difference between the individual values of x and their mean.

However, both the CI and the PI need to be adjusted in order to correct for the uncertainty associated with the other explanatory variables in the model. These explanatory variables are not shown in the diagram of predicted RVP over age in calendar years, but nonetheless exist in the regression model. They will be assumed to be fixed at their respective mean value for simplification. This assumption includes somewhat less variability being contributed by them to the model than for predicted values with explanatory variable values away from their means.

An adjustment term for the CI and PI formulas is developed to account for the explanatory variables that are not displayed. There are $k-1$ terms in the estimating equation that need to be adjusted for, each contributing a term close to $1/(n-1)$ to the variance of a new observation. While this represents a conservative estimate of the variance, it gives a good indication of the model behavior for a typical prediction.

The adjusted formulas for CI and PI are given in Equations 4.10 and 4.11.

$$CI_{adj} = \hat{y}_0 \pm t_{\alpha/2,n-2} \cdot \sqrt{MS_{res} \cdot \left(\frac{1}{n} + \frac{(x_0 - \bar{x})^2}{S_{xx}} + \frac{k-1}{n-1} \right)}. \qquad \textbf{Equation 4.10}$$

$$PI_{adj} = \hat{y}_0 \pm t_{\alpha/2,n-2} \cdot \sqrt{MS_{res} \cdot \left(1 + \frac{1}{n} + \frac{(x_0 - \bar{x})^2}{S_{xx}} + \frac{k-1}{n-1} \right)}. \qquad \textbf{Equation 4.11}$$

where CI_{adj} and PI_{adj} are the adjusted confidence and prediction intervals, respectively.

4.3 Analysis Methodology

The following sections describe the methodology for analyzing the prepared datasets. The general approach for selecting a regression model among the many possible models is described, the identification and deletion of outliers is explained, and the procedure to select economic indicators as explanatory variables in outlined. A schematic of the analysis procedure as explained in these sections is provided in Figure 4.1.

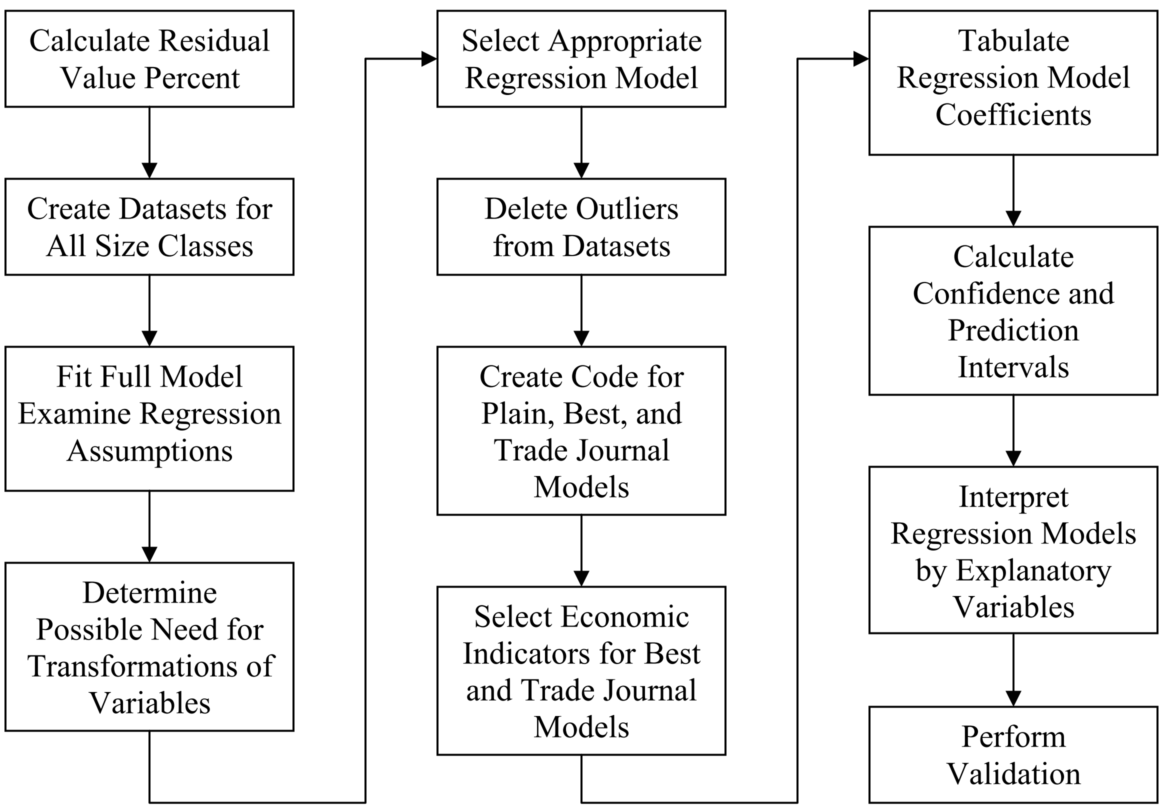


Figure 4.1: Flowchart of Data Analysis

Computer calculations are performed with the SAS® System. This statistical analysis software package offers a wide range of analytical tools. Datasets and instructions for the regression analysis, including the types of equations that are to be fitted, are to be described as program code in its specific programming language. All SAS® codes for data analysis are provided in Appendix C. Table 4.5 contains descriptive parameters of the data used in this study.

Table 4.5: Parameters of Overall Dataset

Item	Value or Range
Number of Entries	35,542
Number of Outliers	340
Number of Units with Age Zero	407
Equipment Age at Sale	0 to 15 years
Equipment Year of Manufacture	1979 to 2002
Equipment Auction Dates	January 15, 1994 to September 28, 2002
Manufacturers	Caterpillar, Deere, Komatsu, Volvo
Residual Value Percent	0.0037 to 1.2337 (including outliers) 0.0037 to 0.9489 (excluding outliers)
Number of Equipment Size Classes	28
Equipment Types	Track and Wheel Excavators, Wheel and Track Loaders, Backhoe Loaders, Integrated Toolcarriers, Rigid Frame and Articulated Trucks, Track Dozers, Motor Graders, Wheel Tractor Scrapers

4.3.1 Selection of Statistical Model

The general principle known as Ockham's Razor will be used to select the regression model in this study. Named after a medieval monk, this principle says that the simplest one of several possible explanations of the same quality for a given problem should be chosen (Schabenberger and Pierce 2002). According to Schabenberger and Pierce (2002, p8), simple in this sense means "simple to fit, simple to interpret, simple to justify, and simple to apply." Applying this strategy will lead to a parsimonious model, i.e. "the simplest possible model that is consistent with the data and knowledge of the problem environment" (Montgomery et al. 2001, p223).

Developing a regression model is as much art as it is science. Choice of a particular model depends on its intended use and on the available data. There is not a single perfect regression model, only the model that performs best as defined by its user. A major consideration is the goodness-of-fit of the regression model to the data as well as its predictive abilities. In this study the model shall be chosen by the maximum adjusted coefficient of determination R^2_{adj}, which predominantly is a measure of the goodness of fit. In analogy to Mitchell (1998), this measure of model performance is chosen over the plain coefficient of determination R^2 because it additionally includes a correction that penalizes for superfluous explanatory variables as described in Section 4.2.6. It is also possible to use the mean square error as the performance measure for goodness-of-fit, as the criterion to choose the model with the maximum R^2_{adj} is equivalent to choosing the model with the minimum MS_{err} (Montgomery et al. 2001). A goodness-of-fit measured by a R^2_{adj} of 0.7 or larger shall be considered good for the purpose of model selection in this study.

Additionally, the prediction error sum of squares (*PRESS*) statistic provides a measure of the predictive abilities of the regression model (Montgomery et al. 2001). Small values of *PRESS* are sought. It is calculated by creating a dataset with one observation removed, calculating the model prediction for this observation and comparing it to the observed value. *PRESS* is then calculated by adding the square of these differences between all actual observations and their predicted values. For larger datasets, the model selection obtained by using the maximum R^2_{adj} should coincide with the model selection obtained by using the minimum *PRESS* (Anderson-Cook 2001).

Prior to developing the statistical model for the regression analysis it is necessary to examine the explanatory variables to gain an impression on the explanatory power that they can contribute to said model. The Pearson coefficients of correlation R_{corr} were calculated for the correlation between the explanatory variables and the response variable, RVP. The SAS® code for this correlation analysis is found in Appendix C.3. Table 4.6 contains the values of R_{corr} for the correlation of age with residual value percent and compares them with the maximum absolute value the R_{corr} that the indicator variables for manufacturer, condition rating, and auction region yielded.

Examining these coefficients of correlation shows that age in calendar years consistently appears to be the explanatory variable that contributes the most explanatory power to the regression model. Due to the negative sign of R_{corr} the explanatory variable age is related to RVP in form of a monotonically decreasing curve. In other words, higher age coincides with lower RVP. Other explanatory variables did not show any clear relationship with the response variable. It is hypothesized, however, that a lower condition rating coincides with lower RVP. The relationship between manufacturer and RVP and between auction region and RVP will the addressed with the results of the regression analysis in Section 4.4. In the cases of Datasets 12, 22, and 24 the absolute value of the correlation between an indicator variable and RVP exceeds the absolute value of the correlation between age and RVP. However, indicator variables provide only very limited information due to the binary values "0" and "1" that they can take on. Moreover, they do not lend themselves to individual intuitive interpretation but only function correctly as a triplet. It is therefore justified to use the numerical explanatory variable age as the main explanatory variable for which the regression model is developed.

Based on these findings it was decided to examine regression models that contain different functions of age that capture the observed monotonically decreasing curve of age in calendar years. Polynomials of age up to the order three were included in all possible combinations. Models with a logarithmic and an exponential function of age were also included. Other explanatory variables are included as additive terms. Equation 4.12 shows the general mathematical form of the examined regression models. Table 4.7 lists the different regression models.

$$RVP = f\ (age^3, age^2, age, manufacturer, condition\ rating, auction\ region, economic\ indicator\ 1, economic\ indicator\ 2)\,.$$

Equation 4.12

Table 4.6: Correlation Coefficients of Explanatory Variables with Residual Value Percent

Equipment Type	Number	Correlation of Age with Residual Value Percent		Correlation of Indicator Variables with Residual Value Percent	
		Coefficient of Correlation	Explanatory Variable	Maximum Coefficient of Correlation	Explanatory Variable
Track Excavators	1	-0.82673	Age	0.48826	c_1
	2	-0.75864	Age	-0.44375	m_2
	3	-0.75054	Age	0.39550	c_1
	4	-0.75303	Age	0.46866	c_1
	5	-0.76472	Age	0.49765	c_1
Wheel Excavators	6	-0.79175	Age	-0.69650	m_2
Wheel Loaders	7	-0.65806	Age	0.41975	c_1
	8	-0.75828	Age	0.39295	c_1
	9	-0.84699	Age	0.56711	c_1
	10	-0.85896	Age	0.63776	c_1
Track Loaders	11	-0.77572	Age	-0.41472	m_2
	12	-0.76430	Age	-0.90133	m_2
Backhoe Loaders	13	-0.36944	Age	0.23751	c_1
	14	-0.74612	Age	0.40154	c_1
Integrated Toolcarriers	15	-0.83392	Age	0.33066 -0.33066	m_2 m_3
Rigid Frame Trucks	16	-0.60403	Age	0.36495	c_1
	17	-0.75923	Age	0.30234	c_2
Articulated Trucks	18	-0.68987	Age	0.27489	c_1
	19	-0.56981	Age	0.29989 -0.29989	m_1 m_3
Track Dozers	20	-0.74935	Age	0.41985	c_1
	21	-0.78646	Age	-0.68086	m_2
	22	-0.72056	Age	-0.84072	m_2
	23	-0.85314	Age	-0.84373	m_2
	24	-0.75019	Age	-0.85224	m_2
Motor Graders	25	-0.87515	Age	-0.77241 0.77241	m_2 m_3
	26	-0.85214	Age	-0.83130 0.83130	m_2 m_3
Wheel Tractor Scrapers	27	-0.77605	Age	0.40882	c_1
	28	-0.82382	Age	0.22237	c_3

Table 4.7: Regression Models for Analysis

Number	Algebraic Form of Regression Model
1	$RVP = \beta_0 + \beta_1 \cdot age + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3$
2	$RVP = \beta_0 + \beta_2 \cdot age^2 + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3$
3	$RVP = \beta_0 + \beta_2 \cdot age^2 + \beta_1 \cdot age + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3$
4	$RVP = \beta_0 + \beta_3 \cdot age^3 + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3$
5	$RVP = \beta_0 + \beta_3 \cdot age^3 + \beta_1 \cdot age + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3$
6	$RVP = \beta_0 + \beta_3 \cdot age^3 + \beta_2 \cdot age^2 + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3$
7	$RVP = \beta_0 + \beta_3 \cdot age^3 + \beta_2 \cdot age^2 + \beta_1 \cdot age + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3$
8	$RVP = \beta_0 + \beta_1 \cdot e^{-\mathrm{age}} + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3$
9	$RVP = \beta_0 + \beta_1 \cdot log_e(age) + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3$
10	$RVP = \beta_0 + \beta_1 \cdot age^{-1} + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3$
11	$RVP = \beta_0 + \beta_1 \cdot age^{-1/2} + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3$

In Table 4.7, *RVP* is the residual value percent, β_0 through β_3 are regression coefficients (β_0 being the intercept), *age* is the age in calendar years, M_i, C_i, and R_i are the regression coefficients for the manufacturer, condition rating, and auction region indicator variables, respectively, and m_i, c_i, and r_i are the manufacturer, condition rating, and auction region indicator variables, respectively.

For each of these regression models the R^2, R^2_{adj}, root *MSE*, and *PRESS* statistics were computed using the SAS® that is provided in Appendix C.2. Values for the statistics are tabulated in Appendix G.1. Table 4.8 lists the values of the adjusted coefficient of determination R^2_{adj} for all regression models and all datasets.

The Regression Models 3, 7, and 9 consistently provide the highest values of R^2_{adj} for all datasets and have been shaded in the table. Examining the *PRESS* statistics shows a high variance between the different regression models for Datasets 1, 8, 13, 14, 18, 20, and 21 caused predominantly by the unsatisfactory predictive capabilities of the exponential Model 8 and the third-order polynomial Model 7 in some cases. The second-order polynomial Model 3 is nested within the third-order polynomial of age in calendar years of Model 7. It is possible to perform a sum of squares reduction test of the full Model 7 and the reduced Model 3 as described in Section 4.4. It was found that at a significance level α of 0.1 the null hypothesis stating that the reduced model performs as good as the full model is rejected for many datasets. The absolute differences between the values of R^2_{adj}, however, are for all but five datasets smaller than 2%. Moreover, the criterion of the using the regression model with the minimum *PRESS* statistic as listed in Appendix G.1 clearly favors Model 3 over Model 7. The choice between Models 3 and 7 thus is made by following Ockham's Razor and choosing the Model 3 that is smaller and simpler by one explanatory variable.

Both Model 3 and Model 9 perform comparably – for about half the datasets Model 3 yield a slightly higher R^2_{adj} and vice versa. Taking the overall average of the R^2_{adj} values shows a slight tendency of Model 9 to yield higher values. Model 9 suggests that loss of RVP with increasing age can be viewed as a natural process that can well be modeled with a natural logarithm function of age. Regression Model 3, on the other hand, contains two terms of age that represent two components of loss in RVP. They are interpreted in analogy to the components of the repair cost model developed by Mitchell (1998). Modeling age allows for a linear decrease in loss as a function of age. The square of age allows for that relationship to slow down with increasing age. Controlling these two components influences how much value a machine loses over time and how rapidly is loses said value. Regression Model 3 is chosen over Model 9 because of its excellent performance with respect to goodness-of-fit and predictive ability and its high interpretability for practical application. This model is shown in Equation 4.13. It will be applied to all datasets to create consistency and comparability between the regression models for the different equipment types and size classes.

Table 4.8: Statistics for Regression Models

Number	Adjusted R^2 for Regression Models										
	1	2	3	4	5	6	7	8	9	10	11
1	0.7084	0.5901	0.7717	0.5315	0.7597	0.7039	0.7856	0.7141	0.7873	0.7375	0.7697
2	0.6485	0.5780	0.6875	0.5328	0.6799	0.6456	0.6963	0.5970	0.6991	0.6433	0.6821
3	0.5947	0.5219	0.6099	0.4374	0.6085	0.5909	0.6091	0.4928	0.5982	0.5230	0.5667
4	0.6101	0.5167	0.6348	0.4341	0.6347	0.6188	0.6342	0.5139	0.6200	0.5434	0.5867
5	0.6853	0.6276	0.7075	0.5743	0.7067	0.6938	0.7019	0.4331	0.7107	0.5690	0.6641
6	0.6865	0.6257	0.7398	0.5994	0.7312	0.6913	0.7455	0.6592	0.7431	0.6897	0.7224
7	0.6074	0.5657	0.6201	0.5269	0.6185	0.6077	0.6204	0.4690	0.6230	0.5554	0.6006
8	0.6736	0.5985	0.7155	0.5443	0.7071	0.6720	0.7273	0.5497	0.7256	0.6355	0.6983
9	0.8039	0.7549	0.8444	0.7235	0.8366	0.8097	0.8544	0.7515	0.8534	0.8030	0.8421
10	0.8393	0.7923	0.8932	0.7717	0.8842	0.8520	0.9024	0.8459	0.8943	0.8681	0.8898
11	0.6747	0.6221	0.7059	0.5824	0.6977	0.6706	0.7283	0.5582	0.7265	0.6716	0.7217
12	0.8631	0.8542	0.8843	0.8514	0.8781	0.8647	0.8982	0.8912	0.8881	0.8970	0.8981
13	0.1494	0.1282	0.1765	0.1152	0.1716	0.1601	0.1929	0.1917	0.1781	0.1993	0.1910
14	0.6093	0.5200	0.6626	0.4559	0.6504	0.6059	0.6849	0.5119	0.6851	0.6102	0.6699
15	0.7042	0.6088	0.7667	0.5360	0.7632	0.7332	0.7662	0.3639	0.7385	0.5181	0.6579
16	0.4860	0.4372	0.5114	0.3997	0.5076	0.4905	0.5147	0.3577	0.5127	0.4320	0.4838
17	0.6927	0.6298	0.6989	0.5572	0.6957	0.6762	0.7232	0.4212	0.7064	0.6534	0.6872
18	0.5326	0.4413	0.5901	0.3732	0.5797	0.5389	0.6006	0.4265	0.5953	0.5171	0.5748
19	0.4243	0.3572	0.4788	0.3056	0.4706	0.4422	0.4856	0.3671	0.4783	0.4417	0.4752
20	0.6112	0.5337	0.6587	0.4777	0.6480	0.6100	0.6808	0.5106	0.6770	0.6113	0.6654
21	0.7333	0.6809	0.7814	0.6513	0.7730	0.7422	0.7906	0.7089	0.7890	0.7526	0.7836
22	0.8280	0.8148	0.8416	0.8071	0.8387	0.8300	0.8456	0.8203	0.8468	0.8401	0.8490
23	0.8534	0.8121	0.8916	0.7944	0.8854	0.8589	0.8968	0.8530	0.8948	0.8707	0.8885
24	0.8331	0.8086	0.8838	0.7977	0.8725	0.8478	0.9064	0.8742	0.8795	0.8982	0.8984
25	0.8177	0.7694	0.8545	0.7388	0.8519	0.8370	0.8554	0.7307	0.8483	0.7914	0.8301
26	0.8724	0.8332	0.9033	0.8094	0.9003	0.8848	0.9048	0.8193	0.9018	0.8599	0.8884
27	0.7228	0.6406	0.7740	0.5729	0.7689	0.7445	0.7769	0.5523	0.7726	0.6791	0.7469
28	0.6967	0.6453	0.7028	0.5920	0.6995	0.6766	0.7146	0.3401	0.6954	0.5169	0.6265

$$RVP = \beta_0 + \beta_1 \cdot age^2 + \beta_2 \cdot age + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3 .$$

Equation 4.13

where *RVP* is the residual value percent, β_0 through β_2 are regression coefficients (β_0 being the intercept), *age* is the age in calendar years, M_i, C_i, and R_i are the regression coefficients for the manufacturer, condition rating, and auction region indicator variables, respectively, and m_i, c_i, and r_i are the manufacturer, condition rating, and auction region indicator variables, respectively.

It needs to be noted that this second-order polynomial model of age in calendar years exhibits a curve of RVP that first decreases and then increases again with higher age. This parabolic increase is not supported by any data. Only machines with an age of up to 15 years were used in the regression analysis and generally showed the tendency to be monotonically decreasing. The regression model should therefore only be used to make predictions up the age at which the minimum RVP occurs. Section 4.4 contains tabulated coefficients for this regression model.

4.3.2 Elimination of Outliers

Observations inconsistent with the basic relationship captured by the other data points are called outliers. These extreme observations significantly differ from others by their sign or magnitude and are easily identified in a scatterplot of the data. Outliers may be influential points, i.e. data points that singularly and significantly alter the regression model. Possible reasons for outliers can be errors in measuring or recording the data points, but they could also indicate that a regression model is performing inadequately in their particular region (Montgomery et al. 2001). In any case, they need to be identified and analyzed. In case it is found that the regression model is insufficient, attempts should be made to improve it. Otherwise, the outliers will be deleted from the dataset.

A variety of methods exists to identify whether a data point is a valid observation or an outlier. Residuals measure how much a data point deviates from the regression model, i.e. they may be seen as “a measure of the variability in the response variable not explained by the regression model. It is also convenient to think of the residuals as the realized or observed values of the model errors” (Montgomery et al. 2001, p132). A type of scaled residuals is used for outlier identification in this study. The studentized residuals r_i have a constant variance and therefore “examination of the studentized residuals is generally recommended” (Montgomery et al. 2001, p134). The condition of Equation 4.14 is used to determine whether a data point qualified as an outlier under the selected regression model:

$$\textit{If } |r_i| > 3 \textit{ then consider data point an outlier.} \qquad \textbf{Equation 4.14}$$

$$\textit{If } |r_i| \le 3 \textit{ then do not consider data point an outlier.}$$

where r_i is the studentized residual of the observation number i from the dataset. Studentized residuals were calculated for the selected second-order polynomial regression model using the SAS® code shown in Appendix C.3. Their values were stored in the EXCEL spreadsheets together with the data points. A new column OUTLIER was created in which the condition of Equation 4.12 was used to mark all outliers with "1" and the valid observations with "0" for sorting.

They are deleted based on the assumption that they may have been unusual in their setup, etc. and thus yielded extreme residual values (Montgomery et al. 2001, p154). A total of 340 outliers, less than one percent of all 35,542 observations, were found in the 28 datasets. They were deleted from the datasets and the coefficients for all final regression models were calculated using the cleaned datasets. Appendix F shows the number of observations in all datasets prior to and after deleting the outliers.

4.3.3 Selection of Macroeconomic Indicators

The selection of explanatory variables for a regression model can be an involved task. The broadest approach would be to examine all 2^k possible models, ranging from a regression model containing only one explanatory variable to a regression model containing all k explanatory variables. However, more efficient ways to select a regression model are available. Three algorithms can assist in the selection of explanatory variables for being included in the regression model. They are the forward selection, the stepwise selection, and the backward elimination. Forward selection begins with the empty model, tests which explanatory variable is most significant if added to the model, adds it to the model, and proceeds with testing the remaining explanatory variables and sequentially adding the most helpful ones to the model. Backward elimination is the reverse process of forward selection. The algorithm begins with the full model, tests which explanatory variable is least significant if deleted from the model, deletes it from the model, and proceeds with sequentially testing the remaining explanatory variables. It is often used for initial identification of variables that should not be included in the regression model. Stepwise selection finally is an extended version of forward selection. After each step of testing and adding the most significant explanatory variables, the algorithm tests which explanatory variable should be deleted. This algorithm has more flexibility in arriving at a regression model that has a high goodness-of-fit without including too few or too many explanatory variables, i.e. underfitting or overfitting the model. Flowcharts for forward, stepwise, and backward selection procedures are provided in Appendices C.8, C.9, and C.10.

An important assumption is made to develop the regression models. Explanatory variables contained in the auction records, the list prices, and size parameters are usually known by the owner of construction equipment. These variables are therefore always included in the regression models. This assumption could lead to overfitting in case fewer explanatory variables suffice for a regression model with high explanatory power. Comparing the coefficient of determination R^2 with the adjusted coefficient of determination R^2_{adj} gives a good indication whether a model contains too many explanatory variables or not. If the values of R^2 and R^2_{adj} are close, the regression model is not overfitted. Interaction terms were not included in the regression model because of the still relatively small sample sizes of some datasets and because of existence of many indicator variables. Should the goodness-of-fit require additional explanatory variables, interaction terms would be considered.

It was decided to develop three types of regression models to accommodate different potential users. The models differ in the economic indicators and in the goodness-of-fit that is achieved:

- Plain Models: These regression models do not contain any economic indicators. They can be used for quick predictions of RVP but have the lowest R^2 and R^2_{adj} values;

- Best Models: These regression models contain economic indicators selected from the complete economic indicator catalog. They require forecasting of the economic indicator values but generally have the highest R^2 and R^2_{adj} values;
- Trade Journal Models: These regression models contain a subset of the economic indicator catalog as shown in Table 4.9. The economic indicators values that need to be forecasted are commonly reported in trade journals, thus reducing the effort of keeping a current economic database for the user. The smaller selection of economic indicators also helps avoiding multicollinearity problems caused by these indicators. These regression models have R^2 and R^2_{adj} values between the values for the two other types of regression models.

In an intermediate step it was examined how many economic indicators should be included in the best models and in the trade journal models to obtain a high goodness-of-fit without overfitting the models. Plotting the goodness-of-fit as measured by the value of R^2 in a diagram over the number of explanatory variables k produces a monotonically increasing curve (Montgomery et al. 2001). Even adding completely random explanatory variables to the regression model would still increase the value of R^2 minimally. Based on the results from models with up to five economic indicators it was decided that two economic indicators should be included in the best models and in the trade journal models. Two economic indicators capture a broader range of the state of the economy than one. Using fewer economic indicators would also ignore a potential improvement in the goodness-of-fit, whereas using more economic indicators would not yield significant improvements.

Standard variable selection procedures may not fulfill the requirement that certain explanatory variables are always included in the regression model. Trial computations showed that age in calendar years in most cases is the explanatory variables with the highest individual predictive power while some indicator variables were not always automatically selected. A significance level α of 0.2 was used in the forward and stepwise selection and in the backward elimination to variables to add explanatory variables to the model or to delete them from it, respectively. Results from forward and stepwise selection were almost always identical for this study, indicating good consistency in the ideal model across model selection approaches. It was decided to examine all possible models instead of modifying the selection algorithms to force these explanatory variables into the model. If two economic indicators are included in the regression model the number of regression models to be examined for each dataset decreases as shown in Table 4.10.

Table 4.9: Macroeconomic Indicators for Trade Journal Models

Number	Abbreviation	Name	Frequency	Original Source	Unit
1	WTR	Construction Put in Place (C30) - Table 5b: Public - Water supply facilities	monthly	Bureau of the Census	Bil. 96$, SAAR
2	SWR	Construction Put in Place (C30) - Table 5b: Public - Sewer systems	monthly	Bureau of the Census	Bil. 96$, SAAR
3	HWY	Construction Put in Place (C30) - Table 5b: Construction put in place: Public - Highways and streets	monthly	Bureau of the Census	Bil. 96$, SAAR
4	TTLCNST	Construction Put in Place (C30) - Table 5b: Total	monthly	Bureau of the Census	Bil. 96$, SAAR
5	INTRST	Interest Rates (H15): 10-Year Constant Maturity Securities	monthly	Federal Reserve Board	% p.a.
6	PPIME	PPI (WPS112): Machinery and equipment - Construction machinery and equipment	monthly	Bureau of Labor Statistics	1982=100, SA
7	HMSTS	Housing Starts and Building Permits (C20): Housing Starts: Total privately owned	monthly	Bureau of the Census	Ths., SAAR
8	EMPLC	Form 790 (EES20000001 (n)): Employment: Construction	monthly	Bureau of Labor Statistics	Ths., SA
9	GDP	Table 1.9 Line 1: NIPA: Gross domestic product	quarterly	Bureau of Economic Analysis	Bil. $, SAAR, nominal

Table 4.10: Number of Models per Dataset

Model Type	Number of Different Macroeconomic Indicator Explanatory Variables	Number of Models
All Possible Models	$k = 35$	$2^k = 34{,}359{,}738{,}368$
Plain Models	$k = 0$	N/A
Best Models	$k = 35$	$\sum_{1}^{k-1}(k-1) = 595$
Trade Journal Models	$k = 9$	$\sum_{1}^{k-1}(k-1) = 36$

The SAS® code that was used for the selection of economic indicators for the best models and for the trade journal models can be found in Appendices C.5 and C.6. All these models were computed and the regression model with the highest value of R^2_{adj} was selected for each dataset under consideration of the variance inflation factors (VIF). The VIF is calculated for each explanatory variable as a measure of potential multicollinearity problems among them. Montgomery et al. (2001) give the criterion of Equation 4.15 when the value of a VIF should be considered problematic.

$$\textit{If VIF} > 10 \textit{ then multicollinearity problem exists.} \qquad \textbf{Equation 4.15}$$

Using this criterion it was found that the initial selection of economic indicators for the best models of Datasets 11, 12, 19 22, and 25 and for the trade journal models of Datasets 8, 10, 11, 17, 18, 20, 21, 23, 25, and 27 would have had multicollinearity problems. The economic indicators for these models were replaced with the economic indicator pair that created the next highest value R^2_{adj} without causing a multicollinearity problem. The final economic indicators of the best models and trade journal models are listed in Tables 4.11 and 4.12.

Table 4.11: Selected Macroeconomic Indicators for Best Models

Equipment Type	Number	Size Range	Macroeconomic Indicator e_1	Macroeconomic Indicator e_2
Track Excavators	1	0-24,999 lbs	EMPLC	CNSCR
	2	25,000-49,999 lbs	STLPRD	TNR
	3	50,000-74,999 lbs	CPI	STLPRD
	4	75,000-99,999 lbs	CNSCR	SVGS
	5	100,000+ lbs	SP	SVGS2
Wheel Excavators	6	All Sizes	LEADG	PPIME
Wheel Loaders	7	0-1.9 CY	CCI	CNSCR
	8	2-3.9 CY	CNSCR	SVGS
	9	4-5.9 CY	ECICOMP	CNSCR
	10	6+ CY	CNSCR	SVGS
Track Loaders	11	0-1.9 CY	PPIME	ECICOMP
	12	2+ CY	LEADG	CPI
Backhoe Loaders	13	0-0.9 CY	BCI	CNSCRNF
	14	1+ CY	ECICOMP	CNSCRNF
Integrated Toolcarriers	15	All Sizes	HWY	ATSLS
Rigid Frame Trucks	16	0-99,999 lbs	LEADG	EMPLC
	17	100,000+ lbs	LEADG	STLPRD
Articulated Trucks	18	0-49,999 lbs	INTRST	SVGS
	19	50,000+ lbs	RTLSLS	CNSCRNF
Track Dozers	20	0-99 HP	STLPRD	SVGS
	21	100-199 HP	STLPRD	SVGS
	22	200-299 HP	INDPRD	PPIMIN
	23	300-399 HP	LEADG	EMPLC
	24	400+ HP	SWR	SVGS2
Motor Graders	25	0-149 HP	PPIME	ECICOMP
	26	150+ HP	ATSLS	CNSCR
Wheel Tractor Scrapers	27	0-74,999 lbs	PPIME	SVGS
	28	75,000+ lbs	BCI	ECICOMP

Comparing the selected economic indicators with the lists of economic indicator pairs of Section 3.6.2.1 showed that with exception of Dataset 15 for the best models the selection procedure did not necessarily yield regression models containing the economic indicator pairs for which the correlation coefficient was not significantly different from zero. Among the economic indicators pairs for the best models it is noteworthy that the LEADG indicator was chosen for both size classes of rigid frame trucks. Among the economic indicator pairs for the trade journal models it is noteworthy that the HMSTS indicator was chosen several times for excavators as well as the SWR indicator for trucks, dozers, graders, and scrapers. GDP was chosen as the second indicator for about half of all datasets. A direct relationship between the function of a particular equipment type and the economic indicators that contribute the highest explanatory power to the respective model could not be found.

Table 4.12: Selected Macroeconomic Indicators for Trade Journal Models

Equipment Type	Number	Size Range	Macroeconomic Indicator e_1	Macroeconomic Indicator e_2
Track Excavators	1	0-24,999 lbs	HMSTS	GDP
	2	25,000-49,999 lbs	INTRST	EMPLC
	3	50,000-74,999 lbs	SWR	INTRST
	4	75,000-99,999 lbs	HMSTS	GDP
	5	100,000+ lbs	HMSTS	EMPLC
Wheel Excavators	6	All Sizes	INTRST	GDP
Wheel Loaders	7	0-1.9 CY	INTRST	GDP
	8	2-3.9 CY	HMSTS	GDP
	9	4-5.9 CY	INTRST	GDP
	10	6+ CY	WTR	GDP
Track Loaders	11	0-1.9 CY	WTR	SWR
	12	2+ CY	HMSTS	GDP
Backhoe Loaders	13	0-0.9 CY	WTR	TTLCNST
	14	1+ CY	SWR	EMPLC
Integrated Toolcarriers	15	All Sizes	HWY	TTLCNST
Rigid Frame Trucks	16	0-99,999 lbs	SWR	HMSTS
	17	100,000+ lbs	SWR	EMPLC
Articulated Trucks	18	0-49,999 lbs	SWR	GDP
	19	50,000+ lbs	WTR	GDP
Track Dozers	20	0-99 HP	SWR	TTLCNST
	21	100-199 HP	HMSTS	GDP
	22	200-299 HP	WTR	TTLCNST
	23	300-399 HP	SWR	INTRST
	24	400+ HP	INTRST	GDP
Motor Graders	25	0-149 HP	HWY	GDP
	26	150+ HP	INTRST	HMSTS
Wheel Tractor Scrapers	27	0-74,999 lbs	SWR	TTLCNST
	28	75,000+ lbs	SWR	PPIME

4.4 Analysis Results

This section presents the results of the statistical analysis. Selected values are presented in tables and diagrams. Tables of the regression coefficients are provided in this section. Statistics for the three types of regression models can be found in Appendix G.

Table 4.13 contains the algebraic form of the plain models, best models, and trade journal models. In Table 4.13, *RVP* is the residual value percent, β_0 through β_2 are regression coefficients (β_0 being the intercept), *age* is the age in calendar years, M_i, C_i, and R_i are the regression coefficients for the manufacturer, condition rating, and auction region indicator variables, respectively, E_{ij} are the regression coefficients for the economic indicators, m_i, c_i, and r_i are the manufacturer, condition rating, and auction region indicator variables, respectively, e_{ij} are the economic indicator values, *b* is the index of the best model, and *t* is the index of the trade journal model. Tables 4.14 through 4.16 contain the coefficients for each of these models.

Table 4.13: Algebraic Form of Final Regression Models

Model	Algebraic Form of Regression Model
Plain Model	$RVP = \beta_0 + \beta_2 \cdot age^2 + \beta_1 \cdot age + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3$
Best Model	$RVP = \beta_0 + \beta_2 \cdot age^2 + \beta_1 \cdot age + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3 + E_{1b} \cdot e_{1b} + E_{2b} \cdot e_{2b}$
Trade Journal Model	$RVP = \beta_0 + \beta_2 \cdot age^2 + \beta_1 \cdot age + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3 + E_{1t} \cdot e_{1t} + E_{2t} \cdot e_{2t}$

Table 4.17 compares the coefficients of determination, R^2, and adjusted coefficients of determination, R^2_{adj}, of the regression models. Noteworthy is the improvement of the fit that is achieved by adding economic indicators to the plain models. Economic indicators contribute less explanatory power to the models than the age, but an improvement of 0.05 to 0.1 of the total variability of the response can be explained by adding economic indicators. In most cases the R^2

and R^2_{adj} exceed 0.7, indicating a very good fit of the regression equation to the data points within the particular dataset. Because of this high goodness-of-fit the use of NLR models was not considered necessary.

Table 4.14: Coefficients for Plain Models

Equipment Type	Number	β_0 (Intercept)	β_2 (Age^2)	β_1 (Age)	M_1	M_2	M_3
Track Excavators	1	0.58972	0.00374	-0.08322	0.0	-0.00512	0.02017
	2	0.59899	0.00201	-0.05154	0.0	-0.07731	-0.04378
	3	0.58169	0.00324	-0.06997	0.0	-0.04967	-0.06366
	4	0.53428	0.00368	-0.08194	0.0	-0.03735	0.04646
	5	0.43101	0.00153	-0.04581	0.0	0.0	0.04545
Wheel Excavators	6	0.73563	0.00302	-0.07393	0.0	-0.10738	-0.07523
Wheel Loaders	7	0.59698	0.001	-0.03594	-0.06025	-0.09599	-0.09104
	8	0.73678	0.00243	-0.06494	-0.13094	-0.09149	-0.08869
	9	0.61938	0.00254	-0.0636	-0.14158	-0.12428	-0.00769
	10	0.64439	0.0034	-0.07782	-0.1204	-0.12773	0.0
Track Loaders	11	0.55178	0.00143	-0.04143	0.0	-0.07294	-0.04785
	12	0.67103	0.00247	-0.05819	0.0	-0.25069	-0.03541
Backhoe Loaders	13	0.48797	0.0014	-0.04106	0.0	0.0	0.0
	14	0.76828	0.00247	-0.06437	0.0	-0.14843	-0.14246
Integrated Toolcarriers	15	0.72345	0.00329	-0.08468	0.0	0.01375	0.0
Rigid Frame Trucks	16	0.55324	0.00143	-0.04361	0.0	-0.1056	0.0
	17	0.56302	0.0011	-0.04817	0.0	-0.19434	0.0
Articulated Trucks	18	0.53409	0.00289	-0.06904	0.06272	-0.03535	0.0
	19	0.51316	0.003	-0.06846	0.07011	0.0	0.0
Track Dozers	20	0.58368	0.00204	-0.05323	0.0	0.0	-0.04005
	21	0.66202	0.0031	-0.07476	0.0	-0.10034	-0.02558
	22	0.64456	0.00249	-0.06027	0.0	-0.27136	0.0
	23	0.62065	0.00327	-0.0776	0.0	-0.16817	0.0
	24	0.5974	0.00341	-0.07417	0.0	-0.15175	0.0
Motor Graders	25	0.74453	0.00252	-0.06769	0.0	-0.0682	0.0
	26	0.78837	0.00258	-0.06825	0.0	-0.1452	0.0
Wheel Tractor Scrapers	27	0.77399	0.00302	-0.08271	0.0	-0.15315	0.0
	28	0.65732	0.00117	-0.05152	0.0	0.0	0.0

Table 4.14 (Continued): Coefficients for Plain Models

Equipment Type	Number	C_1	C_2	C_3	R_1	R_2	R_3	E_1	E_2
Track Excavators	1	0.05172	0.02018	0.01955	-0.05078	-0.00194	-0.00921	N/A	N/A
	2	0.02271	-0.01197	0.01249	-0.03289	-0.00638	-0.00266	N/A	N/A
	3	0.03313	-0.02371	0.03859	-0.03064	-0.01408	0.00981	N/A	N/A
	4	0.03666	-0.03699	0.03172	-0.02806	0.00648	-0.00422	N/A	N/A
	5	0.058	-0.06932	0.03829	-0.07249	-0.04234	0.01024	N/A	N/A
Wheel Excavators	6	0.0116	-0.00855	0.02573	-0.01576	-0.04085	-0.02678	N/A	N/A
Wheel Loaders	7	0.07465	0.00137	0.01192	0.01102	0.00563	0.01904	N/A	N/A
	8	0.02927	-0.02013	0.02033	0.00681	0.00816	0.02213	N/A	N/A
	9	0.0373	0.00944	-0.00155	6.044E-4	0.0074	0.00996	N/A	N/A
	10	0.0303	-0.01601	-6.839E-4	-0.01499	-0.01704	-0.00672	N/A	N/A
Track Loaders	11	0.06268	-0.02097	0.01679	-0.01908	0.02701	-0.00689	N/A	N/A
	12	0.07781	0.01531	0.01232	-0.04705	0.00712	0.00935	N/A	N/A
Backhoe Loaders	13	0.01216	-0.02069	0.01562	0.01173	-0.00315	0.00175	N/A	N/A
	14	0.04734	-0.02229	0.02465	-0.02278	-0.00867	0.03171	N/A	N/A
Integrated Toolcarriers	15	0.01594	-0.0292	0.0119	-0.00466	0.00563	-0.00644	N/A	N/A
Rigid Frame Trucks	16	0.04822	-0.05813	0.04115	0.0066	0.01488	-0.05843	N/A	N/A
	17	-0.06657	0.03599	0.01547	-0.07538	-0.00918	-0.05791	N/A	N/A
Articulated Trucks	18	0.02996	-0.02999	0.03019	0.00632	0.01014	0.01387	N/A	N/A
	19	0.02073	-0.00651	-7.099E-4	-0.02958	0.01453	0.0151	N/A	N/A
Track Dozers	20	0.04288	-0.01667	0.01827	-0.00337	0.00845	0.00987	N/A	N/A
	21	0.04668	-0.02164	0.01716	0.02785	0.01804	0.02694	N/A	N/A
	22	0.09273	-0.00575	0.01425	0.07471	0.05529	0.01704	N/A	N/A
	23	0.06846	0.03169	0.01569	0.03076	0.02929	0.02749	N/A	N/A
	24	0.08504	0.00173	0.0158	-0.00625	-0.01886	-0.01768	N/A	N/A
Motor Graders	25	0.02908	-0.01366	0.01699	-0.05193	-0.02501	-0.0401	N/A	N/A
	26	-0.00589	-0.03832	0.0168	-0.0284	-0.02609	-0.04169	N/A	N/A
Wheel Tractor Scrapers	27	0.03741	-0.0187	0.02634	0.05958	0.0303	-4.672E-4	N/A	N/A
	28	0.08594	0.01942	0.03347	6.6336E-4	0.0	0.00423	N/A	N/A

Table 4.15: Coefficients for Best Models

Equipment Type	Number	β_0 (Intercept)	β_2 (Age^2)	β_1 (Age)	M_1	M_2	M_3
Track Excavators	1	1.35942	0.0043	-0.08702	0.0	-0.06232	-0.08506
	2	0.9968	0.0018	-0.04744	0.0	-0.11137	-0.08277
	3	1.3416	0.00211	-0.05675	0.0	-0.05546	-0.07983
	4	0.74753	0.00305	-0.07163	0.0	-0.08455	-0.01504
	5	0.46816	0.00197	-0.05423	0.0	0.0	0.07347
Wheel Excavators	6	2.43388	0.00365	-0.07646	0.0	-0.19249	-0.06808
Wheel Loaders	7	1.19577	0.00107	-0.03626	-0.084	-0.12296	-0.09382
	8	0.85117	0.00254	-0.06718	-0.15049	-0.11851	-0.09084
	9	0.87161	0.00278	-0.06652	-0.17026	-0.14402	-0.01911
	10	0.75371	0.00351	-0.07844	-0.13163	-0.15887	0.0
Track Loaders	11	0.13399	0.00139	-0.0413	0.0	-0.0954	-0.04843
	12	0.77776	0.00246	-0.05741	0.0	-0.27287	-0.03713
Backhoe Loaders	13	0.83953	0.00159	-0.04514	0.0	0.0	0.0
	14	1.12429	0.00249	-0.06562	0.0	-0.14822	-0.1355
Integrated Toolcarriers	15	0.44283	0.00324	-0.08444	0.0	0.01499	0.0
Rigid Frame Trucks	16	0.36468	0.00156	-0.04519	0.0	-0.1416	0.0
	17	1.22834	7.1514E-4	-0.0419	0.0	-0.20181	0.0
Articulated Trucks	18	0.63519	0.00348	-0.0752	0.05059	-0.08786	0.0
	19	1.18674	0.0033	-0.06959	0.06195	0.0	0.0
Track Dozers	20	0.55133	0.00211	-0.05484	0.0	0.0	-0.04026
	21	0.63403	0.003	-0.07445	0.0	-0.1253	-0.02741
	22	1.00144	0.00246	-0.05947	0.0	-0.31246	0.0
	23	0.25529	0.00295	-0.0715	0.0	-0.18127	0.0
	24	0.44866	0.00329	-0.07109	0.0	-0.17398	0.0
Motor Graders	25	0.34036	0.00215	-0.06074	0.0	-0.09028	0.0
	26	0.65632	0.00254	-0.06769	0.0	-0.15219	0.0
Wheel Tractor Scrapers	27	-0.4796	0.00326	-0.08678	0.0	-0.16752	0.0
	28	0.0302	0.00191	-0.06272	0.0	0.0	0.0

Table 4.15 (Continued): Coefficients for Best Models

Equipment Type	Number	C_1	C_2	C_3	R_1	R_2	R_3	E_1	E_2
Track Excavators	1	0.05109	0.0357	0.01443	-0.02871	-0.00368	0.01775	-1.0273E-4	1.65E-6
	2	0.02325	4.8753E-4	0.00466	-0.034	-0.0055	-0.0017	0.00128	-9.562E-4
	3	0.0323	-0.00941	0.03168	-0.02941	-0.02024	0.00669	-0.00548	0.00116
	4	0.02636	-0.01733	0.01709	-0.0256	-9.273E-4	-0.00318	6.470124E-7	-9.5897E-4
	5	0.07075	-0.0406	0.02717	-0.06532	-0.02734	0.02137	-5.148E-5	-4.35515E-7
Wheel Excavators	6	-0.00451	-0.02137	0.01977	0.00302	-0.03601	-0.02525	0.00629	-0.01646
Wheel Loaders	7	0.07233	0.00486	0.01065	0.02048	0.01443	0.02692	-9.69E-5	7.122597E-7
	8	0.02309	-0.00904	0.00988	0.0105	0.00603	0.02317	5.273183E-7	-5.4864E-7
	9	0.03231	0.01009	-0.00326	2.2418E-4	0.00314	0.00831	-0.00153	3.65478E-7
	10	0.01984	-0.00885	-0.00551	-0.00268	-0.00765	-3.6162E-4	5.437066E-7	-6.6142E-4
Track Loaders	11	0.06192	-0.00839	0.01376	-0.02583	0.02543	-0.00195	0.00651	-0.00370
	12	0.07757	0.02146	0.0099	-0.04724	0.00667	0.01095	0.00171	-0.0018
Backhoe Loaders	13	0.01385	-0.01766	0.01541	0.0112	0.00119	0.0014	-6.688E-5	-0.00161
	14	0.04583	-0.01122	0.01784	-0.02037	-0.00681	0.03309	-0.00181	-0.00147
Integrated Toolcarriers	15	0.01633	-0.03101	0.01362	0.00328	0.00656	-0.00157	0.0033	2.457E-4
Rigid Frame Trucks	16	0.05729	0.00259	0.00555	-0.01059	-0.0057	-0.03462	0.00846	-1.3485E-4
	17	-0.02352	0.02841	0.02659	-0.05788	-0.00361	-0.06046	-0.01056	0.00378
Articulated Trucks	18	0.01293	-4.1702E-4	0.00536	0.00515	0.00629	0.00896	0.01779	-0.0012
	19	0.01343	-0.00111	-0.00273	-0.01332	0.01255	-1.2061E-4	-2.49E-6	-9.4423E-4
Track Dozers	20	0.03577	-0.00754	0.01224	-0.00158	0.00904	0.00916	9.1614E-4	-7.1848E-4
	21	0.04011	-0.00537	0.00589	0.03263	0.01896	0.02629	0.00133	-0.00104
	22	0.07194	-0.00112	0.00419	0.09273	0.0661	0.02542	0.00355	-0.0051
	23	0.0765	0.04325	0.01875	0.02932	0.03116	0.02381	0.00561	-5.247E-5
	24	0.07463	0.01001	-9.6283E-4	-0.00882	-0.02195	-0.01883	0.01735	3.368385E-7
Motor Graders	25	0.0214	0.00169	0.00678	-0.06202	-0.03329	-0.0373	0.0075	-0.00496
	26	-0.00255	-0.03045	0.01612	-0.03283	-0.029	-0.03603	2.4033E-4	4.512954E-7
Wheel Tractor Scrapers	27	0.02691	-0.00319	0.00516	0.08673	0.04652	0.00162	0.01043	-0.00184
	28	0.08227	0.03829	0.04168	0.00216	0.0	1.5119E-4	5.5674E-4	-0.00917

Table 4.16: Coefficients for Trade Journal Models

Equipment Type	Number	β_0 (Intercept)	β_2 (Age^2)	β_1 (Age)	M_1	M_2	M_3
Track Excavators	1	0.79677	0.00393	-0.08606	0.0	-0.03649	-0.02967
	2	0.74335	0.00195	-0.05008	0.0	-0.10486	-0.0745
	3	0.25704	0.00211	-0.05785	0.0	-0.05431	-0.07771
	4	0.89535	0.00304	-0.07267	0.0	-0.08572	-0.01501
	5	0.49556	0.00189	-0.04947	0.0	0.0	0.0358
Wheel Excavators	6	0.99272	0.00358	-0.07536	0.0	-0.18192	-0.06167
Wheel Loaders	7	0.72284	9.7051E-4	-0.03517	-0.07784	-0.11789	-0.08922
	8	0.87404	0.00254	-0.0671	-0.14816	-0.1145	-0.09023
	9	0.69706	0.00273	-0.06554	-0.16866	-0.14253	-0.01859
	10	0.88322	0.00355	-0.07887	-0.1329	-0.15856	0.0
Track Loaders	11	0.4638	0.00148	-0.04287	0.0	-0.09042	-0.0469
	12	0.6688	0.0025	-0.05856	0.0	-0.26362	-0.03603
Backhoe Loaders	13	0.61258	0.00164	-0.04589	0.0	0.0	0.0
	14	0.84294	0.0025	-0.06562	0.0	-0.14785	-0.13428
Integrated Toolcarriers	15	0.70137	0.00334	-0.08617	0.0	0.01193	0.0
Rigid Frame Trucks	16	0.7753	0.00143	-0.04316	0.0	-0.12567	0.0
	17	0.93508	8.5851E-4	-0.04268	0.0	-0.16153	0.0
Articulated Trucks	18	0.86178	0.0035	-0.07511	0.05533	-0.08667	0.0
	19	1.11318	0.00333	-0.06979	0.06377	0.0	0.0
Track Dozers	20	0.57207	0.00208	-0.05414	0.0	0.0	-0.04021
	21	0.74821	0.00305	-0.0751	0.0	-0.11932	-0.02755
	22	0.88429	0.00255	-0.06085	0.0	-0.30717	0.0
	23	0.4916	0.00307	-0.07475	0.0	-0.17985	0.0
	24	0.91872	0.00345	-0.07397	0.0	-0.16261	0.0
Motor Graders	25	0.8306	0.00221	-0.06271	0.0	-0.08524	0.0
	26	0.58248	0.00259	-0.06877	0.0	-0.1484	0.0
Wheel Tractor Scrapers	27	0.66746	0.00335	-0.08735	0.0	-0.16492	0.0
	28	-0.07134	0.00126	-0.05312	0.0	0.0	0.0

Table 4.16 (Continued): Coefficients for Trade Journal Models

Equipment Type	Number	C_1	C_2	C_3	R_1	R_2	R_3	E_1	E_2
Track Excavators	1	0.04677	0.01391	0.03151	-0.05247	-0.0111	-0.0112	2.7396E-4	-5.945E-5
	2	0.02209	-0.00184	0.00512	-0.03705	-0.00851	-0.00465	0.02331	-3.604E-5
	3	0.03367	-0.01516	0.0353	-0.03555	-0.02388	0.00687	0.02529	0.02086
	4	0.02751	-0.01882	0.01764	-0.03174	-0.0016	-0.00347	1.4644E-4	-5.542E-5
	5	0.06463	-0.04977	0.03466	-0.058	-0.02099	0.01529	1.6876E-4	-5.711E-5
Wheel Excavators	6	-0.0083	-0.0249	0.02077	0.00619	-0.02961	-0.0275	0.02159	-3.758E-5
Wheel Loaders	7	0.07171	0.00623	0.00894	0.01827	0.01498	0.02432	0.01599	-2.315E-5
	8	0.02694	-0.00764	0.01235	0.00599	0.00491	0.02199	8.454E-5	-2.627E-5
	9	0.0337	0.01092	-0.00313	-0.00197	0.00456	0.00631	0.0106	-1.139E-5
	10	0.02467	-0.01056	-0.00339	-0.00902	-0.01047	-0.00535	0.00743	-2.889E-5
Track Loaders	11	0.06232	-0.00803	0.01268	-0.02623	0.02967	-7.4849E-4	-0.00661	0.01614
	12	0.0764	0.02137	0.00976	-0.04474	0.00813	0.01107	7.694E-5	-1.23E-5
Backhoe Loaders	13	0.0172	-0.01715	0.01506	0.01183	9.1043E-4	0.00246	0.00539	-9.8777E-4
	14	0.04623	-0.01322	0.01851	-0.01985	-0.00646	0.03187	0.005	-1.905E-5
Integrated Toolcarriers	15	0.018	-0.02826	0.01064	0.00166	0.0063	-0.00526	0.00471	-0.00114
Rigid Frame Trucks	16	0.04803	-0.03816	0.02647	0.00385	0.01224	-0.04951	0.02777	-3.0685E-4
	17	-0.0527	0.03272	0.00385	-0.07988	-0.02926	-0.04454	-0.01413	-4.161E-5
Articulated Trucks	18	0.01351	-0.00881	0.01231	0.00308	0.00682	0.00726	0.01265	-4.49E-5
	19	0.01457	-0.00207	-0.00187	-0.01511	0.01211	-5.7094E-4	0.00941	-6.945E-5
Track Dozers	20	0.0366	-0.00977	0.01417	-0.00361	0.00808	0.00643	0.01357	-6.8574E-4
	21	0.04547	-0.00709	0.00862	0.03196	0.0204	0.02774	1.4661E-4	-3.258E-5
	22	0.07334	0.00345	0.0013	0.08919	0.06539	0.0221	0.02263	-0.00233
	23	0.06919	0.03329	0.01669	0.02934	0.02709	0.02581	0.01049	0.00642
	24	0.09543	0.01192	0.01762	-0.01262	-0.02692	-0.01158	-0.02228	-2.138E-5
Motor Graders	25	0.02516	-0.00322	0.01005	-0.05512	-0.02571	-0.03368	0.00359	-2.651E-5
	26	-0.0014	-0.03434	0.02028	-0.03213	-0.0283	-0.03835	0.02074	5.765E-5
Wheel Tractor Scrapers	27	0.03406	-0.00763	0.01446	0.07859	0.04782	0.00185	0.02323	-6.7331E-4
	28	0.08042	0.01792	0.0343	0.00125	0.0	-2.5605E-4	0.02734	0.0034

Exceptions to the high goodness-of-fit are found among the small wheel loaders (Dataset 7) and for the large backhoe loaders (Dataset 14) where the plain models had values lower than 0.7 but exceeded this value once the economic indicators were added to the regression model. The small backhoe loaders of Dataset 13 showed the lowest fit with R^2 and R^2_{adj} just exceeding 0.4. Closer examination of this dataset in Appendix F shows that it contains machines from only one manufacturer. Apart from the relatively small number of observations with a considerable number of incomplete observations among them, this dataset has an extremely high average age of its observations. Hardly any machines younger than nine calendar years are among the data points, as the box plot of Appendix H shows. Predictions for backhoe loaders should be performed with great care, if at all, because of the poor fit of the regression model.

Small rigid frame trucks (Dataset 16) showed a fit lower than 0.7 for all three regression models. While not as extreme as in the case of small backhoes, this dataset also suffers from a small number of observations and a higher average age. It does not contain any observations of machines younger than three calendar years of age. Articulated trucks show a fit lower than 0.7 for the plain models, but exhibit a significant increase in goodness-of-fit once economic indicators are added to the models. The regression models including economic indicators should therefore be used for prediction of residual values percent. The highest goodness-of-fit even using the plain models was achieved for small track excavators, large wheel and track loaders, integrated toolcarriers, middle-sized and large track dozers, motor graders, and wheel tractor scrapers (Datasets 1, 9, 10, 12, 15, and 21 to 28). Predictions can be made for these size classes already using their respective plain models. Adding economic indicators to these models yielded only little improvement.

Comparing the values of R^2 and R^2_{adj} for each dataset in Table 4.17 shows that their difference is on average smaller than 1%. Only in the cases of large track excavators, small backhoe loaders, and large rigid frame trucks (Datasets 5, 13, and 17) the difference exceeds 2%. Two of these datasets were found to have a relatively small number of observations. It can therefore be concluded that the regression models have not been overfitted with explanatory variables (Montgomery et al. 2001). Root *MSE* is an unbiased estimate of the standard deviation of the errors between measured and calculated RVP. All root *MSE* values obtained with the three regression models were smaller than 0.1.

Table 4.17: R^2 and Adjusted R^2 for Plain Models, Best Models, and Trade Journal Models

Equipment Type	Number	Plain Models		Best Models		Trade Journal Models	
		R^2	R^2_{adj}	R^2	R^2_{adj}	R^2	R^2_{adj}
Track Excavators	1	0.8290	0.8110	0.8813	0.8656	0.8588	0.8402
	2	0.7168	0.7153	0.7569	0.7553	0.7542	0.7526
	3	0.7097	0.7027	0.7421	0.7344	0.7356	0.7277
	4	0.7233	0.7172	0.7707	0.7644	0.7558	0.7490
	5	0.7500	0.7075	0.7924	0.7468	0.7825	0.7346
Wheel Excavators	6	0.7495	0.7398	0.8054	0.7961	0.7990	0.7893
Wheel Loaders	7	0.6560	0.6481	0.7185	0.7106	0.7109	0.7028
	8	0.7438	0.7431	0.7676	0.7668	0.7626	0.7618
	9	0.9137	0.9132	0.9233	0.9226	0.9216	0.9210
	10	0.9147	0.9127	0.9316	0.9296	0.9275	0.9253
Track Loaders	11	0.7273	0.7223	0.7612	0.7559	0.7534	0.7480
	12	0.9253	0.9241	0.9280	0.9266	0.9272	0.9258
Backhoe Loaders	13	0.4130	0.3914	0.4559	0.4306	0.4314	0.4050
	14	0.6913	0.6909	0.7081	0.7076	0.7046	0.7041
Integrated Toolcarriers	15	0.8437	0.8393	0.8552	0.8501	0.8524	0.8472
Rigid Frame Trucks	16	0.5634	0.5519	0.6722	0.6614	0.6703	0.6595
	17	0.7634	0.7412	0.8318	0.8121	0.7924	0.7682
Articulated Trucks	18	0.6715	0.6695	0.7903	0.7888	0.7782	0.7766
	19	0.5891	0.5853	0.7864	0.7839	0.7768	0.7742
Track Dozers	20	0.7132	0.7127	0.7397	0.7392	0.7326	0.7320
	21	0.8065	0.8061	0.8336	0.8331	0.8246	0.8241
	22	0.8711	0.8670	0.8933	0.8890	0.8916	0.8872
	23	0.9008	0.8983	0.9096	0.9067	0.9037	0.9006
	24	0.9064	0.8991	0.9160	0.9076	0.9131	0.9045
Motor Graders	25	0.8668	0.8651	0.8891	0.8873	0.8813	0.8794
	26	0.9162	0.9152	0.9220	0.9208	0.9198	0.9186
Wheel Tractor Scrapers	27	0.8002	0.7978	0.8472	0.8450	0.8228	0.8202
	28	0.7307	0.7185	0.7934	0.7813	0.7790	0.7661

The plain models are composed of a subset of the explanatory variables that exist in the best models and trade journal models and are therefore called nested (Montgomery et al. 2001). A sum of squares reduction test compares the full model (with economic indicators) with its reduced model (without economic indicators) (Schabenberger and Pierce 2002). The null hypothesis that is tested states that no significant improvement to the model is obtained by adding the additional terms.

$$H_0 : E_1 = E_2 = 0\,. \qquad \textbf{Equation 4.16}$$

$$H_1 \;: E_1 \neq E_2 \neq 0\,. \qquad \textbf{Equation 4.17}$$

$$F_{obs} = \frac{\left(SS_{err,\,red} - SS_{err,\,full}\right)/\,q}{MS_{err,\,full}}\,. \qquad \textbf{Equation 4.18}$$

$$\textit{If } F_{obs} \leq F_{1-\alpha,\,q\,n-p} \textit{ then fail to reject } H_0. \qquad \textbf{Equation 4.19}$$

$$\textit{If } F_{obs} > F_{1-\alpha,\,q\,n-p} \textit{ then reject } H_0.$$

where H_0 is the null hypothesis, H_1 is the alternative hypothesis, E_1 and E_2 are the regression coefficients for the economic indicators, F_{obs} is the test statistic for the null hypothesis, $SS_{err,\,red}$ and $SS_{err,\,full}$ are the error sum of squares of the reduced and of the full models, respectively, q is the reduction in number of explanatory variables between the full and reduced models, and $F_{1-\alpha,\,q,\,n-p}$ is the cutoff value from the F-distribution for the hypothesis test. The decision rule is provided in Equation 4.19 (Schabenberger and Pierce 2002). Using a significance level α of 0.1, it is found that for all datasets the null hypothesis is rejected, i.e. at least one of the economic indicators among the explanatory variables contributes significantly to the goodness-of-fit of the regression model. Adding economic indicators the regression models improves them. It is therefore justified to develop the regression models containing economic indicators. Results for these two F-tests are listed in Table 4.18 and in Appendix G.8. The p-value is defined as “the probability of obtaining a value of the test statistic that is at least as extreme as the calculated value when the null hypothesis is true. It is the smallest significance level at which the null hypothesis can be rejected" (Hicks and Turner 1999, p25).

Table 4.18: F-Test Comparison of Nested Model Results

Number	Plain and Best Models			Plain and Trade Journal Models		
	F_{obs}	$F_{0.9, 2, n-p}$	p-Value	F_{obs}	$F_{0.9, 2, n-p}$	p-Value
1	20.8481	2.3823	<0.00001	10.2550	2.3823	0.00012
2	169.7242	2.3063	<0.00001	157.8416	2.3063	<0.00001
3	35.4897	2.3181	<0.00001	29.6104	2.3181	<0.00001
4	54.4119	2.3161	<0.00001	37.7443	2.3161	<0.00001
5	5.1691	2.4520	0.01020	3.7934	2.4520	0.03123
6	39.4482	2.3300	<0.00001	34.1805	2.3300	<0.00001
7	53.3354	2.3174	<0.00001	45.8020	2.3174	<0.00001
8	231.7735	2.3044	<0.00001	187.5156	2.3044	<0.00001
9	123.3903	2.3065	<0.00001	104.0655	2.3065	<0.00001
10	56.4828	2.3173	<0.00001	41.5779	2.3173	<0.00001
11	39.3571	2.3158	<0.00001	29.6287	2.3158	<0.00001
12	18.7424	2.3142	<0.00001	15.2879	2.3142	<0.00001
13	8.4724	2.3497	0.00037	3.4737	2.3497	0.03426
14	288.1675	2.3035	<0.00001	241.9619	2.3035	<0.00001
15	13.4581	2.3249	<0.00001	10.2465	2.3249	0.00005
16	57.6223	2.3252	<0.00001	56.2598	2.3252	<0.00001
17	19.0817	2.4369	<0.00001	6.5743	2.4369	0.00334
18	470.2482	2.3073	<0.00001	399.3391	2.3073	<0.00001
19	457.3614	2.3106	<0.00001	417.4366	2.3106	<0.00001
20	340.0637	2.3039	<0.00001	261.3926	2.3039	<0.00001
21	408.7772	2.3040	<0.00001	274.3761	2.3040	<0.00001
22	29.3456	2.3252	<0.00001	26.6374	2.3252	<0.00001
23	19.0076	2.3207	<0.00001	7.2943	2.3207	0.00081
24	6.8482	2.3618	0.00168	4.8125	2.3618	0.01026
25	76.3394	2.3121	<0.00001	49.3390	2.3121	<0.00001
26	38.8119	2.3106	<0.00001	27.4620	2.3106	<0.00001
27	124.1066	2.3113	<0.00001	54.4496	2.3113	<0.00001
28	23.2018	2.3429	<0.00001	16.7603	2.3429	<0.00001

4.4.1 Results by Manufacturer

The following sections take a closer look at the influence of the categorical explanatory variables manufacturer, condition rating, and auction region as predicted by the three types of regression models. A sensitivity analysis makes comparisons between the influence of the composite of the indicator variables m_1, m_2, and m_3, or c_1, c_2, and c_3, or r_1, r_2, and r_3, respectively. The strong influence of age on RVP has already been established during the analysis of the regression assumptions in Section 4.2.4.

Percent influence of different manufacturers on RVP calculated with the plain models, the best models, and the trade journal models is listed in Table 4.19. Cells with "N/A" indicate that only one manufacturer produced the particular equipment type. Figure 4.2 displays the values in form of a bar chart. Individual bars are shaded to distinguish between the results for plain models (black), best models (grey), and trade journal models (white). The triplet of indicator variables m_1, m_2, and m_3 was set to its four combinations as per Table 3.3 to represent the four different manufacturers. Values are obtained with the assumption that all other explanatory variables in the regression model remain in the model. The separate analysis of the explanatory variable manufacturer is made possible by the MLR model used that treats the influence of manufacturer as an additive term. The quantitative influence of the explanatory variable is established by taking the difference between the manufacturers with the highest RVP and the lowest RVP, respectively.

Examining the table and the diagram gives the following results. Overall the plain models give a lower value for the influence of manufacturer on RVP. The best models and trade journal models are more consistent, which again supports the decision to include economic indicators for the prediction of the RVP. The best models tended to give a slightly higher value than the trade journal models. The consistency of the results gained from the regression models supports their validity.

For track excavators the difference in RVP due to different manufacturers is lowest for the smallest and largest sizes examined. Track excavators of medium size classes show a higher difference in RVP between the manufacturers. For wheel excavators the difference in RVP between manufacturers is considerably more pronounced.

Table 4.19: Percent Influence of Manufacturer

Equipment Type	Number	Size Range	Difference Between Maximum and Minimum Residual Value Percent		
			Plain Models	Best Models	Trade Journal Models
Track Excavators	1	0-24,999 lbs	2.5	8.5	3.6
	2	25,000-49,999 lbs	7.7	11.1	10.5
	3	50,000-74,999 lbs	6.4	8.0	7.8
	4	75,000-99,999 lbs	8.4	8.5	8.6
	5	100,000+ lbs	4.5	7.3	3.6
Wheel Excavators	6	All Sizes	10.7	19.2	18.2
Wheel Loaders	7	0-1.9 CY	12.7	13.3	12.9
	8	2-3.9 CY	9.1	11.9	11.5
	9	4-5.9 CY	13.4	15.1	15.0
	10	6+ CY	12.8	15.9	15.9
Track Loaders	11	0-1.9 CY	7.3	9.5	9.0
	12	2+ CY	25.1	27.3	26.4
Backhoe Loaders	13	0-0.9 CY	N/A	N/A	N/A
	14	1+ CY	14.8	14.8	14.8
Integrated Toolcarriers	15	All Sizes	1.4	1.5	1.2
Rigid Frame Trucks	16	0-99,999 lbs	10.6	14.2	12.6
	17	100,000+ lbs	19.4	20.2	16.2
Articulated Trucks	18	0-49,999 lbs	9.8	13.8	14.2
	19	50,000+ lbs	7.0	6.2	6.4
Track Dozers	20	0-99 HP	4.0	4.0	4.0
	21	100-199 HP	10.0	12.5	11.9
	22	200-299 HP	27.1	31.2	30.7
	23	300-399 HP	16.8	18.1	18.0
	24	400+ HP	15.2	17.4	16.3
Motor Graders	25	0-149 HP	6.8	9.0	8.5
	26	150+ HP	14.5	15.2	14.8
Wheel Tractor Scrapers	27	0-74,999 lbs	15.3	16.8	16.5
	28	75,000+ lbs	N/A	N/A	N/A

Figure 4.2: Percent Influence of Manufacturer

For wheel loaders there appears a tendency of increasing difference in RVP with increasing size of the machines, with exception of the smallest size examined. For track loaders there is clearly a very strong difference in RVP between the manufacturers. Backhoe loaders of the smaller size class are only produced by one manufacturer so that no comparison is possible. Larger backhoe loaders show a pronounced difference of about 15% in RVP between the manufacturers. A comparison between the two manufacturers of integrated toolcarriers shows only a small difference in RVP.

For rigid frame trucks there is a notable difference between the manufacturers that produce these machines. The larger size class shows a difference in RVP of about 20% for the comparison of manufacturers. For articulated trucks the difference in RVP is less than for rigid frame trucks. The results from the regression models showed that the larger size class of articulated trucks incurs less difference in RVP between manufacturers than for smaller machines.

For track dozers a clear tendency exists that the differences between the two manufacturers become more pronounced as size increased, except for the largest two size classes. The largest difference in RVP between manufacturers of over 25% is found for medium size track dozers.

For motor graders the difference in RVP lies under 10% for the smaller size class and at about 15% for the larger size class. For small wheel tractor scrapers the comparison between the manufacturers shows that the difference in RVP lies at about 15%. Wheel tractor scrapers of the larger size class are only produced by one manufacturer.

4.4.2 Results by Condition Rating

Average percent influence of different condition ratings on RVP calculated with the plain models, the best models, and the trade journal models are displayed in Figures 4.3, 4.4, and 4.5. Numerical values are provided in Table 4.20. The triplet of indicator variables c_1, c_2, and c_3 was set to its six combinations as per Table 3.6 to represent the six different condition ratings. It was found however, that the results for the extreme condition ratings new and poor strongly deviated from the pattern exhibited by the remaining condition ratings. It is therefore advised to use the regression models only to make predictions for machines of excellent, very good, good, and fair condition.

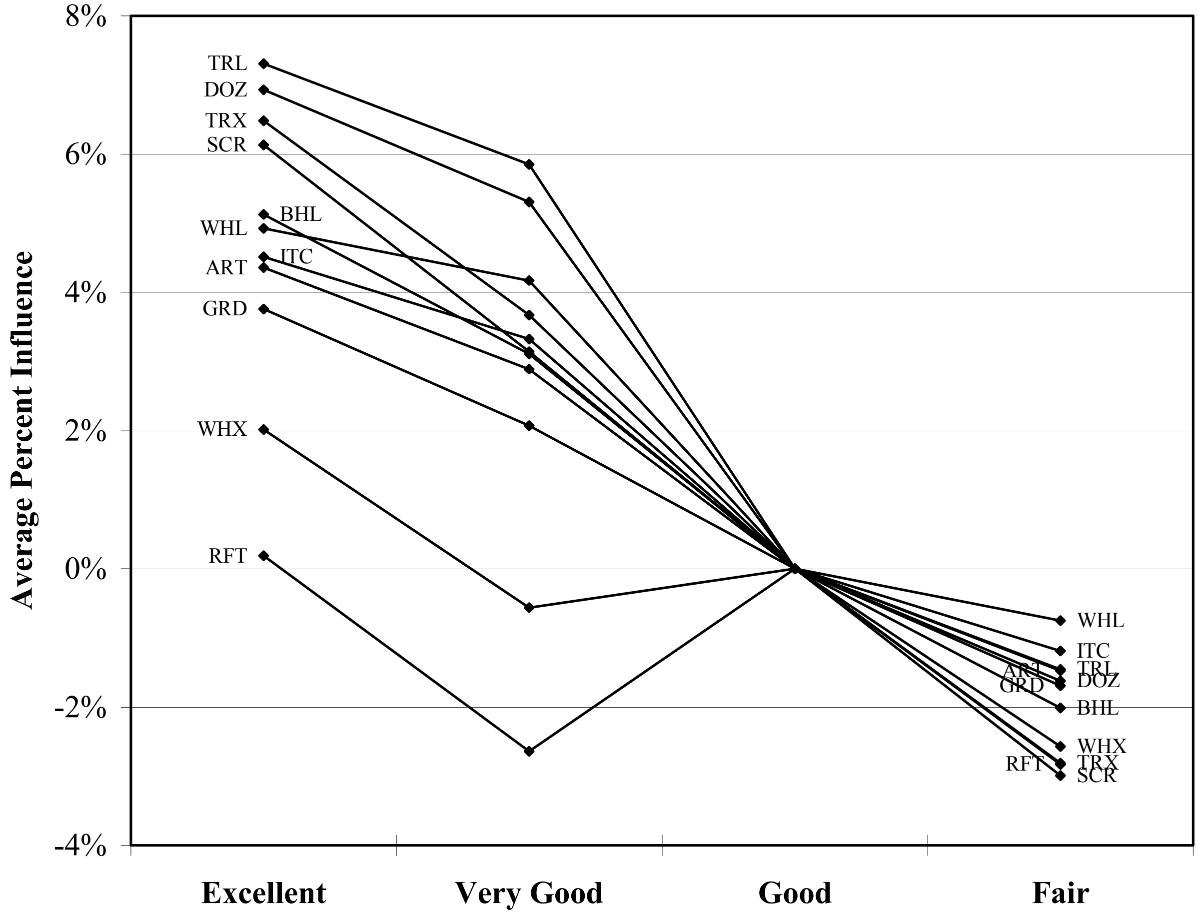


Figure 4.3: Average Percent Influence of Condition Rating for Plain Models

Percent change was averaged for each equipment type for more clarity. Abbreviations in the figures are TRX = track excavators, WHX = wheel excavators, WHL = wheel loaders, TRL = track loaders, BHL = backhoe loaders, ITC = integrated toolcarriers, RFT = rigid frame trucks, ART = articulated trucks, DOZ = dozers, GRD = motor graders, and SCR = wheel tractor scrapers. Again the assumption is made that all other explanatory variables are fixed and the quantitative influence between different condition ratings is calculated by taking the difference in RVP. For comparison among condition ratings a good condition was chosen as baseline.

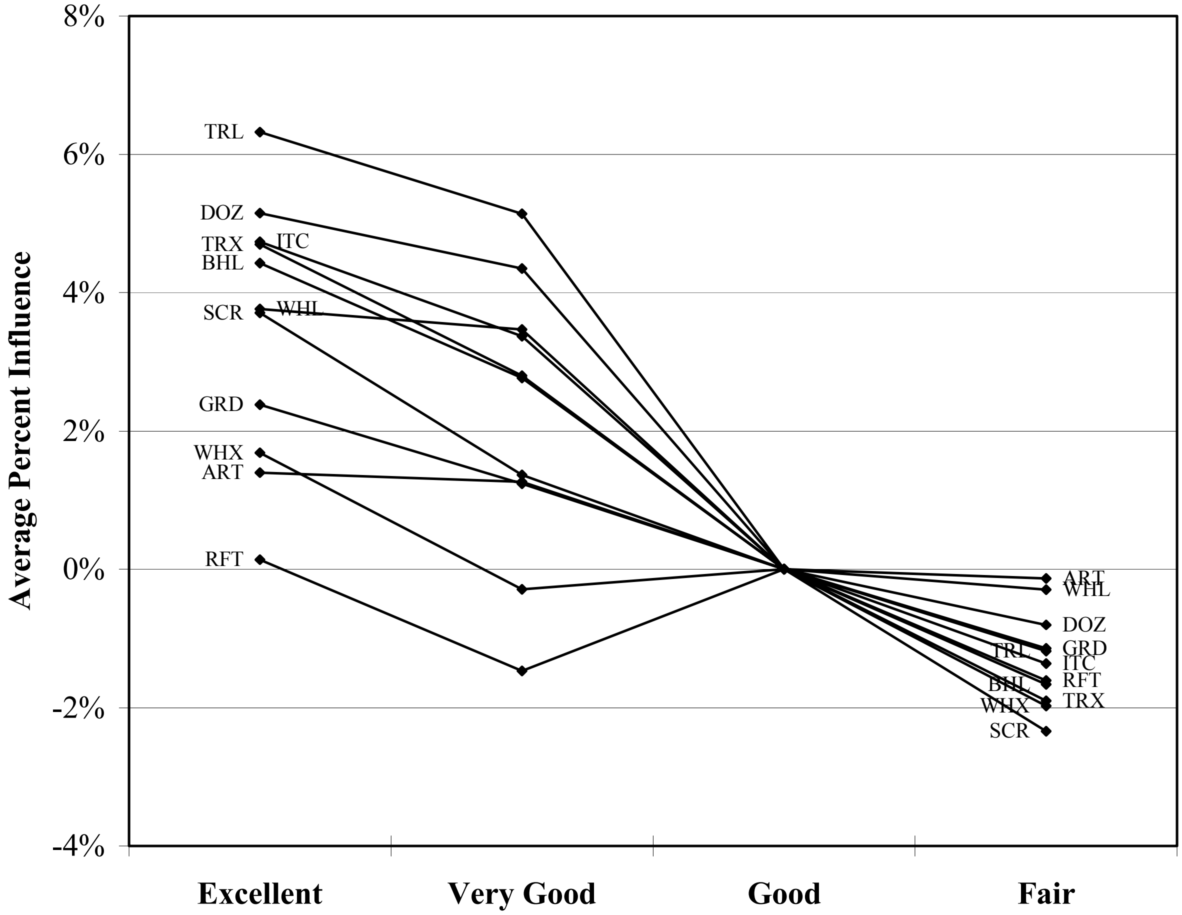


Figure 4.4: Average Percent Influence of Condition Rating for Best Models

Examining Figures 4.3, 4.4, and 4.5 clearly shows that the hypothesized behavior of lower RVP coinciding with a lower condition rating is confirmed. They also show that some equipment types retain their RVP longer than others. Rigid frame trucks exhibit a curious pattern of a higher RVP from very good to good condition. A possible explanation is that they undergo a major overhaul or rebuild at this stage and thus despite their increasing age and lower condition gain residual value in equipment auctions.

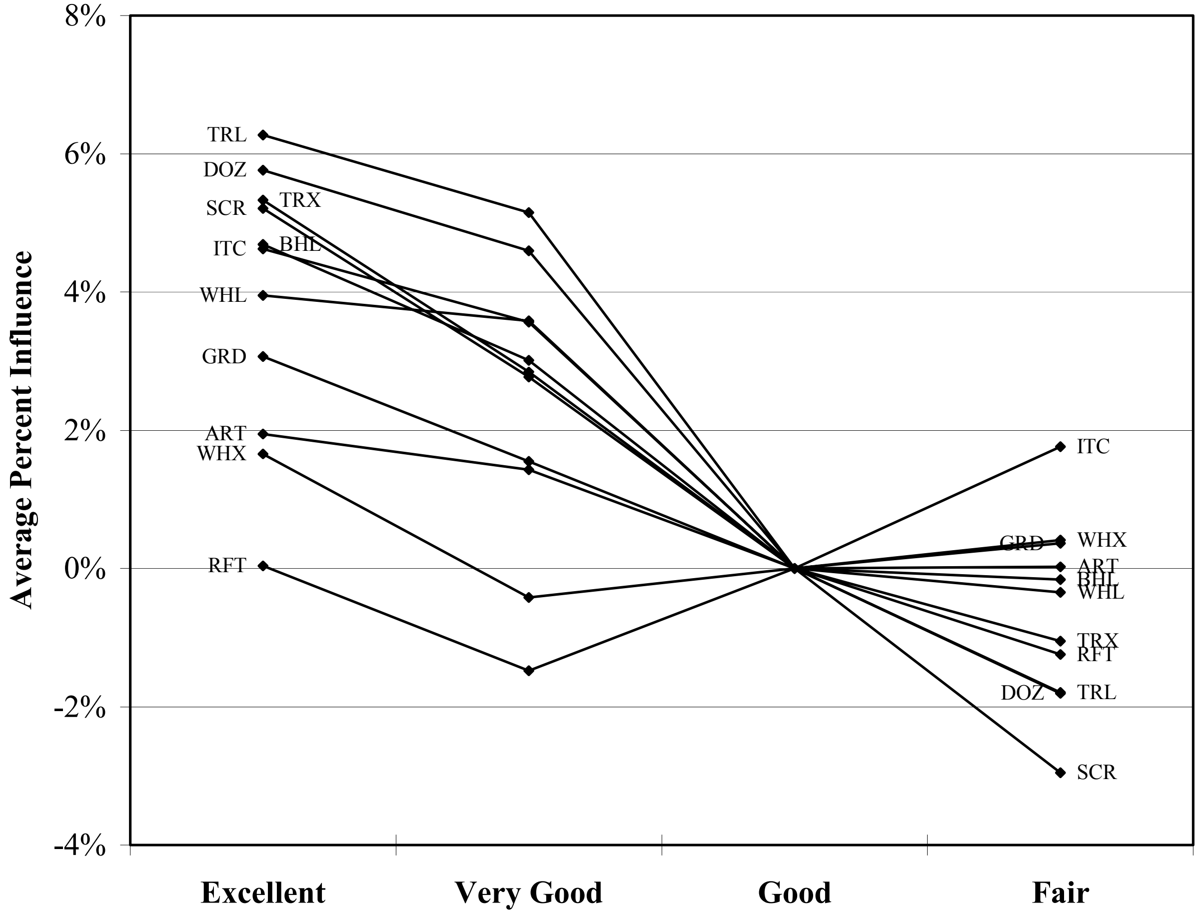


Figure 4.5: Average Percent Influence of Condition Rating for Trade Journal Models

Comparing the values for excellent and fair condition as listed in Table 4.21 shows that track excavators and loaders, dozers, and scrapers lose the most RVP with declining condition rating. Backhoe loaders and integrated toolcarriers, wheel excavators and loaders, and graders lose less RVP. The least loss in RVP is found for rigid frame trucks and articulated trucks. A reason for this could lie in a different average utilization that different equipment types are subjected to. Differences in typical maintenance and repair for the equipment types may be another reason. Finally, larger equipment is more solidly built and thus would lose less RVP. This phenomenon is particularly pronounced in the small overall loss in RVP that rigid frame trucks experience. It is found that condition rating appears to be a measure that is specific to each equipment type.

Table 4.20: Percent Influence of Condition Rating

Equipment Type	Plain Models			
	Excellent	Very Good	Good	Fair
Track Excavators	6.5	3.7	0.0	-2.8
Wheel Excavators	2.0	-0.6	0.0	-2.6
Wheel Loaders	4.9	4.2	0.0	-0.8
Track Loaders	7.3	5.9	0.0	-1.5
Backhoe Loaders	5.1	3.1	0.0	-2.0
Integrated Toolcarriers	4.5	3.3	0.0	-1.2
Rigid Frame Trucks	0.2	-2.6	0.0	-2.8
Articulated Trucks	4.4	2.9	0.0	-1.5
Dozers	6.9	5.3	0.0	-1.6
Motor Graders	3.8	2.1	0.0	-1.7
Wheel Tractor Scrapers	6.1	3.1	0.0	-3.0
Equipment Type	**Best Models**			
	Excellent	**Very Good**	**Good**	**Fair**
Track Excavators	4.7	2.8	0.0	-1.9
Wheel Excavators	1.7	-0.3	0.0	-2.0
Wheel Loaders	3.8	3.5	0.0	-0.3
Track Loaders	6.3	5.1	0.0	-1.2
Backhoe Loaders	4.4	2.8	0.0	-1.7
Integrated Toolcarriers	4.7	3.4	0.0	-1.4
Rigid Frame Trucks	0.1	-1.5	0.0	-1.6
Articulated Trucks	1.4	1.3	0.0	-0.1
Dozers	5.1	4.3	0.0	-0.8
Motor Graders	2.4	1.2	0.0	-1.1
Wheel Tractor Scrapers	3.7	1.4	0.0	-2.3
Equipment Type	**Trade Journal Models**			
	Excellent	**Very Good**	**Good**	**Fair**
Track Excavators	5.3	2.8	0.0	-1.1
Wheel Excavators	1.7	-0.4	0.0	0.4
Wheel Loaders	4.0	3.6	0.0	-0.3
Track Loaders	6.3	5.1	0.0	-1.8
Backhoe Loaders	4.7	3.0	0.0	-0.2
Integrated Toolcarriers	4.6	3.6	0.0	1.8
Rigid Frame Trucks	0.0	-1.5	0.0	-1.2
Articulated Trucks	1.9	1.4	0.0	0.0
Dozers	5.8	4.6	0.0	-1.8
Motor Graders	3.1	1.5	0.0	0.4
Wheel Tractor Scrapers	5.2	2.8	0.0	-3.0

Table 4.21: Loss of Residual Value Percent with Declining Condition Rating

Equipment Type	Difference in Average Residual Value Percent between Excellent and Fair Condition Rating			
	Plain Model	Best Model	Trade Journal Model	Average
Track Excavators	9.3	6.6	7.8	7.9
Wheel Excavators	4.6	3.7	3.7	4.0
Wheel Loaders	5.7	4.1	4.3	4.7
Track Loaders	8.8	7.5	7.4	7.9
Backhoe Loaders	7.1	6.1	6.4	6.5
Integrated Toolcarriers	5.7	6.1	5.7	5.8
Rigid Frame Trucks	3.0	1.7	1.6	2.1
Articulated Trucks	5.8	1.5	2.5	3.3
Dozers	8.6	6.0	6.9	7.1
Motor Graders	5.4	3.5	4.6	4.5
Wheel Tractor Scrapers	9.1	6.0	7.6	7.6

4.4.3 Results by Auction Region

Tables 4.22, 4.23, and 4.24 list the average percent influence of the auction region on RVP. The settings of the triplet r_1, r_2, and r_3 were listed in Table 3.9 and the same assumption as for the previous two sections is made. Values were averaged for each equipment type, same as has been done for condition rating. The quantitative influence of the explanatory variable can be established by comparing two different regions and taking the difference of their percent influence. Qualitative differences between the regions are indicated by their rank in Roman numerals across each row of the table. Categories are ranked from I as having the highest RVP to V as having the lowest RVP. The results of comparing the different auctions give a less clear picture than for manufacturers and condition rating.

The Northeast shows the highest RVP for track excavators and for backhoe loaders and the lowest RVP for dozers and wheel tractor scrapers. The South shows the highest RVP for integrated toolcarriers and rigid frame trucks and a rather low RVP for dozers and wheel tractor scrapers. The Midwest shows a very high RVP for wheel and track loaders, backhoe loaders, and articulated trucks. The West consistently shows the highest RVP for wheel excavators and the lowest RVP for track loaders and articulated trucks. Canada exhibits a very low RVP for track loaders, rigid frame and articulated trucks, and motor graders. On the other hand, dozers and wheel tractor scrapers show the highest RVP there. A possible reason for the varying influence of the auction regions may be the environmental conditions. Further research is warranted to investigate the factors that affect construction equipment in different geographical regions, such as e.g. climatic and geological influences.

Table 4.22: Average Percent Influence of Auction Region for Plain Models

Equipment Type	Auction Region									
	Northeast		South		Midwest		West		Canada	
	%	Rank	%	Rank	%	Rank	%	Rank	%	Rank
Track Excavators	0.1	I	-1.2	III	-1.1	II	-4.3	V	-4.2	IV
Wheel Excavators	-2.7	II	-4.1	III	-6.8	V	-1.6	I	-4.3	IV
Wheel Loaders	1.1	II	0.1	III	1.2	I	0.1	III	1.2	I
Track Loaders	0.1	III	1.7	II	1.8	I	-3.3	V	-3.2	IV
Backhoe Loaders	1.7	I	-0.6	III	1.1	II	-0.6	III	1.1	II
Integrated Toolcarriers	-0.6	IV	0.6	I	-0.1	II	-0.5	III	-1.1	V
Rigid Frame Trucks	-5.8	IV	0.3	I	-5.5	III	-3.4	II	-9.3	V
Articulated Trucks	1.4	II	1.2	III	2.7	I	-1.2	V	0.3	VI
Dozers	1.3	V	1.8	VI	3.1	II	2.5	III	3.7	I
Motor Graders	-4.1	III	-2.6	I	-6.6	IV	-4.0	II	-8.1	V
Wheel Tractor Scrapers	0.2	V	1.5	VI	1.7	III	3.0	II	3.2	I

Table 4.23: Average Percent Influence of Auction Region for Best Models

Equipment Type	Auction Region									
	Northeast		South		Midwest		West		Canada	
	%	Rank	%	Rank	%	Rank	%	Rank	%	Rank
Track Excavators	0.8	I	-1.2	III	-0.3	II	-3.7	V	-2.8	IV
Wheel Excavators	-2.5	III	-3.6	VI	-6.1	V	0.3	I	-2.2	II
Wheel Loaders	1.5	III	0.4	V	1.8	II	0.7	IV	2.2	I
Track Loaders	0.5	III	1.6	II	2.1	I	-3.7	V	-3.2	VI
Backhoe Loaders	1.7	I	-0.3	IV	1.4	II	-0.5	V	1.3	III
Integrated Toolcarriers	-0.2	V	0.7	I	0.5	II	0.3	III	0.2	IV
Rigid Frame Trucks	-4.8	III	-0.5	I	-5.2	IV	-3.4	II	-8.2	V
Articulated Trucks	0.4	III	0.9	II	1.4	I	-0.4	V	0.0	VI
Dozers	1.3	V	2.1	VI	3.4	II	2.9	III	4.2	I
Motor Graders	-3.7	II	-3.1	I	-6.8	IV	-4.7	III	-8.4	V
Wheel Tractor Scrapers	0.1	V	2.3	VI	2.4	III	4.4	II	4.5	I

Table 4.24: Average Percent Influence of Auction Region for Trade Journal Models

Equipment Type	Auction Region									
	Northeast		South		Midwest		West		Canada	
	%	Rank	%	Rank	%	Rank	%	Rank	%	Rank
Track Excavators	0.1	I	-1.3	II	-1.3	II	-4.3	IV	-4.2	III
Wheel Excavators	-2.8	III	-3.0	IV	-5.7	V	0.6	I	-2.1	II
Wheel Loaders	1.2	II	0.3	III	1.5	I	0.3	III	1.5	I
Track Loaders	0.5	III	1.9	II	2.4	I	-3.5	V	-3.0	VI
Backhoe Loaders	1.7	I	-0.3	IV	1.4	II	-0.4	V	1.3	III
Integrated Toolcarriers	-0.5	V	0.6	I	0.1	III	0.2	II	-0.4	IV
Rigid Frame Trucks	-4.7	III	-0.9	I	-5.6	IV	-3.8	II	-8.5	V
Articulated Trucks	0.3	III	0.9	II	1.3	I	-0.6	V	-0.3	IV
Dozers	1.4	V	1.9	IV	3.3	II	2.7	III	4.1	I
Motor Graders	-3.6	II	-2.7	I	-6.3	IV	-4.4	III	-8.0	V
Wheel Tractor Scrapers	0.1	V	2.4	IV	2.5	III	4.0	II	4.1	I

4.5 Validation

This section describes the procedure that is applied for validating the prediction stability as the intended use of the regression model. Two different methods of validation are possible to achieve this purpose (Montgomery et al. 2001). External validation would use newly collected and analyzed data whose results are compared with previously obtained ones. Internal validation would use a part of the already obtained data for evaluation of the capability of a regression model that is derived from the remaining data. Validation of the model stability in this study is carried out in analogy to Mitchell (1998). The method of choice for this study is internal validation because of the availability of the large number of data points that have already been prepared, whereas collecting, preparing, and analyzing new data would be time-consuming. Internal validation will be applied to the datasets for all 28 size classes.

Each dataset is split into two halves for internal validation. If the comparison between these halves is found satisfactory, it will be concluded that using the total datasets for regression analysis as in the preceding sections of this chapter is indeed permissible and valid. One half of the dataset is called the estimation dataset and is used to obtain the coefficients of a regression model. The second half is called the prediction dataset and is used for comparing its original response values with newly estimated response values. The new response values are calculated using the coefficients from the estimation dataset. A schematic of the internal validation procedure is provided in Figure 4.6. It is also called cross-validation (Snee 1977). Table 4.25 lists a sample residual value percent from the original and the new response to illustrate the outcome of the validation procedure.

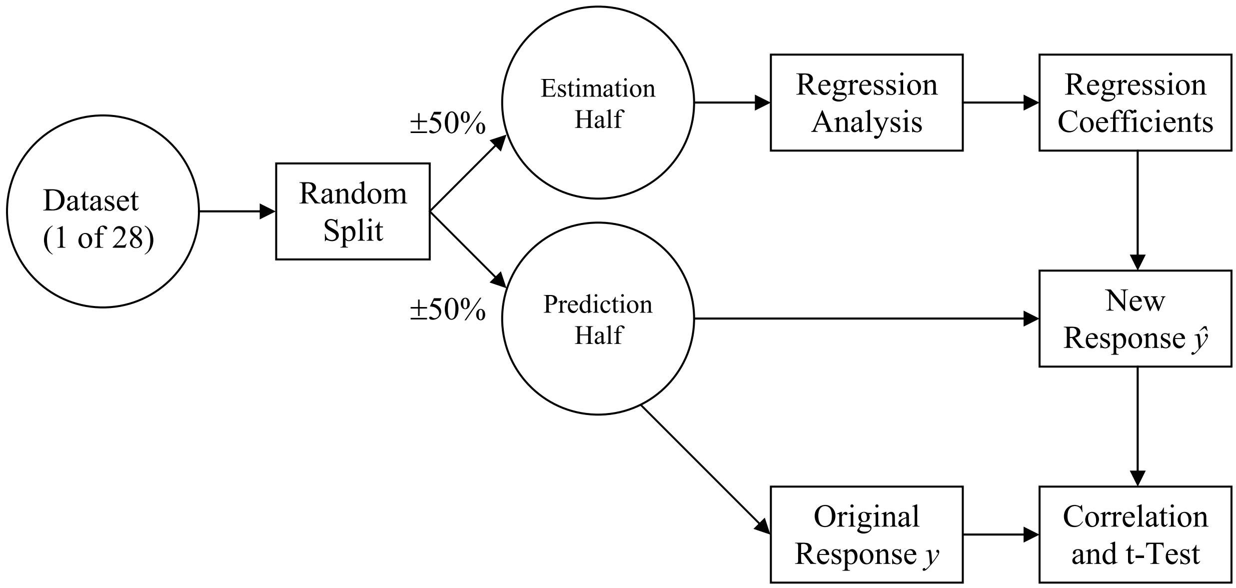


Figure 4.6: Internal Validation Procedure

Table 4.25: Sample Residual Value Percent from Estimation and Prediction Models

Prediction Half Original Response y	**Estimation Half New Response ŷ**	**Prediction Half Original Response y**	**Estimation Half New Response ŷ**
0.1184	0.1250	0.4104	0.3656
0.3005	0.3243	0.4616	0.4142
0.5115	0.4717	0.3281	0.4142
0.4117	0.3660	0.3056	0.3660
0.4117	0.3660	0.3784	0.3270
0.3314	0.3660	0.2861	0.2063
0.3335	0.3270	0.1415	0.1864
0.4251	0.4549	0.1655	0.2063
0.2818	0.3824	0.5383	0.5604
0.5003	0.4322	0.5258	0.5436

Equation 4.20 contains a criterion by Snee (1977) for the minimum number of data points in a dataset to allow splitting of this dataset:

$$n \geq 2 \cdot p + 25\,. \qquad \textbf{Equation 4.20}$$

where n is the number of complete observations in the dataset and p is the number of estimated parameters for the regression model. For the plain models p is 12 and for the best models and trade journal models that additionally include two economic indicators p is 14.

$$n \geq 2 \cdot 12 + 25 = 49 \textit{ for plain models.} \qquad \textbf{Equation 4.21}$$
$$n \geq 2 \cdot 14 + 25 = 53 \textit{ for best models and trade journal models.}$$

All 28 datasets except Dataset 5 have a number of complete observations n exceeding both conditions of Equation 4.21. Dataset 5 still fulfills the first condition. Data splitting can therefore be used for validation. Data are preferably split into equal-sized halves (Snee 1977). If the stability of the plain models can be shown, it is not necessary to additionally test the best models and trade journal models for stability, since the plain models are nested within the best models and the trade journal models, respectively. Stability in this context means that different data on which the model is based should create similar model predictions. A model is considered stable when its predicted response values remain stable between the original and the newly calculated response values. This can be measured by determining their Pearson coefficient of correlation R_{corr}. A high value of R_{corr} signifies high predictive stability of the model for the purpose of this validation.

4.5.1 Data Splitting

Data splitting is performed in the EXCEL spreadsheet in which the 28 datasets have been stored. The DUPLEX algorithm described by Snee (1977) is useful for regression models that are used for extrapolations, but not necessary here. Applying a random split to each dataset has the advantage of obtaining two halves that are expected to have similar properties. A new column RND is created and either the value “0” or the value “1” is randomly assigned to each observation. Sorting each of the 28 datasets by this random split variable gives its estimation and prediction datasets. These two halves may not contain exactly the same number of observations due to the random generation of the “0” and “1” values. With larger datasets this problem diminishes according to the probabilistic Law of Large Numbers. Data points for which the value of the explanatory variable condition rating is unknown are ignored in this validation because these incomplete observations do not allow estimation of a new response value. Table 4.26 shows the number of observations in all prediction and estimation datasets. Total observations is the number of all observations in the particular dataset and complete observations is the number of observations for which the values of all explanatory variables were recorded.

4.5.2 Estimation and Prediction Models

During the validation procedure a normal regression analysis is applied to the estimation datasets to obtain their regression coefficients. The SAS® code for validation of the plain models is provided in Appendix C.7. All coefficients and related statistics are recorded in the EXCEL spreadsheet along with the estimation datasets. Coefficients and statistics of the validation regression models can be found in Appendices G.9 and G.10.

The regression coefficients from each estimation dataset are then used with its respective prediction dataset. A new column RVP2 is created and estimated response values are newly calculated from the regression coefficients and the values of explanatory variables in the prediction dataset. Comparing the original response y and the newly estimated response $\hat{y}$ gives an indication of the model stability.

4.5.3 Correlation of Responses

For all 28 prediction datasets the Pearson coefficient of correlation R_{corr} between the original response y and the newly estimated response $\hat{y}$ is calculated in EXCEL. It serves as an estimator for the true correlation coefficient ρ of the population to the predicted response from the model. Equation 4.22 provides the formula for calculating R_{corr}:

Table 4.26: Number of Observations in Prediction and Estimation Datasets

Number	Total Observations	Estimation Model Total Observations	Estimation Model Complete Observations n	Prediction Model Total Observations	Prediction Model Complete Observations n
1	106	57	41	49	41
2	1888	932	703	956	723
3	427	204	168	223	189
4	465	234	204	231	205
5	63	36	26	27	25
6	268	121	94	147	115
7	490	237	179	253	195
8	3857	1928	1466	1929	1495
9	1695	837	680	858	688
10	440	219	190	221	185
11	562	291	228	271	190
12	645	342	239	303	232
13	226	116	67	110	61
14	7530	3772	2810	3758	2744
15	333	154	115	179	138
16	350	187	130	163	120
17	106	42	20	64	35
18	1658	822	573	836	573
19	970	482	326	488	351
20	5320	2702	2043	2618	1925
21	4594	2264	1851	2330	1903
22	290	154	136	136	114
23	363	181	153	182	155
24	125	64	51	61	54
25	697	347	287	350	288
26	790	414	358	376	321
27	781	404	317	377	309
28	163	85	77	78	70

$$R_{corr}\ (y,\hat{y}) = \frac{S_{y\hat{y}}}{\sqrt{S_{yy}\cdot S_{\hat{y}\hat{y}}}}\ . \qquad \textbf{Equation 4.22}$$

where R_{corr} is the Pearson coefficient of correlation of the sample, y is the original response, $\hat{y}$ is the estimated response, S_{yy} is the sum of squares of y with itself, $S_{\hat{y}\hat{y}}$ is the sum of squares of $\hat{y}$ with itself, and $S_{y\hat{y}}$ is the cross product sum of squares of y with $\hat{y}$. In analogy to Mitchell (1998), the null hypothesis stating that the correlation coefficient of the population ρ is equal to zero is tested. This test examines whether there is any relationship between the original and the newly estimated response values as measured by R_{corr}.

$$H_0 : \rho = 0 . \qquad \textbf{Equation 4.23}$$

$$H_1 : \rho \neq 0 . \qquad \textbf{Equation 4.24}$$

$$t_{obs} = R_{corr} \cdot \sqrt{\frac{n-2}{1-R^2_{corr}}} . \qquad \textbf{Equation 4.25}$$

$$\text{If } |t_{obs}| \leq t_{1-\alpha/2,n-2} \text{ then fail to reject } H_0. \qquad \textbf{Equation 4.26}$$

$$\text{If } |t_{obs}| > t_{1-\alpha/2,n-2} \text{ then reject } H_0.$$

where H_0 is the null hypothesis, H_1 is the alternative hypothesis, ρ is the correlation coefficient of the population, t_{obs} is the test statistic for the null hypothesis, R_{corr} is the Pearson coefficient of correlation of the sample, n is the number of complete observations in the prediction dataset, and $t_{1-\alpha/2,n-2}$ is the cutoff value for the hypothesis test. The decision rule is provided in Equation 4.26 (Neter et al. 1996). Using a significance level α of 0.1, it is found that for all datasets the null hypothesis is rejected, i.e. as expected R_{corr} in all cases is significantly different from zero. In other words, there is a relationship between the original and the newly estimated response values. Results for this t-test are listed in Table 4.27 and in Appendix G.10.

A stronger test is performed based on Neter et al. (1996). It involves a Fisher R-to-z transformation of the two correlation coefficients that are compared as shown in Equation 4.29.

The cutoff value is taken from a standard Gaussian distribution. In this test the Pearson coefficient of correlation R_{corr} of the between the original and newly estimated response values from the prediction dataset is compared with the square root of the adjusted coefficient of determination R_{adj} from the estimation dataset. The comparison is made with the adjusted correlation coefficient R_{adj} and not with R because two population samples (the estimation and prediction datasets) are compared. Per definition R^2 is the fraction of variability of the response in the observed sample explained by the model. On the other hand, R^2_{adj} is the unbiased estimate of the fraction of the variability of the response in the population explained by the model. This test requires that the two samples from the two populations are independent of each other, which is ensured through the random splitting of the dataset. The null hypothesis stating that the correlation coefficients ρ_1 and ρ_2 of the populations are equal is tested. This test examines whether R_{corr} and R_{adj} are equal.

$$H_0 : \rho_1 = \rho_2 .$$ **Equation 4.27**

$$H_1 : \rho_1 \neq \rho_2 .$$ **Equation 4.28**

$$z^* = \frac{1}{2} \cdot \log_e \cdot \left(\frac{1+R}{1-R} \right).$$ **Equation 4.29**

$$z_{obs} = \frac{z_1^* - z_2^*}{\sqrt{\dfrac{1}{n_1 - 3} + \dfrac{1}{n_2 - 3}}} .$$ **Equation 4.30**

If $|z_{obs}| \leq z_{1-\alpha/2,\, n-2}$ *then fail to reject* H_0. **Equation 4.31**

If $|z_{obs}| > z_{1-\alpha/2,\, n-2}$ *then reject* H_0.

Table 4.27: Student's t-Test Validation Results

Number	R^2	R^2_{adj}	Correlation R^2_{corr}	t_{obs}	$t_{0.95,\, n-2}$	p-Value
1	0.8297	0.7927	0.7977	4.1290	1.6849	0.00009
2	0.7276	0.7246	0.6957	19.1385	1.6470	<0.00001
3	0.7435	0.7302	0.6593	9.0780	1.6530	<0.00001
4	0.7698	0.7594	0.6685	9.4558	1.6524	<0.00001
5	0.8369	0.7805	0.6273	2.7565	1.7139	0.00562
6	0.8201	0.8038	0.7168	7.4190	1.6585	<0.00001
7	0.6338	0.6159	0.7006	9.7611	1.6528	<0.00001
8	0.7473	0.7459	0.7365	28.6403	1.6459	<0.00001
9	0.9085	0.9072	0.9225	23.7766	1.6471	<0.00001
10	0.9201	0.9163	0.9228	11.6388	1.6532	<0.00001
11	0.7408	0.7315	0.7206	9.7288	1.6530	<0.00001
12	0.9213	0.9189	0.9327	13.2605	1.6515	<0.00001
13	0.4548	0.4140	0.4149	4.1820	1.6711	0.00005
14	0.6965	0.6957	0.6846	36.1069	1.6454	<0.00001
15	0.8580	0.8491	0.8174	9.1687	1.6561	<0.00001
16	0.5725	0.5508	0.5527	5.9716	1.6579	<0.00001
17	0.7642	0.6978	0.8151	3.9524	1.6924	0.00019
18	0.6765	0.6726	0.6745	16.2256	1.6475	<0.00001
19	0.5907	0.5829	0.5889	11.0744	1.6492	<0.00001
20	0.7144	0.7134	0.7164	31.7923	1.6456	<0.00001
21	0.8056	0.8047	0.8027	34.9998	1.6457	<0.00001
22	0.8843	0.8770	0.8625	8.6258	1.6586	<0.00001
23	0.8993	0.8940	0.8966	10.4499	1.6549	<0.00001
24	0.9230	0.9101	0.8751	5.3689	1.6747	<0.00001
25	0.8608	0.8571	0.8732	14.4682	1.6502	<0.00001
26	0.9214	0.9196	0.9068	15.6939	1.6496	<0.00001
27	0.7965	0.7918	0.8079	13.9952	1.6498	<0.00001
28	0.7140	0.6880	0.7791	6.0608	1.6676	<0.00001

where H_0 is the null hypothesis, H_1 is the alternative hypothesis, ρ_1 and ρ_2 is the correlation coefficients of the populations, z_{obs} is the test statistic for the null hypothesis, R is a correlation coefficient, n_1 and n_2 are the numbers of complete observations in the two samples, and $z_{1-\alpha/2,n-2}$ is the cutoff value for the hypothesis test. The decision rule is provided in Equation 4.31 (Neter et al. 1996). Using again a significance level α of 0.1, it is found that except for Datasets 1, 4, and 5 the null hypothesis is not rejected, i.e. as expected R_{corr} is not significantly different from R_{adj}. In other words, the correlation coefficients ρ_1 and ρ_2 of the populations are equal. Comparing the original and new response has shown that the predictions of the regression models have internal stability.

Dataset 5 had already been identified as having a small number of data points as per Equation 4.20 and is the only with under 100 complete observations. Dataset 1 has just over 100 complete observations. Both Datasets 1 and 4 contain only entries with a maximum age of 13 years and show a somewhat low average age among their entries that is pointing toward an uneven distribution of observations across age. While residual value predictions for very small and very large track excavator using the regression models of this study are still possible they should be used with caution.

Results for this z-test are listed in Table 4.28 and in Appendix G.10. The p-values were calculated using the absolute of the value of the test statistic for the null hypothesis. Stability of results obtained from the plain models based on the prediction datasets has been shown. By inference it is concluded that for all three types of regression models the quality of the predictions has been shown. With the noted exceptions of three small datasets, the datasets passed the internal validation procedure. The adequacy of the three types of regression models has been validated.

4.5.4 Regression Coefficients

A final validation is performed by examining the calculated regression coefficients themselves (Montgomery et al. 2001) for their dimension and sign. Most intercepts have values between zero and one. The intercept values give an indication of the purchase prices of new machines that were sold at the auction. Purchase prices are usually lower than the list prices, as discussed in Section 3.4. However, the overall number of machines identified as new in the datasets was small and the condition rating of a considerable number of observations was missing. New machines mostly sold by distributors and not at auctions. Intercept values obtained from analyzing auction results therefore may not necessarily be good representations of the average purchase prices for the different size classes of equipment.

Table 4.28: Fisher's z-Test Validation Results

Number	R^2	R^2_{adj}	Correlation R^2_{corr}	z_{obs}	$z_{0.95,\ n-2}$	p-Value
1	0.8297	0.7927	0.7977	2.7754	1.6449	0.00276
2	0.7276	0.7246	0.6957	0.6836	1.6449	0.24711
3	0.7435	0.7302	0.6593	1.1038	1.6449	0.13483
4	0.7698	0.7594	0.6685	1.9186	1.6449	0.02752
5	0.8369	0.7805	0.6273	1.6981	1.6449	0.04475
6	0.8201	0.8038	0.7168	1.2646	1.6449	0.10300
7	0.6338	0.6159	0.7006	-0.5150	1.6449	0.30327
8	0.7473	0.7459	0.7365	0.3989	1.6449	0.34497
9	0.9085	0.9072	0.9225	-1.3887	1.6449	0.08246
10	0.9201	0.9163	0.9228	-0.3671	1.6449	0.35677
11	0.7408	0.7315	0.7206	0.2963	1.6449	0.38350
12	0.9213	0.9189	0.9327	0.6381	1.6449	0.26170
13	0.4548	0.4140	0.4149	-1.2631	1.6449	0.10327
14	0.6965	0.6957	0.6846	0.9713	1.6449	0.16570
15	0.8580	0.8491	0.8174	1.2633	1.6449	0.10323
16	0.5725	0.5508	0.5527	0.1001	1.6449	0.46012
17	0.7642	0.6978	0.8151	0.7783	1.6449	0.21820
18	0.6765	0.6726	0.6745	-0.0730	1.6449	0.47089
19	0.5907	0.5829	0.5889	0.1918	1.6449	0.42394
20	0.7144	0.7134	0.7164	0.2921	1.6449	0.38510
21	0.8056	0.8047	0.8027	0.0015	1.6449	0.49939
22	0.8843	0.8770	0.8625	0.4504	1.6449	0.32622
23	0.8993	0.8940	0.8966	0.2107	1.6449	0.41658
24	0.9230	0.9101	0.8751	0.6017	1.6449	0.27367
25	0.8608	0.8571	0.8732	-0.9875	1.6449	0.16169
26	0.9214	0.9196	0.9068	0.8944	1.6449	0.18555
27	0.7965	0.7918	0.8079	-0.5207	1.6449	0.30130
28	0.7140	0.6880	0.7791	-1.3682	1.6449	0.08563

Among the tabulated coefficients in Tables 4.14 through 4.16 and in Appendices G.2, G.4, and G.6 the coefficients for Age^2 are always positive and the coefficients for *Age* are always negative. Values of these fixed and variable components of loss in RVP as introduced in Section 4.3.1 are consistent with the decreasing curve of RVP over age. In particular, it can be observed that the regression coefficients for Age^2 grow slightly larger for larger machines, such as for track excavators, wheel loaders, and dozers. This innocuous observation confirms the hypothesis that larger machines retain their RVP longer than smaller machines of the same equipment type. Mathematically, a larger coefficient for the second-order term of age will cause the parabolic curve of RVP over age to remain at a higher level.

The indicator variables for manufacturer, condition rating, and auction region all are correctly set to zero as described in Section 4.2.7. Coefficients for economic indicators with large numerical values show small values. Further examination of the dimension of the regression coefficients did not show any anomalies.

4.6 Conclusion

This chapter has documented the second half of the methodology of this study. It described general concepts related to regression analysis and the effect of using categorical variables and normalizing the residual value. The statistical analysis included selection of the model form that best fits the data, deletion of outliers, and selection of economic indicators for three general models that were developed. The best model form is shown again in Equation 4.32.

$$RVP = \beta_0 + \beta_1 \cdot age^2 + \beta_2 \cdot age + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3 .$$

Equation 4.32

where *RVP* is the residual value percent, β_0 through β_2 are regression coefficients (β_0 being the intercept), *age* is the age in calendar years, M_i, C_i, and R_i are the regression coefficients for the manufacturer, condition rating, and auction region indicator variables, respectively, and m_i, c_i, and r_i are the manufacturer, condition rating, and auction region indicator variables, respectively.

Based on the plain model of Equation 4.32, the best models and trade journal models were developed by including economic indicators as explanatory variables. Results for the plain models, best models, and trade journal models were summarized. Comparisons by size class, manufacturer, condition rating, and region were made to give insights into the nature of the residual value. Figure 4.7 displays a sample fitted curved of residual value percent over age in calendar years that was generated for track excavators of up to 24,999 lbs of standard operating weight. Caterpillar was chosen as manufacturer for this diagram. Condition rating was assumed as good. Economic indicator values from November 31, 2002 were used. The auction region was Northeast. A complete set of diagrams for all equipment size classes is contained in Appendix H.

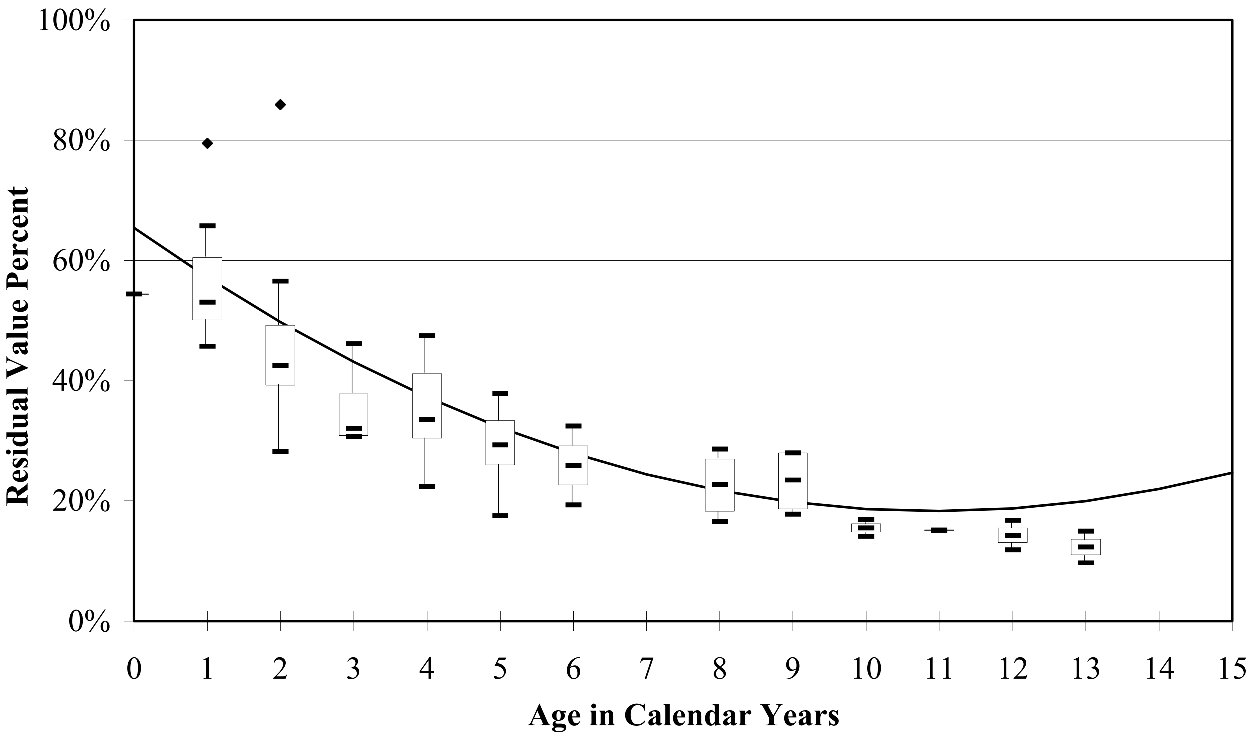


Figure 4.7: Track Excavators (0-24,999 lbs)

Chapter 5 Residual Value Calculator

5.1 Introduction

This chapter describes the Residual Value Calculator (RVC). The RVC was developed for use in validating the regression models and provide equipment managers with an implementation tool to predict the residual value for different types of used heavy construction equipment. Worksheets containing all necessary formulas and their coefficients were set up in Microsoft® EXCEL in a clear input-output structure. The following sections describe the input and output of this spreadsheet tool, the underlying calculations, and the statistical measures indicating goodness-of-fit of the model. The final section assembles helpful information on how the tool can be used for sensitivity analysis and on how to update and expand it.

The file *Residual Value Calculator.xls* is freely available to any interested user, provided the copyright protection of its content is respected. Macros need to be enabled in EXCEL for proper functioning.

5.1.1 Purpose

Residual value is an important aspect in calculating the owning costs of heavy construction equipment. However, currently the ability to predict residual value is very limited. The study that is described in the other parts of this document alleviates this situation by presenting a comprehensive statistical analysis of auction records and economic indicator values using MLR techniques. Tabulated coefficients of the regression equations in Tables 4.14 through 4.16 allow equipment managers to predict the residual value with more accuracy and reliability than previously possible.

The RVC has been developed to disseminate the results of this research and to implement them in practice. The tool is intended to serve equipment managers in better predicting the residual value of the machines under their supervision. Improving the quality of the prediction improves the quality of the owning cost calculation. The tool can further be used for sensitivity analyses as described in Section 5.4.4 to assist in optimizing equipment management policies.

5.1.2 Layout

The first worksheet of the RVC workbook has been formatted to print all user-supplied input values and calculated output values onto a single letter-size page as shown in Figure 5.1. This worksheet is called *1 – Residual Value Calculator*. Its input section consists of three parts and ten input values, which are discussed in more detail in Sections 5.2.1 through 5.2.3: *Purchase*, *Sale*, and *Economy at Time of Sale*. Its output section displays the predicted residual value, statistical measures of goodness-of-fit, and a diagram showing the RVP over calendar years. These sections are discussed in Sections 5.3.1 and 5.3.2.

5.1.3 EXCEL Macros and Commands

The RVC uses a variety of EXCEL macros and commands. EXCEL macros are written in Microsoft® Visual Basic® for Applications 6.3. They enable the functioning of several clickable buttons in the worksheets, which allow the user to jump to other worksheets within the RVC. One individual macro consisting of a worksheet name and cell reference is necessary for each target location. The code of all macros can be found in Appendix B.1.

EXCEL commands assist in providing the user-friendliness of the RVC and are also used to structure the calculations into several steps. The `VLOOKUP` command is used to automatically retrieve coefficients from the coefficient master table. These coefficients are then combined with user-supplied input values in the calculations. Several statistical values are also looked up and are used in the goodness-of-fit output. Important EXCEL commands are listed in Appendix B.2.

5.2 Input

The input section in worksheet *1 – Residual Value Calculator* is divided into three parts for clarity:

- *Purchase* requests information about the purchase of the machine;
- *Sale* requests information about the anticipated sale;
- *Economy at Time of Sale* requests information about the forecasted economic situation under which the sale occurs.

Ten input values are required for predicting the residual value. Table 5.1 gives a complete list of the different options that the user can select for these ten input values. The input cells for equipment type and size class, manufacturer, condition rating, auction region, and age are set up as drop down menus. A clickable link to this chapter is provided at the top of the worksheet.

5.2.1 Purchase Input

The following paragraphs describe the *Purchase* input part in detail.

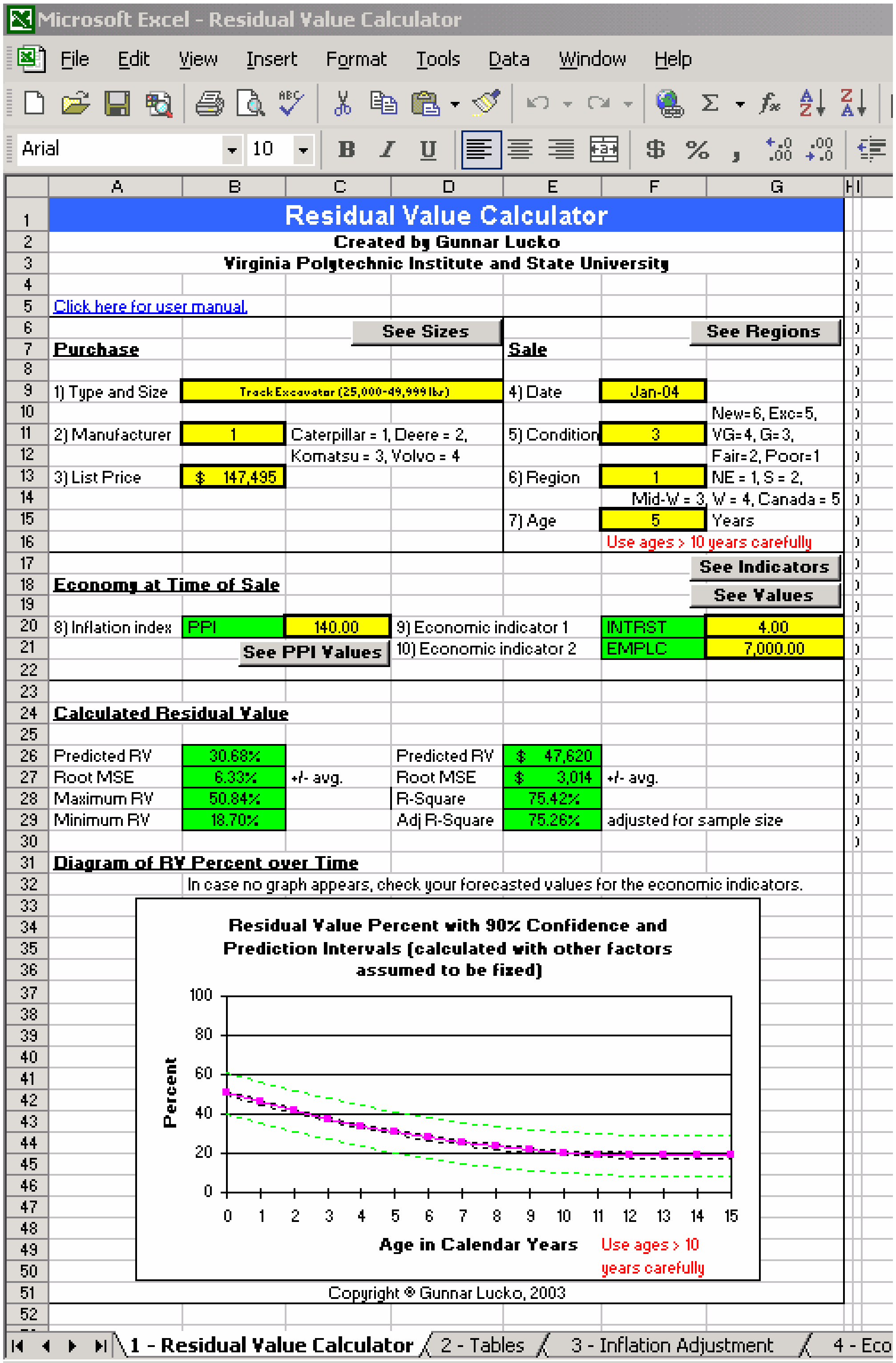


Figure 5.1: Residual Value Calculator Layout

Table 5.1: Input Selection Options

Section	Number	Input	Options	
Purchase	1	Type and Size Class	Track Excavators	0-24,999 lbs
				25,000-49,999 lbs
				50,000-74,999 lbs
				75,000-99,999 lbs
				100,000+ lbs
			Wheel Excavators	All Sizes
			Wheel Loaders	0-1.9 CY
				2-3.9 CY
				4-5.9 CY
				6+ CY
			Track Loaders	0-1.9 CY
				2+ CY
			Backhoe Loaders	0-0.9 CY
				1+ CY
			Integrated Toolcarriers	All Sizes
			Rigid-Frame Trucks	0-99,999 lbs
				100,000+ lbs
			Articulated Trucks	0-49,999 lbs
				50,000+ lbs
			Track Dozers	0-99 HP
				100-199 HP
				200-299 HP
				300-399 HP
				400+ HP
			Motor Graders	0-149 HP
				150+ HP
			Wheel Tractor Scrapers	0-74,999 lbs
				75,000+ lbs
	2	Manufacturer	Caterpillar, Deere, Komatsu, Volvo [availability depending on Input 1]	
	3	List Price (MSRP)	U.S. $	
Sale	4	Date	Month / Year	
	5	Condition Rating	New, Excellent, Very Good, Good, Fair, Poor	
	6	Auction Region	Northeast, South, Midwest, West, Canada	
	7	Age	1 to 15 Years	
Economy at Sale	8	Inflation Index	[PPI Value]	
	9 and 10	Economic Indicators e_1 and e_2	[Indicator Values]	

Table 5.2: List of Equipment Size Classes

Equipment Type	Number	Size from	Size to	Unit	Size Parameter
Track Excavators	1	0	24,999	lbs	Standard Operating Weight
	2	25,000	49,999		
	3	50,000	74,999		
	4	75,000	99,999		
	5	100,000	Open		
Wheel Excavators	6	All	All	lbs	Standard Operating Weight
Wheel Loaders	7	0	1.9	CY	General Purpose Bucket Size
	8	2	3.9		
	9	4	5.9		
	10	6	Open		
Track Loaders	11	0	1.9	CY	General Purpose Bucket Size
	12	2	Open		
Backhoe Loaders	13	0	0.9	CY	General Purpose Bucket Size (of backhoe)
	14	1	Open		
Integrated Toolcarriers	15	All	All	HP	Net HP (flywheel)
Rigid Frame Trucks	16	0	99,999	lbs	Standard Operating Weight (empty)
	17	100,000	Open		
Articulated Trucks	18	0	49,999	lbs	Standard Operating Weight (empty)
	19	50,000	Open		
Track Dozers	20	0	99	HP	Net HP (flywheel)
	21	100	199		
	22	200	299		
	23	300	399		
	24	400	Open		
Motor Graders	25	0	149	HP	Net HP (flywheel)
	26	150	Open		
Wheel Tractor Scrapers	27	0	74,999	lbs	Standard Operating Weight (empty)
	28	75,000	Open		

5.2.1.1 Input 1: Type and Size

Input 1 is the equipment type and size class. The user can click on the button next to the input cell to see a list of all equipment types and size classes along with their definitions. For each machine type a parameter commonly associated with the type was used to define size classes. These size parameters are standard operating weight, general purpose bucket size, and net (flywheel) HP. Table 5.2 lists the ranges of the 28 size classes that were defined for the 11 equipment types for which data were collected and analyzed in this study.

5.2.1.2 Input 2: Manufacturer

Following the selection of equipment type and size class, the user has to enter the manufacturer of the equipment as Input 2, choosing among Caterpillar, Deere, Komatsu, and Volvo. It should be noted that not all of the manufacturers produce all of the listed equipment types and sizes. Selection options in the drop down menu are therefore automatically adjusted depending on Input 1.

5.2.1.3 Input 3: List Price

The next input is the Manufacturers Suggested Retail Price (MSRP) in Input 3, commonly referred to as the original list price. This price was published by the manufacturer and its distributors during the year of manufacture. An inflation adjustment of the list price to the time of sale is performed automatically once the values of Inputs 4, 7, and 8 have been entered.

5.2.2 Sale Input

The *Purchase* input part has described the original circumstances of obtaining the machine. The following *Sale* input part defines the scenario that the user creates for an anticipated present or future sale of the machine. Two applications of residual value prediction have been introduced in Section 1.8. Calculations for either of the two approaches as shown in Figure 5.2 can be performed using the RVC because the mathematical model for them is the same.

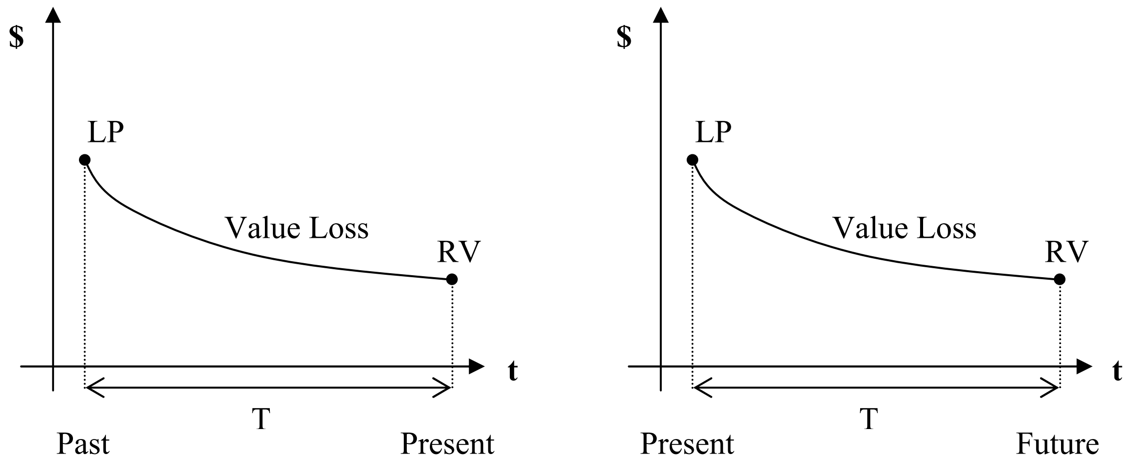


Figure 5.2: Applications of Residual Value Prediction

5.2.2.1 Input 4: Date

Input 4 requires the user to specify the anticipated month and year of the sale. Both month *and* year have to be entered in the format MM-YYYY for correctly calculating the inflation correction. Should only a year be entered, EXCEL incorrectly converts this to the number of days that have passed since January 1, 1900. The earliest date can be January 1, 1965 to avoid equipment manufactured prior to 1950 for which no inflation correction data were available. The latest date can be December 31, 2020 to avoid excessive extrapolation. An error message as shown in Figure 5.3 will be displayed should the date be outside these boundaries.

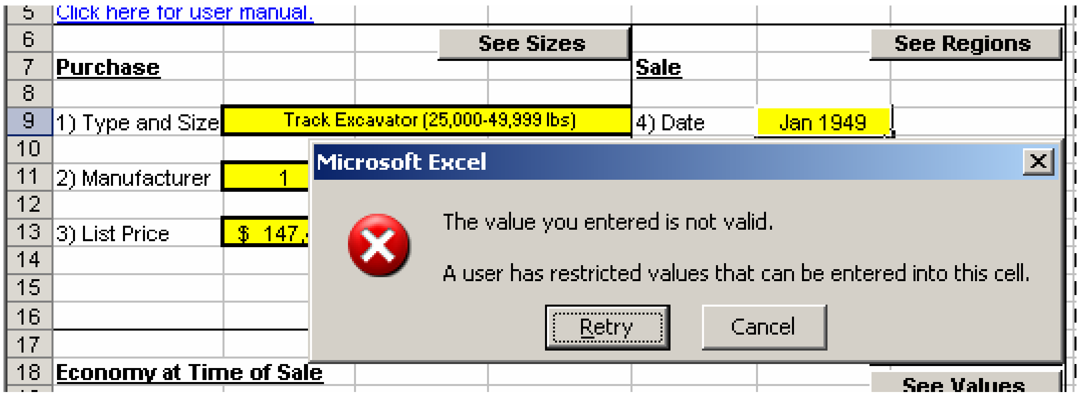


Figure 5.3: Invalid Entry for Year of Original List Price

5.2.2.2 Input 5: Condition Rating

Input 5 asks the user for the condition rating of the particular machine at the time of its sale. Six levels are possible: 6 = New, 5 = Very Good, 4 = Good, 3 = Good, 2 = Fair, and 1 = Poor. While these levels are represented by a numerical value, an actual quantitative measure for condition rating does not exist. The hierarchical order among these categories is not considered in the calculations, as explained in Section 4.2.7. The number of the chosen condition rating is automatically converted to binary numbers by the RVC. More information about determining condition ratings is available from equipment appraisers, who use standard checklists to examine the parts of a machine and determine its overall condition rating. Table 5.3 presents the original definitions used by the equipment auction firms from whom data for this study were obtained.

Table 5.3: Definitions of Condition Ratings

Condition Rating	Green Guide™ Auction Reports	Last Bid®	Top Bid
New	N/A	New unit	low or no hour machine
Excellent	Has seen very little or limited use.	Some use, but almost new mechanically	low hours, very little use
Very Good	Above average condition; may have been overhauled or may or may not have had enough use to require overhaul.	In above average mechanical condition; low hours or recently overhauled	above-average condition
Good	Average condition, with no known defects except as noted; in operating condition, but may need some repair or parts replacement soon.	In average mechanical condition; may need minor repairs or replacement of worn parts soon	an average piece of equipment, may need minor repairs
Fair	Has seen considerable service and may require repair or replacement of worn parts.	In below average mechanical condition; high hours or older unit	has been in service for a considerable time, may need repairs
Poor	Has seen hard service; needs repairs to be reliable, and may not be operational.	Needs major repairs	has undergone extensive service, may need repair, or be inoperative
Verified	N/A	Verified. Auction attended by EquipmentWatch field agent who verifies Make, Model, Serial Number and Condition.	N/A
(-)	N/A	(dash) Non-Verified. Data provided by Auctioneer. Erroneous transactions are corrected or omitted from database.	N/A

Sources: Primedia 1999, pviii, `<http://www.ironmax.com>`, `<http://www.equipmentworld.com>`.

5.2.2.3 *Input 6: Auction Region*

It is then necessary to enter the region in which the sale is anticipated to take place in Input 6. One of five regions can be chosen. Four of these are identical to the Census regions in the U.S., 1 = Northeast, 2 = South, 3 = Midwest, and 4 = West. An own region has been defined for 5 = Canada. Table 5.4 contains a list of these five regions used in the RVC and the individual states that the U.S. regions are composed of. The user can refer to this list in worksheet *2 – Tables* by clicking on the button next to the input cell. Numbering the regions does not imply any quantitative measure. As for the condition rating the numbers are only used for identification. A hierarchical order among the regions does not exist. The number of the chosen region is automatically converted to binary numbers by the RVC.

Table 5.4: List of Regions

Census Region and Canada	Number	States
Northeast	1	CT, MA, ME, NH, NJ, NY, PA, RI, VT
South	2	AL, AR, DC, DE, FL, GA, KY, LA, MD, MS, NC, OK, SC, TN, TX, VA, WV
Midwest	3	IA, IL, IN, KS, MI, MN, MO, ND, NE, OH, SD, WI
West	4	AK, AZ, CA, CO, HI, ID, MT, NM, NV, OR, UT, WA, WY
Canada	5	All Provinces and Territories

5.2.2.4 *Input 7: Age*

Age in calendar years at the time of sale is Input 7. It is counted from the year of manufacture and is limited to a maximum of 15 years for two reasons. The original data used to determine the coefficients for the prediction model spanned a range of 15 years, as older equipment was assumed to be relatively rare and also to have higher variance of the residual value. A warning cautions against using ages larger than 10 years. Extrapolation needs to be performed carefully and will be less accurate the further into the future it reaches. This particularly applies to forecasting the inflation-corrected (Input 8) economic situation as captured through the economic indicators (Inputs 9 and 10).

Considering the two applications of residual value prediction mentioned in Section 5.2.2, age is defined as the calendar years that a machine has now, if the RVP shall be predicted for the present time, and it is defined as the calendar years that a machine will have later, if the RVP shall be predicted for a future time. Age can be used to adjust for above or below average use of the machine. If the user notes annual hours of use do not concur with industry averages as published in trade journals such as e.g. *Construction Equipment*, the age in calendar years can be decreased or increased proportionally.

5.2.3 Economy at Time of Sale Input

The *Economy at Time of Sale* input part captures the economic situation at the time of the anticipated present or future sale of the machine.

5.2.3.1 Input 8: Inflation Index

Input 8 requests the forecasted PPI. It is used for inflation correction in the spreadsheet calculations. The curve in Figure 5.4 shows historical PPI values since 1980 as reported by the Bureau of Labor Statistics. Clicking on the button located adjacent to the input cell allows the user to view tabulated monthly values of the PPI in worksheet *3 – Inflation Correction* to assist in forecasting the PPI.

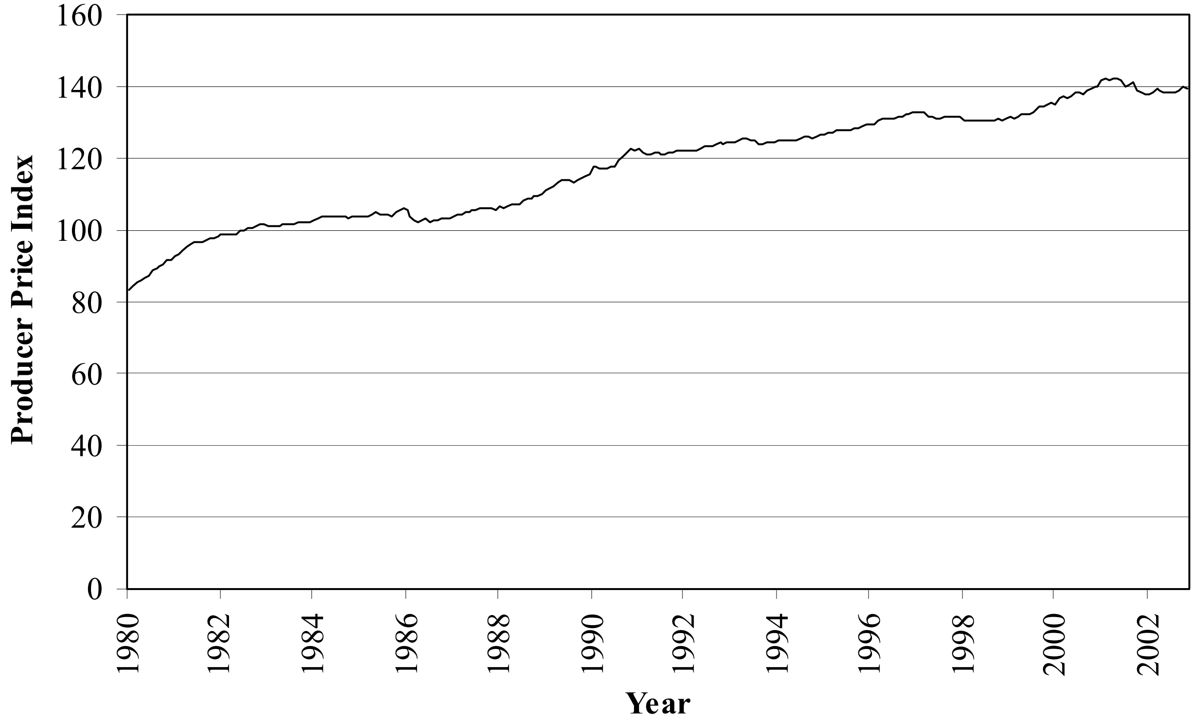


Figure 5.4: History of Producer Price Index Values

5.2.3.2 Inputs 9 and 10: Economic Indicators 1 and 2

Depending on the chosen equipment type and size class, different pairs of economic indicators are requested to be forecasted for the final Inputs 9 and 10. These pairs have been identified in the statistical analysis to best contribute to the prediction. A table that lists all economic indicators is provided following the coefficient master table in worksheet *2 – Tables*. Included are the abbreviations used throughout the tool, the full name and official source, the unit (if applicable), the frequency, and a clickable link to the respective Web site from which it can be obtained. The complete table can also be found in Appendix D.

For better forecasting the user can view a graphical representation of the economic indicator values over time in worksheet *5 – Indicator Diagrams* as shown in Figure 5.5. The user can also refer to a database with historical values in worksheet *4 – Economic Indicators* by clicking on the respective button. The values contained therein should be kept current by the user.

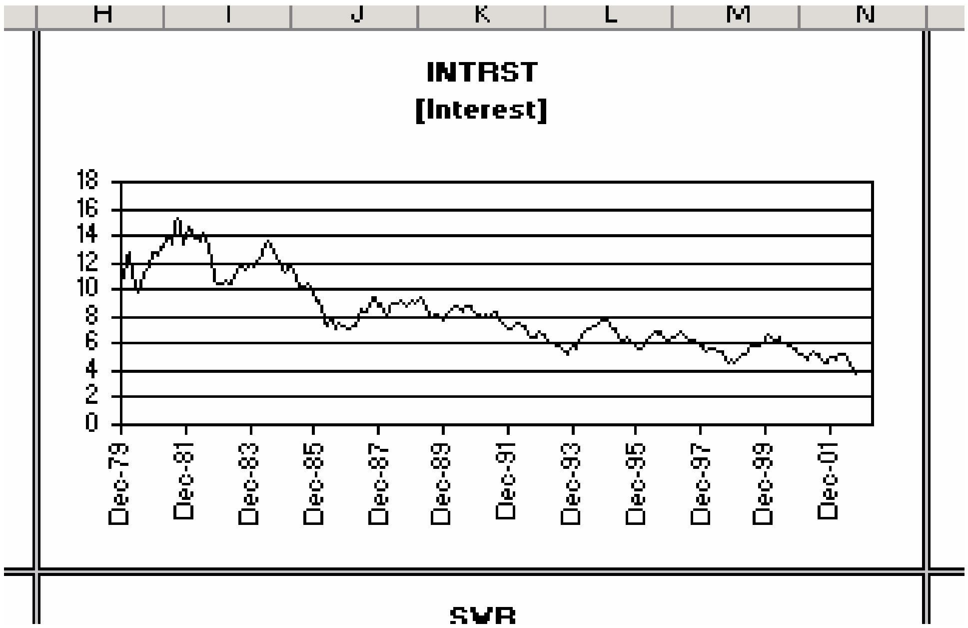


Figure 5.5: History of Economic Indicator Values

5.3 Output

Numerical and graphical output is calculated by the RVC after all required input values have been provided by the user. Included in the output are the predicted residual value, statistical measures of goodness-of-fit, and a graphic of the RVP over age in calendar years as shown in Figure 5.6. The following paragraphs explain the elements of the output part of worksheet *1 – Residual Value Calculator*. Section 5.4 gives detailed information about the spreadsheet calculations.

5.3.1 Numerical Output

The RVC produces several different numerical output values based on the user-supplied input values and the tabulated prediction model coefficients. They include the predicted RVP, its maximum and minimum values, the predicted residual value as a dollar amount, and goodness-of-fit statistics.

5.3.1.1 Residual Value

The predicted residual value is displayed in two forms. It is shown as percent of the list price and it is shown as a dollar amount that has been inflation-corrected with the PPI (Input 8) to the anticipated month and year of the sale. The root *MSE* is given in percent and dollar terms as a measure of the average range of error around the predicted residual value. It represents the average distance between the estimated and the actual value (Montgomery et al. 2001). The maximum and minimum RVP for the entire age range are also displayed. Note that the RVP is assumed to remain at a constant value once it has reached its minimum rather than follow the quadratic equation of age from the regression model for high ages.

5.3.1.2 Statistics

The coefficient of determination R^2 and the adjusted coefficient of determination R^2_{adj} are displayed in the output. R^2 and the R^2_{adj} are commonly used to measure the goodness-of-fit of the prediction model with its original data. They give an indication of how much predictive power can be expected from the regression model versus how much of the variability in the residual value will remain unexplained due to unknown or random error sources. The R^2 value is always slightly higher than the R^2_{adj} value, which contains a correction term to account for different sample sizes in the original regression analysis that yielded the coefficients.

5.3.2 Graphical Output

A diagram displays RVP over age in calendar years as shown in Figure 5.6. Note that the curve of residual value percent is displayed by a solid line with squares marking the values for each year. It is surrounded by two dashed bands. Forming a narrow dashed band around the curve is the 90% CI for this prediction. The CI expresses that one is 90% confident that the true mean of the RVP lies within its upper and lower limits. The wider dashed band is the 90% PI. It describes that one is 90% confident that a new observation of the RVP would fall within this range. Due to its statistical definition the PI is always larger than the CI.

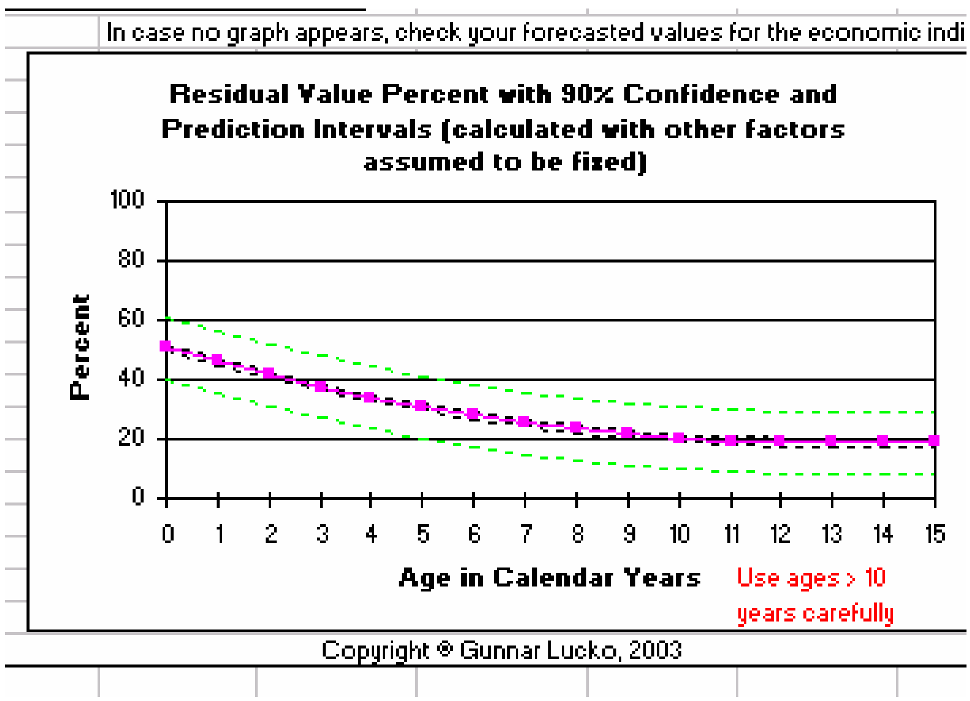


Figure 5.6: Output Residual Value Percent over Age with Confidence and Prediction Intervals

Both intervals are narrowest at the center of the explanatory variables and are growing larger towards the ends of the dataset. In other words, the predictions for very low and very high ages will have a higher variance than for machines in the middle age range.

The CI and the PI were calculated with the modified formulas of Section 5.4.2.1 for this graphic to account for the fact that only the explanatory variable age is displayed. All other factors are assumed to remain fixed at their various means for the purpose of this graphical representation.

Should no curve be visible in the diagram after all input values have been entered it is advisable to check Input 9 and Input 10 first. An error in the dimension of these indicators can distort the prediction considerably since they are multiplied with their tabulated coefficients and then added to the predicted RVP.

5.4 Spreadsheet Calculations

The following sections provide explanations on the mathematical background of the RVC. The regression equation and its coefficients are presented after a review of the statistical analysis. Predictions of the residual value are calculated with these coefficients and the input values that are provided by the user.

5.4.1 Regression Analysis

This section gives a brief summary of the methodology that was followed in this study. Equipment auction results were collected from two data sources and assembled into one dataset. The data covered a range of about 10 years worth of U.S. and Canadian construction equipment auctions. Machines of up to 15 calendar years of age at the time of sale were considered in the analysis. Information included in the analysis were the date and location of the auction, the auction firm and the auction price that was achieved, the equipment manufacturer, model, and serial number, as well as the year of manufacture, the overall condition rating at sale, and a very brief description of special options or known flaws, if applicable. Not every entry was complete and in some instances transcription errors were detected in the database. Gaps were carefully filled and corrections were made as far as possible using EXCEL macros.

Parameters describing the size of the equipment were added to the database by matching them to each particular manufacturer and model. Economic indicator values that had been collected covering the entire time span were matched with the auction date of each entry to represent the economic background at that particular time.

The fully prepared dataset was then divided into 28 equipment type and size classes. For each class a multiple linear regression analysis was performed in several steps. Outliers were identified and deleted from the data. It was found that a quadratic model of age in calendar years augmented by additive terms for the other explanatory variables (including two economic indicators) provides a very feasible model for the residual value. Regression model intercepts and coefficients were calculated and tabulated along with statistical measures of goodness-of-fit.

5.4.2 Residual Value Prediction

Equation 5.1 gives the algebraic form of the trade journal model that is used in the RVC. Cell references have been replaced by variable names for ease of understanding. This predictive model for RVP is a second-order polynomial model of the age in calendar years plus linear terms of other factors.

$$RVP = \beta_0 + \beta_1 \cdot age^2 + \beta_2 \cdot age + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3 + E_{1t} \cdot e_{1t} + E_{2t} \cdot e_{2t}$$

Equation 5.1

where RVP is the residual value percent, β_0 through β_2 are regression coefficients (β_0 being the intercept), *age* is the age in calendar years, M_i, C_i, and R_i are the regression coefficients for the manufacturer, condition rating, and auction region indicator variables, respectively, m_i, c_i, and r_i

are the manufacturer, condition rating, and auction region indicator variables, respectively, E_{it} are the regression coefficients for the economic indicators from the trade journal models, and e_{it} are the economic indicator values from the trade journal models. The intercept and all coefficients are stored in the coefficient master table in worksheet *2 – Tables*. The currently active row from which coefficients are retrieved is indicated by a red cell.

5.4.3 Confidence and Prediction Intervals

In Section 4.2.9 it has been explained how the standard formulas for the CI and PI had to be adjusted to correctly display them in a diagram with the curve of the predicted RVP over age in calendar years. Equations 5.2 and 5.3 give the corrected formulas that are used in the RVC.

$$CI_{adj} = \hat{y}_0 \pm t_{\alpha/2,n-2} \cdot \sqrt{MS_{res} \cdot \left(\frac{1}{n} + \frac{(x_0 - \bar{x})^2}{S_{xx}} + \frac{k-1}{n-1} \right)}. \qquad \textbf{Equation 5.2}$$

$$PI_{adj} = \hat{y}_0 \pm t_{\alpha/2,n-2} \cdot \sqrt{MS_{res} \cdot \left(1 + \frac{1}{n} + \frac{(x_0 - \bar{x})^2}{S_{xx}} + \frac{k-1}{n-1} \right)}. \qquad \textbf{Equation 5.3}$$

where CI_{adj} and PI_{adj} are the adjusted confidence and prediction intervals, respectively, $\hat{y}_0$ is the estimate of RVP at one particular value x_0 of age, $t_{\alpha/2,n-2}$ is the t-test statistic for significance level α and n complete observations, MS_{res} is the mean square residuals, $\bar{x}$ is the mean age, S_{xx} is the sum of squares of the cross product of x with itself, and k is the number of explanatory variables in the regression model. The number of explanatory variables k is equal to $p-1$, the number of parameters estimated for the regression model minus one.

5.4.4 Sensitivity Analysis

The RVC allows for easy sensitivity analysis. Predicted residual values are automatically updated in the worksheet as soon as any input cell is changed. It is thus possible to enter different values in an input cell of interest to create different scenarios for the machine and observe the impact on the predicted residual value both numerically and graphically. Care needs to be taken to not overlook updating the pair of economic indicator forecasts in Inputs 9 and 10 in case a comparison between different size classes is sought. All input values other than the age of the machine enter the prediction model as additive terms and thus merely shift the location of the curve in the diagram vertically.

5.4.5 Database Updating

The RVC has one coefficient master table in its worksheet *2 – Tables* in which all results from the regression analysis of auction results and economic data are stored. Additionally, the RVC retrieves the average annual PPI value from worksheet *3 – Inflation Adjustment* to perform the inflation adjustment. Worksheets *4 – Economic Indicators* and its graphical equivalent *5 – Indicator Diagrams* have been provided solely to assist the user to forecast the pair of economic indicators in Inputs 9 and 10. These two worksheets are not used in any of the calculations of the tool.

It is therefore easily possible to update the database of the RVC. Newly generated regression results need to be arranged in a table of the same column order as the coefficient master table. They can then be copied through a text editor into the space of the coefficient master table. Links in worksheets *1 – Residual Value Calculator* and *2 – Tables* that refer to this table need to be updated afterwards in case the cell reference has been lost.

References to the master table exist in the following cells in worksheet *1 – Residual Value Calculator*: In the input section, the two cells showing the economic indicator abbreviations of Input 10 contain references to the master table. In the output section, the two cells with RVP and root *MSE* in percent, and the two cells displaying R^2 and R^2_{adj} also contain references. In worksheet *2 – Tables* the six cells directly next to the table in which CI and PI are calculated contain references to the coefficient master table.

The list of average annual PPI values can be amended by adding new values to the column of monthly PPI values in worksheet *3 – Inflation Adjustment*. New values for the average annual PPI can be calculated as the average of 12 monthly values in the pre-formatted last column of that worksheet.

New economic indicator values can be added to the respective column in worksheet *4 – Economic Indicators*. Diagrams in worksheet *5 – Indicator Diagrams* then are updated by clicking on the curve displaying the economic indicator of interest and entering the row number of the cell where the updated column now ends.

5.6 Sample Calculation

A sample calculation shall be performed to illustrate the use of the RVC. Residual value for a track excavator between 25,000 and 49,999 lbs of standard operating weight shall be calculated. This option accordingly is chosen as Input 1. Caterpillar is specified as manufacturer in Input 2, which is coded with a “1” in the input cell. The original list price was $147,495.00 and is entered in Input 3. This completes the information that is provided on the purchase. The machine is anticipated to be sold in January 2004 and the date is entered as Input 4. Its condition at this time is assumed to be good, which is coded with a “3” in Input 5. The auction region where the machine is anticipated to be sold is Northeast, which is coded with a “1” in Input 6. At the time of sale the machine will be five years old, which is entered as Input 7. The PPI at this time is assumed to be 140, which is entered as Input 8. Entering the purchase information has prompted the RVC to request forecasted values for the interest rate (Input 9) in percent per year and the employment in the Construction Industry (Input 10) in thousands of workers. The assumed values are chosen as 4% and seven million workers, written as 7,000 thousands.

The RVC calculates the predicted RVP as 30.68% at the age of five years, which amounts to \$47,620 with a root MSE of 6.33%, which amounts to \$3,014. Root MSE is a measure of the average range of error around the predicted RVP. The maximum RVP was 50.84% and the minimum RVP was 18.70% at an age of 13 years and older. An impression of the goodness-of-fit of the model with the data from which it was originally developed is provided through the values of R^2 (75.42%) and R^2_{adj} (75.26%). A diagram containing the curve of RVP over age in calendar years and the 90% CI and PI is provided additionally. The entire worksheet *1 – Residual Value Calculator* for this sample calculation is shown in Figure 5.1.

5.7 Conclusion

This chapter has presented the functioning of the RVC, a spreadsheet tool that incorporates the results of this study on residual value of heavy construction equipment. Its input, output, and the exact functioning of its spreadsheet calculations have been explained step-by-step. How to employ the tool for sensitivity analysis was explained and how to update its database with new regression results or with current economic indicator values was described. A sample calculation using the RVC concluded the chapter.

Chapter 6 Contributions

6.1 Introduction

This chapter reviews the work that has been performed in this study. It addresses the research hypothesis that was stated in Chapter 1, highlights the results of this research, describes how the accomplished work contributes to the body of knowledge, and recommends topics for further research.

6.2 Research Hypothesis

Section 1.6 stated the central hypothesis for this study. It postulated that "*[i]t is possible to develop a statistically significant model for the residual value of heavy construction equipment.*" Regression analysis was to be used to analyze data from public sources. Data that were collected and prepared included records from equipment auctions, size parameters and list prices published by the equipment manufacturers, and economic indicators that capture the state of the economy at the time of the auction.

Chapter 4 described the statistical analysis that was performed on the data. The standard assumptions for regression analysis were found to be met by the datasets. Explanatory variables for the regression model were age in calendar years, manufacturer, condition rating, and auction region coded with indicator variables, and two economic indicators as numerical variables. The response variable was RVP, defined as the inflation-corrected auction price divided by the inflation-corrected list price. Inflation correction using the PPI was performed to bring the auction prices and list prices to the same date.

The performance measures that were specified for the regression models were an adjusted coefficient of determination R^2_{adj} larger than 0.7 and a root *MSE* smaller than 0.1. Goodness-of-fit was examined for different MLR models, including models with exponential and logarithmic forms of age, the most significant explanatory variable. Variance inflation factors were used to select the economic indicators that contributed most to the regression models without being themselves highly correlated.

Among the MLR models that were examined, the regression model that provided the overall best goodness-of-fit with the data and the best predictive capabilities was found to be a second-order polynomial of age plus the terms for manufacturer, condition rating, auction regions, and two economic indicators. Outliers were deleted from among the observations to form the final datasets. Coefficients and statistics for this model were tabulated in the appendices to this study. Three types of the model were developed and are presented in Section 6.5. The plain model provides quick estimates of residual value without forecasting the situation of the economy, the best model uses a selection of all economic indicators, and the trade journal model uses economic indicators that are considered to be specifically related to the Construction Industry. This model has been implemented in the RVC that is described in Section 6.4.

With the noted exception of the relatively small and unevenly distributed Dataset 13, the final regression models achieved outstanding values for the respective statistical performance measures. The root *MSE* values for all datasets were smaller than 0.1. It was found that the values of the coefficients of determination R^2 and of the adjusted coefficients of determination R^2_{adj} were extremely close, which clearly indicates that the regression models were not overfitted with unnecessary explanatory variables. The adjusted coefficients of determination R^2_{adj} generally exceeded 0.7 and for several datasets even exceeded 0.9. Regression models have thus been able to explain most of the variability in the data with their explanatory variables. This underlines that the explanatory variables used in this study have been selected well. Including economic indicators in the regression models was shown to contribute to the quality of the models in a statistically significant way. It has thus been proven that the economic situation needs to be considered to accurately predict the residual value for a given machine. A validation for the regression models was performed by randomly splitting the datasets and performing regression analysis on these halves. The stability of the predictions made with the regression models was confirmed statistically for all datasets with the exception of Datasets 1, 4, and 5, which only passed a weaker statistical test.

Overall, it is concluded that the aforementioned research hypothesis of this study was not rejected. It is indeed possible to develop a statistically significant model for the residual value of heavy construction equipment by performing regression analysis on publicly accessible data on the machines and the economic situation at the time of their sale. The model is again shown in Equation 6.1. Subsequently, this plain model it was amended by economic indicators to generate the best model and the trade journal model. With their high goodness-of-fit the regression models developed in this study provide excellent predictive capabilities to owners of heavy construction equipment.

$$RVP = \beta_0 + \beta_1 \cdot age^2 + \beta_2 \cdot age + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3 .$$

Equation 6.1

where *RVP* is the residual value percent, β_0 through β_2 are regression coefficients (β_0 being the intercept), *age* is the age in calendar years, M_i, C_i, and R_i are the regression coefficients for the manufacturer, condition rating, and auction region indicator variables, respectively, and m_i, c_i, and r_i are the manufacturer, condition rating, and auction region indicator variables, respectively.

6.3 Research Results

The most important findings from this study are revisited and highlighted in the following.

- Age was the explanatory variable that contributed the most explanatory power to the regression models (Section 4.3.1, Table 4.6);
- Economic indicators contributed significantly to the regression models (Section 4.4, Table 4.18);
- Regression models yielded consistent results in comparing the difference in RVP between the manufacturers (Section 4.4.1, Table 4.19, Figure 4.2);
- Track excavators of medium size classes showed an increasing difference in RVP with increasing size between manufacturers. For wheel excavators the difference in RVP was more pronounced (Section 4.4.1, Table 4.19, Figure 4.2);
- Wheel loaders and track loaders show the same tendency of increasing difference in RVP with increasing size between manufacturers. Large backhoe loaders show a very pronounced difference in RVP between manufacturers. Integrated toolcarriers exhibit only little difference between manufacturers with respect to their RVP (Section 4.4.1, Table 4.19, Figure 4.2);
- Rigid frame trucks show a notable difference in RVP between the manufacturers and an increase of this difference with size. For articulated trucks the difference was less strong and decreased with increasing size (Section 4.4.1, Table 4.19, Figure 4.2);
- Track dozers clearly followed the trend of increasing difference in RVP with larger size with exception of the two largest size classes (Section 4.4.1, Table 4.19, Figure 4.2);
- Motor graders also follow the trend of increasing difference in RVP with larger size. Small wheel tractor scrapers have similar differences (Section 4.4.1, Table 4.19, Figure 4.2);
- Lower condition rating of a machine clearly coincides with a lower RVP. New equipment and equipment with a poor condition rating were sold infrequently at auctions and deviated from this pattern (Section 4.4.2, Figures 4.3 through 4.5);
- Different equipment types show different overall losses of residual value with declining condition rating. Track excavators and loaders, dozers, and scraper exhibited the largest decrease in RVP. Trucks exhibited the smallest decrease in RVP (Section 4.4.2, Figures 4.3 through 4.5);

- Auction region has a measurable impact on the RVP that depends on the particular equipment type. Canada was found to have low residual values for certain equipment types (Section 4.4.3, Tables 4.22 through 4.24);
- Within the same equipment type, larger machines lose less RVP than smaller machines over the same time period (Section 4.5.4).

6.4 Research Implementation

The RVC is a tool that was developed to implement the results of this study in the Construction Industry practice. It has been designed for easy application of the regression equations by the user. The interactive spreadsheet has been set up with all necessary formulas and coefficients that were derived from this research.

In the input section of the RVC the user specifies the equipment type and size class and enters information about the purchase, the sale, and the economic situation anticipated for the time of sale. In particular, the user chooses the manufacturer, list price, condition rating, auction date, condition rating, auction region, age, inflation index value, and economic indicator values as the input for the prediction. If the user assumes that the machine under consideration has incurred annual hours of use above or below the industry average as published e.g. in *Construction Equipment*, it is possible to consider this in the prediction by adjusting the input value of age accordingly. The RVC requests forecasted values for the pair of economic indicators that contribute the most explanatory power to the regression model for an optimum prediction. Historical values and diagrams of all economic indicators are provided to assist with the forecast. An inflation adjustment of the list price is performed during the spreadsheet calculations. Manufacturer, condition rating, and auction region are automatically converted from verbal descriptors to the indicator variables necessary for the regression equation.

Based on the user-supplied input the RVC calculates the residual value as percent of the original list price and as a current dollar amount. Root *MSE* is displayed both as percent and as a dollar amount to provide the user with a measure of accuracy of the prediction. The values of R^2 and

R^2_{adj} are displayed to give an impression of the goodness-of-fit that has been achieved with the regression models for the particular equipment type and size class. A diagram presents RVP over age graphically. It also displays the 90% CI and PI to provide an additional measure of accuracy. The user can be 90% confident that the true mean residual value or new observations, respectively, would be included within the range of these intervals.

6.5 Contribution to the Body of Knowledge

This study makes its contribution to the body of knowledge by improving owning cost calculations for heavy construction equipment through adding better information on the residual value. It responds to a need in the Construction Industry to perform more accurate analyses of the costs associated with owning and operating heavy construction equipment.

Residual value was identified as the element of owning costs that was considered most uncertain. It is used whenever an economic analysis of the equipment is performed, e.g. determining the revenue that a machine has to generate as hourly charges or calculating the economic life of the equipment for an investment decision. No previous study has addressed this issue comprehensively for heavy construction equipment, whereas studies for the areas of agriculture and forestry have been identified. The importance and significant impact of residual value on owning and operating cost calculations has been demonstrated in sample calculations presented in Section 1.9. This study therefore adds the missing piece of information to the owning costs of construction equipment.

Carrying out this study has created a proven research methodology whose first half included collecting and preparing relevant market data and was presented in Chapter 3. The second half of this methodology included converting the actual data to accurate predictions of the residual value using statistical methods and was presented in Chapter 4. Applying the methodology in its entirety helps avoiding the drawbacks of using merely empirical assumptions about residual value, which have been used in practice until now. Practical application of the statistical results gained from this study is made possible by the development of the RVC that was presented in

Chapter 5. This spreadsheet tool performs all calculations that are necessary for making residual value predictions based on user-supplied input values. Section 6.2 finally has described how the stipulations of the research hypothesis have been fulfilled in this study.

This study has given equipment managers a set of regression equations to predict residual value for a broad variety of equipment types and size classes at their disposal. Equipment types have been selected for their prevalence in the operations of the Construction Industry. Different sizes of equipment are reflected by individually fitted regression equations. The influence of the factors age, manufacturer, condition rating, auction region, and the state of the economy are considered in the prediction. Considering the influence of the economy has been found to be significant.

Table 6.1 once again presents the algebraic form of the plain models, best models, and trade journal models that have been developed in this study. In Table 6.1, *RVP* is the residual value percent, β_0 through β_2 are regression coefficients (β_0 being the intercept), *age* is the age in calendar years, M_i, C_i, and R_i are the regression coefficients for the manufacturer, condition rating, and auction region indicator variables, respectively, E_{ij} are the regression coefficients for the economic indicators, m_i, c_i, and r_i are the manufacturer, condition rating, and auction region indicator variables, respectively, e_{ij} are the economic indicator values, *b* is the index of the best model, and *t* is the index of the trade journal model.

Table 6.1: Algebraic Form of Final Regression Models

Model	Algebraic Form of Regression Model
Plain Model	$RVP = \beta_0 + \beta_2 \cdot age^2 + \beta_1 \cdot age + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3$
Best Model	$RVP = \beta_0 + \beta_2 \cdot age^2 + \beta_1 \cdot age + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3 + E_{1b} \cdot e_{1b} + E_{2b} \cdot e_{2b}$
Trade Journal Model	$RVP = \beta_0 + \beta_2 \cdot age^2 + \beta_1 \cdot age + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3 + E_{1t} \cdot e_{1t} + E_{2t} \cdot e_{2t}$

This study has achieved to develop regression models that predict the residual value with a high degree of accuracy. Its overall contribution lies in improving cost analyses performed by equipment managers through reducing the uncertainty that had been associated with the residual value and thus leading to better decisions on the economy of owning and operating heavy construction equipment.

6.6 Future Research

Topics for future research were identified through the performance of this research. The following sections give recommendations for these areas of investigation.

6.6.1 Meter Hours and Mileage

Auction records that were obtained from the identified data sources provided rich data on the equipment that was being sold at the auctions. Section 3.3.2.12 described how hour meters are used to measure cumulative hours of use, or meter hours, of the equipment. Mileage is measured with the odometer. Both meter hours and mileage attempt to measure the use of the machine that causes the wear and tear that is reflected by the condition rating. Age, on the other hand, is a less specific measure that simply grows with time even if a machine is not used.

Neither meter hours nor mileage was available to serve as an explanatory variable for this study as they are not recorded by the data sources. Further research would be necessary to develop means of recording these data and to use them for residual value prediction. Based on the literature reviewed in Chapter 2 it is hypothesized that these two measures could further contribute to the explanatory power of regression models such as the ones developed in this study. It would be necessary to examine the degree of correlation that these two measures exhibit with the known explanatory variable age, as Perry and Glyer (1989) have identified significant correlation between age and meter hours. Interaction terms in the statistical models could capture the combined influence of these measures on the residual value.

6.6.2 Special Options and Attachments

Residual values in this study have been determined and analyzed using the assumption that the analyzed equipment was of standard setup and equipped with standard options, as described in Section 3.4.1.3. Observations in all datasets were searched for unusual or missing features and deleted as far as identifiable, as described in Section 3.3.2.6. Detecting and deleting outliers additionally helped to purge the datasets from observations with unusually high or low RVP due to non-standard options, extreme condition ratings, and similar inconsistencies.

Results of this research can already be applied to equipment with non-standard options. In this case, the user multiplies the predicted RVP with the list price that applies at the time of sale to determine the predicted residual value in dollar terms. The user would then make an adjustment for the particular option based on the best available judgement and experience.

Further research would be necessary to detail the influence that special options and attachments could have on the residual value and to directly include it in the regression model. A methodology to analyze how special options and attachments influence the residual value would include composing a database with prices of special options and attachments and identifying a data source for descriptions of the setup of equipment at the time of its sale.

6.6.3 Other Equipment Types and Applications

This study has developed and documented a clear methodology for residual value analysis of heavy construction equipment. In setting its scope it has selected the equipment types that are predominant in the Construction Industry and for whom a sufficient number of data points were available from current auction records.

Future research could seek to expand the number of different equipment types and manufacturers for which regression coefficients have been calculated to less common types and other manufacturers. Definition of the scope for such research would depend on the particular needs of the owners of equipment, such as e.g. construction contractors and would require availability of data to make valid statistical predictions.

It is possible to use this methodology in related industries in which heavy equipment is also operated, most notably the Mining Industry. Examining other application areas of heavy equipment could also allow gaining insights into how different patterns of use affect the residual value. Further research on the influence of the geographical region on the residual value of equipment and associated factors is also recommended.

6.7 Closure

This study has provided a comprehensive analysis of the residual value of used heavy construction equipment using statistical methods. It has added an important piece of knowledge to the owning cost calculation for such equipment and enables its users to make better predictions of the residual value of their machines at any point in time, considering the state of the machine as well as the economic situation under which it is anticipated to be sold.

The objectives of this study that were been outlined at the beginning of this study have been fully achieved under consideration of the stated scope and limitations. The methodology used for this study can easily be applied to other equipment types and areas of interest. Use of the regression models developed by this study is hoped to contribute to the economic success of construction contractors that own and operate heavy construction equipment.

Appendices

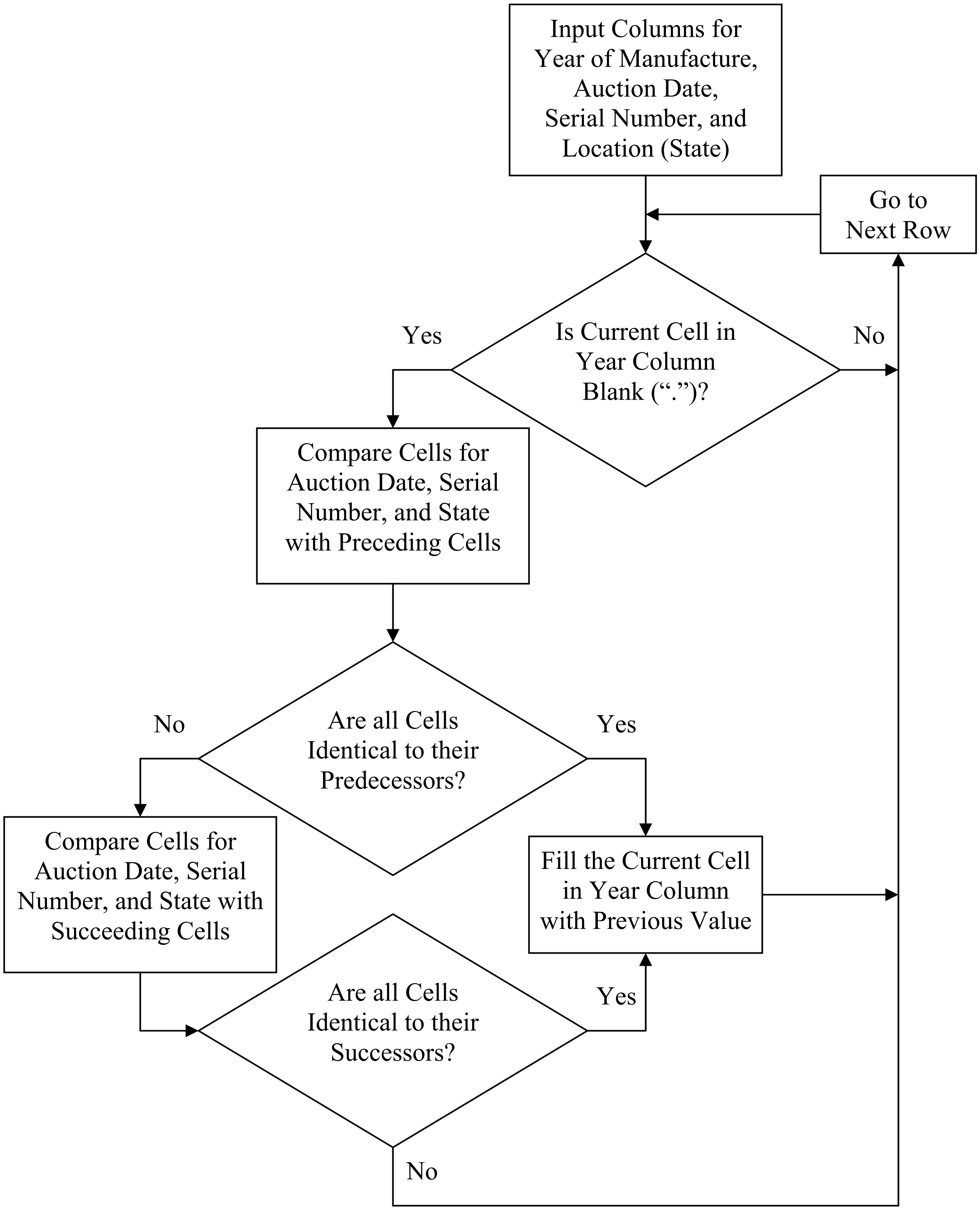
Appendix A: EXCEL Macros for Data Preparation

The following Microsoft® Visual Basic® for Applications 6.3 code for the EXCEL macros *AddYears* and *DeleteDoubles* was written by Gunnar Lucko. The code for the macros *MatchEconomy* and *MatchParameters* was originally written by Mr. Brian A. Marshall of the Statistical Consulting Center at Virginia Tech. It was subsequently modified by Gunnar Lucko to account for the specific format of the auction records.

Appendix A.1: Macro *AddYears*

```
Sub AddYears()
Set Column1 = Application.InputBox("Please select column where
     years need to be added:", "Select Column", Type:=8)
Set Column2 = Application.InputBox("Please select column that
     contains the auction dates:", "Select Column", Type:=8)
Set Column3 = Application.InputBox("Please select column that
     contains the serial number:", "Select Column", Type:=8)
Set Column4 = Application.InputBox("Please select column that
     contains the state:", "Select Column", Type:=8)
i = Column1.Row
l = Column1.Column
p = Column1.Rows.Count
m = Column2.Column
n = Column3.Column
q = Column4.Column
While i <= p + 5
     If Cells(i, l).Value = "." Then
          If CDate(Cells(i, m)) >= CDate(Cells(i - 1, m)) And
               Cells(i, n).Value = Cells(i - 1, n).Value And
               Cells(i, q).Value = Cells(i - 1, q).Value Then
               Cells(i, l).Value = Cells(i - 1, l).Value
          ElseIf CDate(Cells(i, m)) <= CDate(Cells(i + 1, m))
               And Cells(i, n).Value = Cells(i + 1, n).Value And
               Cells(i, q).Value = Cells(i + 1, q).Value Then
               Cells(i, l).Value = Cells(i + 1, l).Value
          End If
     End If
i = i + 1
Wend
End Sub
```

Appendix A.2: Macro *AddYears* Flowchart

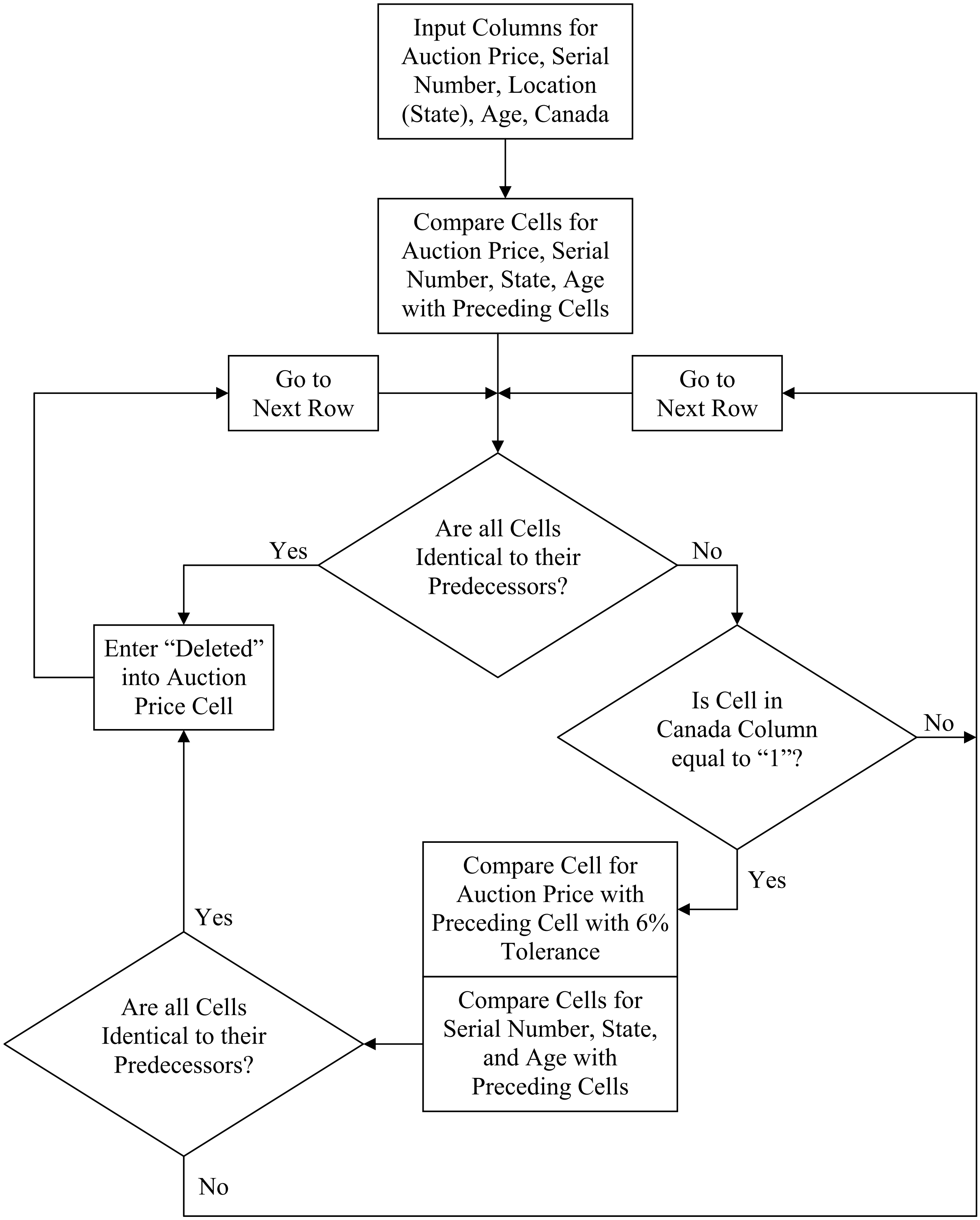


Appendix A.3: **Macro *DeleteDoubles***

```
Sub DeleteDoubles()
Set Column1 = Application.InputBox("Please select column where
     prices will be compared:", "Select Column", Type:=8)
Set Column2 = Application.InputBox("Please select column that
     contains the age:", "Select Column", Type:=8)
Set Column3 = Application.InputBox("Please select column that
     contains the serial number:", "Select Column", Type:=8)
Set Column4 = Application.InputBox("Please select column that
     contains the state:", "Select Column", Type:=8)
Set Column5 = Application.InputBox("Please select column that
     denotes Canadian location:", "Select Column", Type:=8)
i = Column1.Row
j = Column1.Row
l = Column1.Column
p = Column1.Rows.Count
m = Column2.Column
n = Column3.Column
q = Column4.Column
r = Column5.Column
While i <= p + 5
     If Cells(i, n).Value = Cells(i - 1, n).Value Then
          If Cells(i, l).Value = Cells(i - 1, l).Value And
               Cells(i, m).Value = Cells(i - 1, m).Value And
               Cells(i, q).Value = Cells(i - 1, q).Value Then
               Cells(i - 1, l).Value = "DELETED"
          End If
     End If
i = i + 1
Wend
While j <= p + 5
     If Cells(j, r).Value = 1 And Cells(j - 1, r).Value = 1 Then
          If Cells(j, l).Value / Cells(j - 1, l).Value <= 1.06
               And Cells(j, l).Value / Cells(j - 1, l).Value >=
               0.94 Then
               If Cells(j, n).Value = Cells(j - 1, n).Value And
                    Cells(j, q).Value = Cells(j - 1, q).Value
                    Then
                    Cells(j - 1, l).Value = "DELETED"
               End If
          ElseIf Cells(j - 1, l).Value / Cells(j, l).Value <=
               1.06 And Cells(j - 1, l).Value / Cells(j,
               l).Value >= 0.94 Then
```

```
               If Cells(j, n).Value = Cells(j - 1, n).Value And
                    Cells(j, q).Value = Cells(j - 1, q).Value
                    Then
                    Cells(j - 1, l).Value = "DELETED"
               End If
          End If
     End If
j = j + 1
Wend
End Sub
```

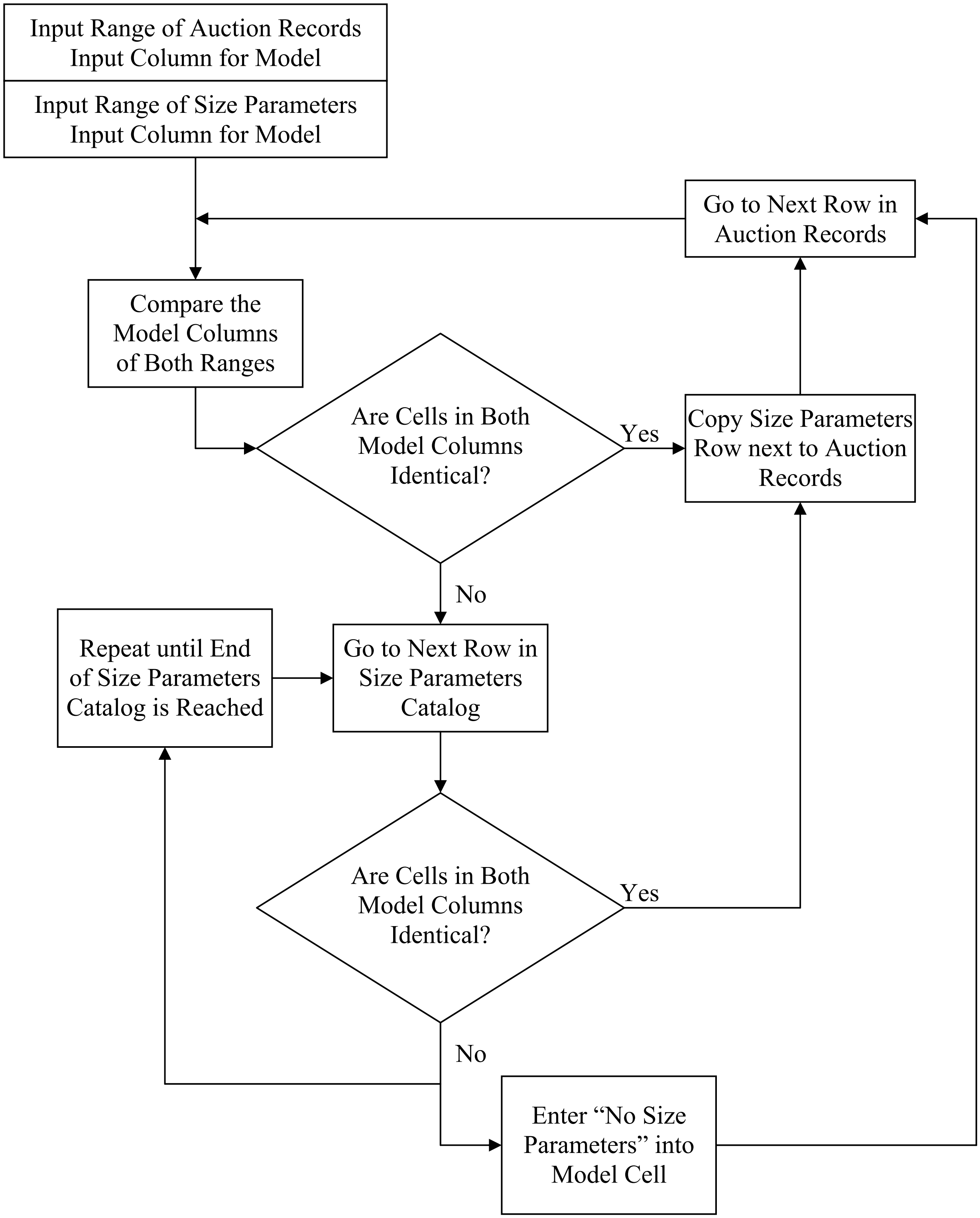
Appendix A.4: Macro *DeleteDoubles* Flowchart



Appendix A.5: Macro *MatchParameters*

```
Sub MatchParameters()
Set rg1 = Application.InputBox("Please enter range of the
      auction records:", "Enter Range", Type:=8)
Set rg1col = Application.InputBox("Please select column
     containing model:", "Select Column", Type:=8)
Set rg2 = Application.InputBox("Please enter range of the size
     parameters:", "Enter Range", Type:=8)
Set rg2col = Application.InputBox("Please select column
     containing model:", "Select Column", Type:=8)
i = rg1.Row
j = rg2.Row
k = rg1.Column
l = rg2.Column
m = rg1col.Column
n = rg2col.Column
rg1long = rg1.Rows.Count
rg2long = rg2.Rows.Count
rg1wide = rg1.Columns.Count
rg2wide = rg2.Columns.Count
While i < rg1.Row + rg1long
     While Cells(i, m).Value > Cells(j, n).Value
          j = j + 1
     Wend
          If j <= rg2.Row + rg2long Then
               If Cells(i, m).Value = Cells(j, n).Value Then
                    Set rg2Row = Range(Cells(j, l), Cells(j, l +
                    rg2wide - 1))
                    rg2Row.Copy Cells(i, k + rg1wide + rg2wide)
               Else
                    Cells(i, k + rg1wide + rg2wide).Value = "NO
                    SIZE PARAMETERS"
               End If
          End If
     i = i + 1
     j = rg2.Row
Wend
End Sub
```

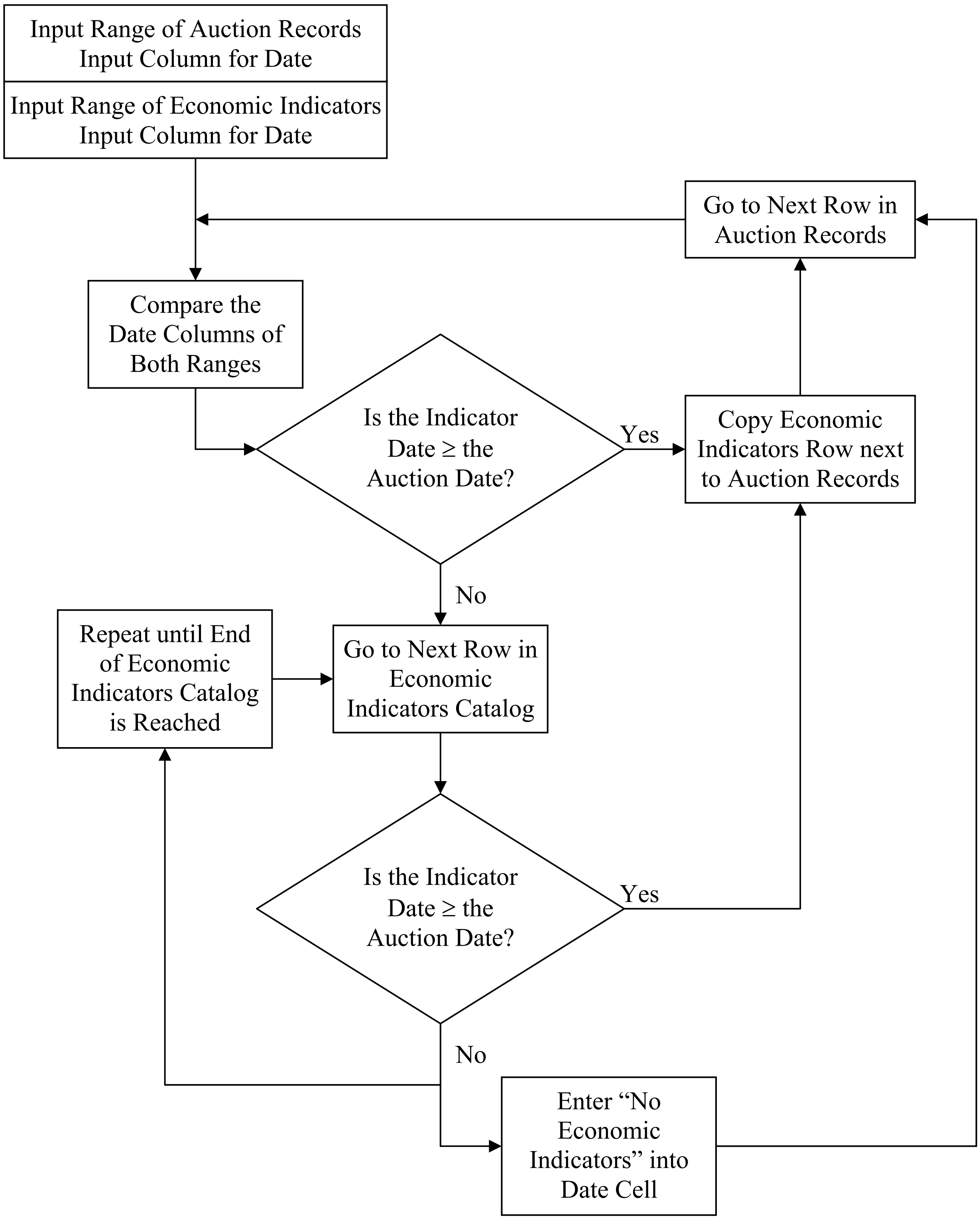
Appendix A.6: Macro *MatchParameters* Flowchart



Appendix A.7: **Macro *MatchEconomy***

```
Sub MatchEconomy()
Set rg1 = Application.InputBox("Please enter range of the
     auction records:", "Enter Range", Type:=8)
Set rg1col = Application.InputBox("Please select column
     containing auction dates:", "Select Column", Type:=8)
Set rg2 = Application.InputBox("Please enter range of the
     economic indicator values:", "Enter Range", Type:=8)
Set rg2col = Application.InputBox("Please select column
     containing economy dates:", "Select Column", Type:=8)
i = rg1.Row
j = rg2.Row
k = rg1.Column
l = rg2.Column
m = rg1col.Column
n = rg2col.Column
rg1long = rg1.Rows.Count
rg2long = rg2.Rows.Count
rg1wide = rg1.Columns.Count
rg2wide = rg2.Columns.Count
While i < rg1.Row + rg1long
     While CDate(Cells(i, m)) > CDate(Cells(j, n))
          j = j + 1
     Wend
          If j <= rg2.Row + rg2long Then
               Set rg2Row = Range(Cells(j, l), Cells(j, l +
               rg2wide - 1))
               rg2Row.Copy Cells(i, k + rg1wide + rg2wide)
          Else
               rg2.Cells(i, k + rg1wide + rg2wide) = "NO
               ECONOMIC INDICATORS"
          End If
     i = i + 1
     j = rg2.Row
Wend
End Sub
```

Appendix A.8: Macro *MatchEconomy* Flowchart



Appendix B: EXCEL Macros and Commands for Residual Value Calculator

Appendix B.1: EXCEL Macros

The following Microsoft® Visual Basic® for Applications 6.3 code for the EXCEL macros was written by Gunnar Lucko. These macros enable the use of clickable buttons for switching to a different spreadsheet and/or active cell location in a spreadsheet.

```
Sub ChangeSheettoMenu()
     Sheets("1 - Residual Value Calculator").Select
     Range("A6").Select
End Sub


Sub SeeRegionList()
     Sheets("2 - Tables").Select
     Range("A109").Select
End Sub


Sub SeeEquipmentClasses()
     Sheets("2 - Tables").Select
     Range("A121").Select
End Sub


Sub SeePPIValues()
     Sheets("3 - Inflation Adjustment").Select
     Range("A1").Select
End Sub


Sub SeeIndicatorValues()
     Sheets("4 - Economic Indicators").Select
     Range("A1").Select
End Sub
```

```
Sub SeeIndicatorDiagrams()
     Sheets("5 - Indicator Diagrams").Select
     Range("A1").Select
End Sub
```

Appendix B.2: Excel Commands

The following Microsoft® EXCEL commands and cell formats were particularly used in the Residual Value Calculator. Programming code is indicated by the font. To see their functioning refer to the actual EXCEL file.

Looking Up Values

```
=VLOOKUP(B9,'2 - Tables'!C8:AE35,2,FALSE)
```

This command allows finding and displaying a value from a particular column of a table, depending on the row of the table chosen by the user.

Drop-Down Menus

Data/Validation/Validation criteria:
Allow: *List*
Source: =$K$3:$K$30

This command allows creating a drop-down menu in a cell containing a list of clickable options. Note: The validation list has to be located in the same spreadsheet as the drop-down cell.

Active Row Indicator

Enter the following command into all row header cells of the list:
`=IF('1 - Residual Value Calculator'!$B$9=C8,"Active",0)`
and set up conditional formatting for all row header cells as follows:
IF `Cell Value equal to ="Active"` THEN Format/Patterns/Cell shading:
Color: *Red*

This command allows having a row header cell light up in red when the respective row in the table is selected by the user.

Appendix C: SAS® Codes for Data Analysis

The following SAS® version 8.02 codes for the statistical analysis were written by Gunnar Lucko. Comments are denoted by a preceding asterisk.

Appendix C.1: Correlation of Macroeconomic Indicators

```
options center ls=74;
title "Correlation of Macroeconomic Indicators";
data ECONOMY;
input LEADG CCI BCI WTR SWR HWY TTLCNST INDPRD STLPRD INTRST CPI
     PPI PPIMIN PPIME ATSLS HMSLS HMSTS Northeast Midwest South
     West Canada GDSTRD TTLTRD TTLINV RTLSLS SP NSDQ EMPLY EMPLC
     ECICOMP OUTHR GDP CNSCRNF CNSCR SVGS SVGS2 CHCK TNR;
datalines;
     . . .
     [Actual data lines omitted]
     . . .
;
proc corr;
     var LEADG CCI BCI WTR SWR HWY TTLCNST INDPRD STLPRD INTRST
          CPI PPI PPIMIN PPIME ATSLS HMSLS HMSTS Northeast
          Midwest South West Canada GDSTRD TTLTRD TTLINV RTLSLS
          SP NSDQ EMPLY EMPLC ECICOMP OUTHR GDP CNSCRNF CNSCR
          SVGS SVGS2 CHCK TNR;
run;
quit;
```

Appendix C.2: Selection of Statistical Model

```
options center ls=74;
title "Statistical Model Selection";
data ALLDATASET;
input number type make size cond loc m1 m2 m3 age c1 c2 c3 r1 r2
     r3 RVP LEADG CCI BCI WTR SWR HWY TTLCNST INTRST CPI PPI
     INDPRD SP STLPRD NSDQ HMSLS ATSLS HMSTS EMPLY EMPLC PPIMIN
     PPIME GDSTRD TTLTRD TTLINV RTLSLS RGHMSTS ECICOMP OUTHR GDP
     CNSCRNF CNSCR SVGS SVGS2 CHCK TNR;
X2age=age**2;
X3age=age**3;
IEXage=exp(-age);
Iage=1/(age);
ISQage=1/sqrt(age);
LOGage=log(age);
datalines;
     . . .
     [Actual data lines omitted]
     . . .
;
proc reg;
     title "1. Model age";
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 age;
proc rsreg;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 age / press;
proc reg;
     title "2. Model age^2";
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age;
proc rsreg;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age / press;
proc reg;
     title "3. Model age^2, age";
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age;
proc rsreg;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age / press;
          * Note: This model selected as best;
proc reg;
     title "4. Model age^3";
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X3age;
proc rsreg;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X3age / press;
proc reg;
     title "5. Model age^3, age";
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X3Age age;
```

```
proc rsreg;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X3Age age / press;
proc reg;
     title "6. Model age^3, age^2";
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X3Age X2age;
proc rsreg;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X3Age X2age / press;
proc reg;
     title "7. Model age^3, age^2, age";
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X3age X2age age;
proc rsreg;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X3age X2age age /
          press;
proc reg;
     title "8. Model e^(-age)";
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 IEXage;
proc rsreg;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 IEXage / press;
proc reg;
     title "9. Model log(age)";
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 LOGage;
proc rsreg;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 LOGage / press;
proc reg;
     title "10. Model age^(-1)";
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 Iage;
proc rsreg;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 Iage / press;
proc reg;
     title "11. Model age^(-1/2)";
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 ISQage;
proc rsreg;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 ISQage / press;
run;
quit;
```

Appendix C.3: Data Plots and Identification of Outliers

```
options center ls=74;
title "Data Plots and Outlier Identification";
data ALLDATASET;
input number type make size cond loc m1 m2 m3 age c1 c2 c3 r1 r2
     r3 RVP LEADG CCI BCI WTR SWR HWY TTLCNST INTRST CPI PPI
     INDPRD SP STLPRD NSDQ HMSLS ATSLS HMSTS EMPLY EMPLC PPIMIN
     PPIME GDSTRD TTLTRD TTLINV RTLSLS RGHMSTS ECICOMP OUTHR GDP
     CNSCRNF CNSCR SVGS SVGS2 CHCK TNR;
X2age=age**2;
datalines;
     . . .
     [Actual data lines omitted]
     . . .
;
proc means;
proc corr;
     var m1 m2 m3 age c1 c2 c3 r1 r2 r3 RVP;
proc plot;
     plot RVP*X2age RVP*age RVP*m1 RVP*m2 RVP*m3 RVP*c1 RVP*c2
          RVP*c3 RVP*r1 RVP*r2 RVP*r3;
proc reg;
     title "3. Model age^2, age";
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age;
     output out=out1 RESIDUAL=ei1 RSTUDENT=ti1 STUDENT=ri1
          PREDICTED=pred1;
proc print;
     var ei1 ri1 ti1 pred1;
proc plot;
     plot ti1*pred1 ti1*X2age ti1*age ti1*m1 ti1*m2 ti1*m3
          ti1*c1 ti1*c2 ti1*c3 ti1*r1 ti1*r2 ti1*r3;
proc univariate noprint;
     qqplot ei1 / normal;
run;
quit;
```

Appendix C.4: Calculation of Coefficients for Plain Models

```
options center ls=74;
title "Coefficients for Plain Models";
data EXCSIZE1;
input number type make size cond loc m1 m2 m3 age c1 c2 c3 r1 r2
     r3 RVP LEADG CCI BCI WTR SWR HWY TTLCNST INTRST CPI PPI
     INDPRD SP STLPRD NSDQ HMSLS ATSLS HMSTS EMPLY EMPLC PPIMIN
     PPIME GDSTRD TTLTRD TTLINV RTLSLS RGHMSTS ECICOMP OUTHR GDP
     CNSCRNF CNSCR SVGS SVGS2 CHCK TNR;
X2age=age**2;
datalines;
     . . .
     [Actual data lines omitted]
     . . .
;
proc means;
proc reg;
     title "3. Model age^2, age";
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age / vif;
          * Note: Coefficients taken from this model;
proc means;
     var age;
run;
quit;
```

Appendix C.5: Calculation of Coefficients for Best Models

```
options center ls=74;
title "Coefficients for Best Models";
data EXCSIZE1;
input number type make size cond loc M1 M2 M3 age R1 R2 R3 reg1
     reg2 reg3 RVP LEADG CCI BCI WTR SWR HWY TTLCNST INTRST CPI
     PPI INDPRD SP STLPRD NSDQ HMSLS ATSLS HMSTS EMPLY EMPLC
     PPIMIN PPIME GDSTRD TTLTRD TTLINV RTLSLS RGHMSTS ECICOMP
     OUTHR GDP CNSCRNF CNSCR SVGS SVGS2 CHCK TNR;
X2age=age**2;
datalines;
     . . .
     [Actual data lines omitted]
     . . .
;
proc reg;
     model RVP = m1 m2 m3 c1 C2 c3 r1 r2 r3 X2age age LEADG CCI
          / vif;
     . . .
     [Combinations of all macroeconomic indicators omitted]
     . . .
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age CHCK TNR /
          vif;
run;
quit;
```

Appendix C.6: Calculation of Coefficients for Trade Journal Models

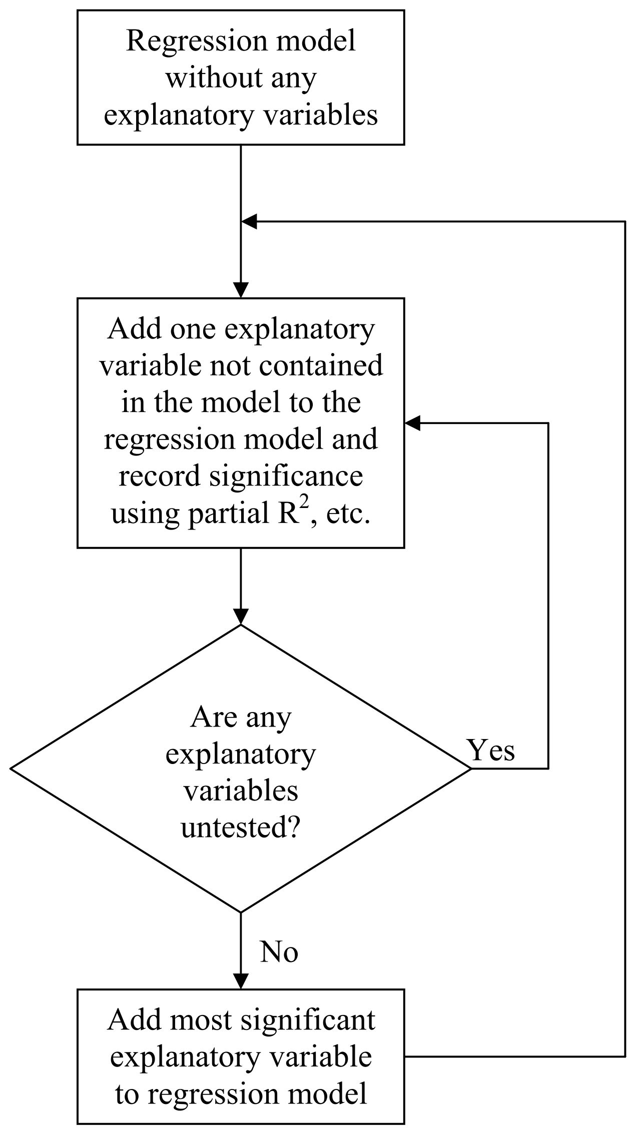
```
options center ls=74;
title "Coefficients for Trade Journal Models";
data EXCSIZE1;
input number type make size cond loc m1 m2 m3 age c1 c2 c3 r1 r2
     r3 RVP LEADG CCI BCI WTR SWR HWY TTLCNST INTRST CPI PPI
     INDPRD SP STLPRD NSDQ HMSLS ATSLS HMSTS EMPLY EMPLC PPIMIN
     PPIME GDSTRD TTLTRD TTLINV RTLSLS RGHMSTS ECICOMP OUTHR GDP
     CNSCRNF CNSCR SVGS SVGS2 CHCK TNR;
X2age=age**2;
datalines;
     . . .
     [Actual data lines omitted]
     . . .
;
proc reg;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age WTR SWR /
          vif;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age WTR HWY /
          vif;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age WTR
          TTLCNST / vif;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age WTR INTRST
          / vif;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age WTR PPIME
          / vif;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age WTR HMSTS
          / vif;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age WTR EMPLC
          / vif;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age WTR GDP /
          vif;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age SWR HWY /
          vif;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age SWR
          TTLCNST / vif;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age SWR INTRST
          / vif;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age SWR PPIME
          / vif;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age SWR HMSTS
          / vif;
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age SWR EMPLC
          / vif;
```

```
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age SWR GDP /
           vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age HWY
           TTLCNST / vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age HWY INTRST
           / vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age HWY PPIME
           / vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age HWY HMSTS
           / vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age HWY EMPLC
           / vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age HWY GDP /
           vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age TTLCNST
           INTRST / vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age TTLCNST
           PPIME / vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age TTLCNST
           HMSTS / vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age TTLCNST
           EMPLC / vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age TTLCNST
           GDP / vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age INTRST
           PPIME / vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age INTRST
           HMSTS / vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age INTRST
           EMPLC / vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age INTRST GDP
           / vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age PPIME
           HMSTS / vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age PPIME
           EMPLC / vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age PPIME GDP
           / vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age HMSTS
           EMPLC / vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age HMSTS GDP
           / vif;
      model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age EMPLC GDP
           / vif;
run;
quit;
```

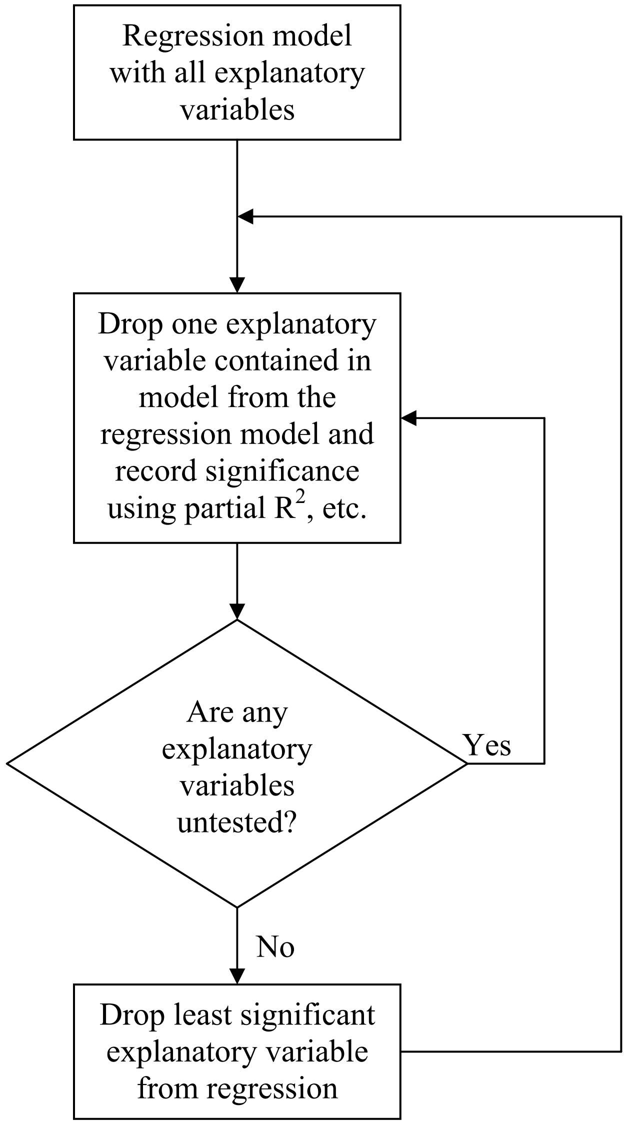
Appendix C.7: Validation of Plain Models

```
options center ls=74;
title "Validation for Plain Models";
data EXCSIZE1;
input number type make size cond loc m1 m2 m3 age c1 c2 c3 r1 r2
     r3 RVP LEADG CCI BCI WTR SWR HWY TTLCNST INTRST CPI PPI
     INDPRD SP STLPRD NSDQ HMSLS ATSLS HMSTS EMPLY EMPLC PPIMIN
     PPIME GDSTRD TTLTRD TTLINV RTLSLS RGHMSTS ECICOMP OUTHR GDP
     CNSCRNF CNSCR SVGS SVGS2 CHCK TNR;
X2age=age**2;
datalines;
     . . .
     [Actual data lines omitted]
     . . .
;
proc reg;
     title "Coefficients for Plain Models";
     model RVP = m1 m2 m3 c1 c2 c3 r1 r2 r3 X2age age / vif;
          * Note: Coefficients taken from this model;
run;
quit;
```

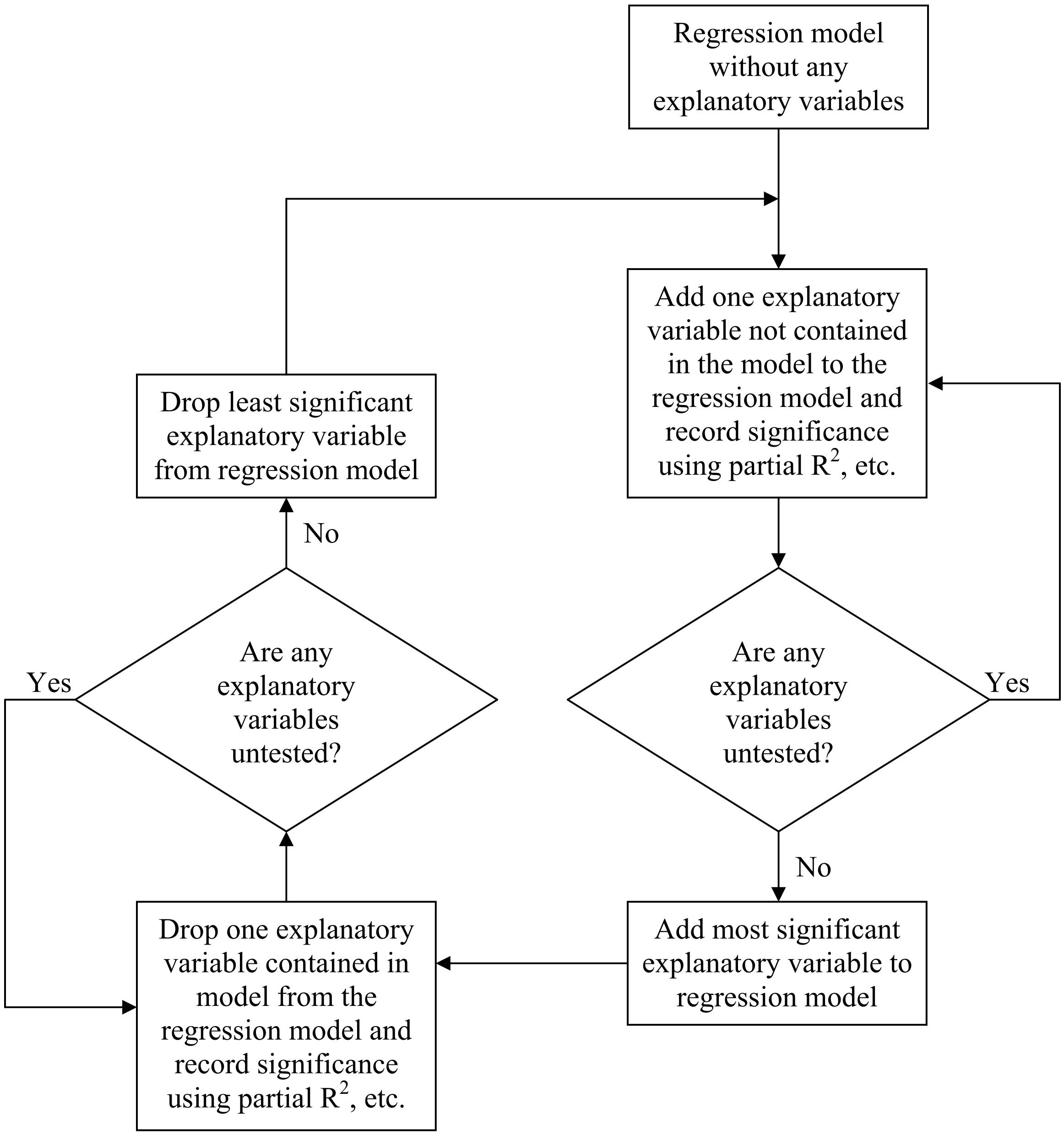
Appendix C.8: Forward Selection Flowchart



Appendix C.9: Backward Elimination Flowchart



Appendix C.10: Stepwise Selection Flowchart



Appendix D: Detailed List of Macroeconomic Indicators

Number	Abbreviation	Name	Frequency	Original Source	Unit
1	LEADG	Weekly Leading Index	weekly	Economic Cycle Research Institute	1992 = 100
2	CCI	Construction Cost Index	monthly	Engineering News Record	N/A
3	BCI	Building Cost Index	monthly	Engineering News Record	N/A
4	WTR	Construction Put in Place (C30) - Table 5b: Public - Water supply facilities	monthly	Bureau of the Census	Bil. 96$, SAAR
5	SWR	Construction Put in Place (C30) - Table 5b: Public - Sewer systems	monthly	Bureau of the Census	Bil. 96$, SAAR
6	HWY	Construction Put in Place (C30) - Table 5b: Construction put in place: Public - Highways and streets	monthly	Bureau of the Census	Bil. 96$, SAAR
7	TTLCNST	Construction Put in Place (C30) - Table 5b: Total	monthly	Bureau of the Census	Bil. 96$, SAAR
8	INDPRD	Industrial Production (G.17): Construction Supplies	monthly	Federal Reserve Board	1992=100, SA
9	STLPRD	Industrial Production (G.17): Construction Steel SIC=331PT	monthly	Federal Reserve Board	1992=100, SA
10	INTRST	Interest Rates (H15): 10-Year Constant Maturity Securities	monthly	Federal Reserve Board	% p.a.
11	CPI	CPI (CUSR0000SA0): Urban Consumer - All items	monthly	Bureau of Labor Statistics	1982-84=100, SA
12	PPI	PPI (WPSSOP3000): Finished goods	monthly	Bureau of Labor Statistics	1982=100, SA
13	PPIMIN	PPI (WPS132101): Nonmetallic mineral products - Construction sand/gravel/crushed stone	monthly	Bureau of Labor Statistics	1982=100, SA
14	PPIME	PPI (WPS112): Machinery and equipment - Construction machinery and equipment	monthly	Bureau of Labor Statistics	1982=100, SA
15	ATSLS	Production, Exports and Inventories: Auto and Truck Sales: Auto Sales: Domestic	monthly	Bureau of Economic Analysis	Ths., SA
16	HMSLS	New Home Sales (C25): New single-family houses sold	monthly	Bureau of the Census	Ths., SAAR
17	HMSTS	Housing Starts and Building Permits (C20): Housing Starts: Total privately owned	monthly	Bureau of the Census	Ths., SAAR
18	RGHMSTS	New Privately Owned Housing Units Started (Seasonally Adjusted Annual Rate) and Table 027-0002: Housing starts, under construction and completions, seasonally adjusted; Canada; Total units	monthly for all regions	Bureau of the Census and Statistics Canada	Ths., SAAR

Appendix D (Continued): Detailed List of Macroeconomic Indicators

Number	Abbreviation	Name	Frequency	Original Source	Unit
19	GDSTRD	International Trade in Goods & Services - Exhibit 5: Trade: Balance - Goods	monthly	Bureau of the Census	Mil. $, SA
20	TTLTRD	International Trade in Goods & Services - Exhibit 1: Trade: Balance - Total	monthly	Bureau of the Census	Mil. $, SA
21	TTLINV	Shipments Inventories and Orders (M3) - NAICS version: Total Inventories - Manufacturing Excluding Defense	monthly	Bureau of the Census	Mil. $, SA
22	RTLSLS	Retail Sales: Total	monthly	Bureau of the Census	Mil. $, SA
23	SP	S&P Stock Price Index: 500 Composite	monthly	Standard & Poor's	1941-43=10
24	NSDQ	Nasdaq: Composite Index	monthly	The Nasdaq Stock Market, Inc.	N/A
25	EMPLY	Form 790 (EES00000001 (n)): Employment: Total Nonfarm	monthly	Bureau of Labor Statistics	Ths., SA
26	EMPLC	Form 790 (EES20000001 (n)): Employment: Construction	monthly	Bureau of Labor Statistics	Ths., SA
27	ECICOMP	Employment Cost Index (ECS12302I): Compensation - Private industry - Construction Industry workers	quarterly	Bureau of Labor Statistics	June 1989 =100, SA
28	OUTHR	Productivity & Costs (PRS85006093): Nonfarm Business - Output Per Hour All persons	quarterly	Bureau of Labor Statistics	1992=100
29	GDP	Table 1.9 Line 1: NIPA: Gross domestic product	quarterly	Bureau of Economic Analysis	Bil. $, SAAR, nominal
30	CNSCRNF	Flow of Funds Accounts (Release Z.1, Table B.102, Line 16): Balance Sheet of Nonfarm Nonfinancial Corporate Business: Consumer credit	quarterly	Federal Reserve Board	Bil. $, NSA
31	CNSCR	Flow of Funds Accounts (Release Z.1, Table F.222, Line 3): Consumer Credit: Nonfinancial corporate business	quarterly	Federal Reserve Board	Mil. $, SAAR
32	SVGS	Flow of Funds Accounts (Release Z.1, Table B.102, Line 9): Balance Sheet of Nonfarm Nonfinancial Corporate Business: Time and savings deposits	quarterly	Federal Reserve Board	Bil. $, NSA
33	SVGS2	Flow of Funds Accounts (Release Z.1, Table F.205, Line 19): Nonfarm Nonfinancial Corporate Business: Time and savings deposits	quarterly	Federal Reserve Board	Mil. $, SAAR
34	CHCK	Flow of Funds Accounts (Release Z.1, Table F.204, Line 15): Checkable Deposits and Currency: Corporate	quarterly	Federal Reserve Board	Mil. $, SAAR
35	TNR	Turner Building Cost Index	quarterly	Turner Construction Company	N/A

Note: Links to the Web sites of the sources are provided in the Residual Value Calculator.

Appendix E: Correlation between Macroeconomic Indicators

Name	CCI	BCI	WTR	SWR	HWY	TTLCNST	INDPRD	STLPRD	INTRST	CPI	PPI	PPIMIN	PPIME
LEADG	0.97	0.98	0.67	-0.12	0.93	0.95	0.95	0.75	-0.90	0.97	0.95	0.97	0.97
CCI		1.00	0.64	-0.24	0.91	0.94	0.94	0.75	-0.88	0.99	0.98	0.99	0.99
BCI			0.64	-0.25	0.91	0.94	0.94	0.76	-0.88	0.99	0.98	0.99	0.99
WTR				0.24	0.71	0.76	0.63	0.54	-0.66	0.68	0.66	0.66	0.72
SWR					-0.04	-0.08	-0.15	-0.36	-0.05	-0.20	-0.21	-0.20	-0.24
HWY						0.95	0.90	0.72	-0.87	0.93	0.90	0.92	0.92
TTLCNST							0.94	0.79	-0.88	0.95	0.93	0.96	0.96
INDPRD								0.82	-0.83	0.92	0.88	0.94	0.90
STLPRD									-0.56	0.74	0.69	0.74	0.90
INTRST										-0.89	-0.87	-0.89	-0.88
CPI											0.99	0.99	1.00
PPI												0.98	0.99
PPIMIN													0.98
PPIME													
ATSLS													
HMSLS													
HMSTS													
Northeast													
Midwest													
South													
West													
Canada													
GDSTRD													
TTLTRD													
TTLINV													
RTLSLS													
SP													
NSDQ													
EMPLY													
EMPLC													
ECICOMP													
OUTHR													
GDP													
CNSCRNF													
CNSCR													
SVGS													
SVGS2													
CHCK													

Appendix E (Continued): Correlation between Macroeconomic Indicators

Name	ATSLS	HMSLS	HMSTS	Northeast	Midwest	South	West	Canada	GDSTRD	TTLTRD	TTLINV	RTLSLS
LEADG	-0.04	0.79	0.25	-0.17	0.76	0.06	0.24	0.19	-0.84	-0.76	0.91	0.88
CCI	-0.10	0.79	0.24	-0.21	0.72	0.11	0.20	0.43	-0.93	-0.91	0.86	0.99
BCI	-0.09	0.79	0.24	-0.21	0.72	0.12	0.20	0.37	-0.91	-0.88	0.88	0.97
WTR	-0.26	0.40	-0.19	-0.31	0.46	-0.33	-0.17	0.32	-0.14	-0.16	0.24	0.27
SWR	0.17	-0.19	-0.13	0.29	0.06	-0.44	0.10	-0.11	0.71	0.64	-0.53	-0.61
HWY	-0.01	0.72	0.20	-0.16	0.75	0.00	0.19	0.33	-0.72	-0.64	0.61	0.71
TTLCNST	-0.13	0.76	0.16	-0.22	0.72	0.00	0.13	0.48	-0.90	-0.86	0.77	0.92
INDPRD	0.00	0.86	0.37	-0.05	0.76	0.17	0.34	0.30	-0.94	-0.88	0.93	0.97
STLPRD	-0.12	0.65	0.20	-0.32	0.53	0.21	0.09	0.24	-0.86	-0.78	0.86	0.90
INTRST	0.03	-0.76	-0.23	0.07	-0.77	0.02	-0.26	-0.40	0.70	0.62	-0.51	-0.66
CPI	-0.13	0.75	0.16	-0.27	0.71	0.02	0.14	0.42	-0.93	-0.92	0.87	0.99
PPI	-0.15	0.69	0.11	-0.31	0.67	-0.01	0.09	0.38	-0.93	-0.91	0.88	0.96
PPIMIN	-0.11	0.79	0.23	-0.18	0.72	0.07	0.21	0.46	-0.96	-0.94	0.84	1.00
PPIME	-0.27	0.69	-0.01	-0.49	0.67	-0.04	-0.06	0.32	-0.90	-0.88	0.91	0.98
ATSLS		0.17	0.48	0.51	0.17	0.30	0.56	-0.57	0.13	0.32	-0.04	-0.24
HMSLS			0.67	0.19	0.75	0.48	0.60	0.42	-0.86	-0.81	0.79	0.90
HMSTS				0.64	0.55	0.85	0.89	0.25	-0.78	-0.71	0.76	0.83
Northeast					0.16	0.33	0.66	0.38	-0.57	-0.58	0.46	0.59
Midwest						0.24	0.49	0.28	-0.55	-0.38	0.33	0.44
South							0.59	0.21	-0.78	-0.69	0.75	0.82
West								0.19	-0.67	-0.62	0.70	0.72
Canada									-0.49	-0.54	0.03	0.39
GDSTRD										0.99	-0.80	-0.96
TTLTRD											-0.75	-0.94
TTLINV												0.88
RTLSLS												
SP												
NSDQ												
EMPLY												
EMPLC												
ECICOMP												
OUTHR												
GDP												
CNSCRNF												
CNSCR												
SVGS												
SVGS2												
CHCK												

Appendix E (Continued): Correlation between Macroeconomic Indicators

Name	SP	NSDQ	EMPLY	EMPLC	ECICOMP	OUTHR	GDP	CNSCRNF	CNSCR	SVGS	SVGS2	CHCK	TNR
LEADG	0.91	0.82	0.98	0.89	0.96	0.96	0.97	0.88	-0.12	0.82	0.14	0.09	0.88
CCI	0.90	0.80	0.98	0.88	1.00	0.98	0.99	0.84	-0.16	0.88	0.13	0.05	0.98
BCI	0.91	0.81	0.98	0.88	0.99	0.98	0.99	0.84	-0.16	0.87	0.13	0.06	0.96
WTR	0.61	0.47	0.70	0.61	0.67	0.66	0.68	0.61	-0.15	0.48	0.03	0.02	0.27
SWR	-0.31	-0.35	-0.16	-0.14	-0.22	-0.22	-0.23	-0.01	0.11	-0.34	-0.20	0.06	-0.65
HWY	0.83	0.74	0.93	0.85	0.92	0.92	0.92	0.87	-0.07	0.77	0.14	0.05	0.74
TTLCNST	0.90	0.80	0.97	0.91	0.96	0.97	0.97	0.82	-0.15	0.86	0.14	0.03	0.93
INDPRD	0.94	0.86	0.97	0.98	0.94	0.96	0.96	0.78	-0.11	0.89	0.15	0.06	0.96
STLPRD	0.84	0.78	0.80	0.81	0.78	0.79	0.80	0.58	-0.13	0.74	0.20	0.02	0.90
INTRST	-0.75	-0.63	-0.88	-0.77	-0.88	-0.88	-0.87	-0.82	0.12	-0.73	-0.10	-0.07	-0.74
CPI	0.89	0.78	0.98	0.87	0.99	0.98	0.99	0.87	-0.16	0.85	0.12	0.04	0.99
PPI	0.86	0.76	0.96	0.82	0.98	0.95	0.97	0.88	-0.16	0.82	0.11	0.04	0.96
PPIMIN	0.91	0.80	0.98	0.90	1.00	0.99	0.99	0.83	-0.17	0.90	0.13	0.03	0.99
PPIME	0.90	0.79	0.97	0.84	0.98	0.96	0.98	0.84	-0.18	0.79	0.14	0.01	0.96
ATSLS	-0.14	-0.09	-0.10	-0.02	-0.12	-0.11	-0.13	0.01	0.16	-0.13	0.00	0.12	-0.17
HMSLS	0.80	0.72	0.78	0.84	0.78	0.82	0.79	0.53	-0.14	0.81	0.13	0.10	0.90
HMSTS	0.27	0.27	0.20	0.35	0.20	0.26	0.21	0.03	0.04	0.36	0.10	0.12	0.82
Northeast	-0.20	-0.17	-0.21	-0.03	-0.25	-0.18	-0.24	-0.27	0.15	-0.05	-0.03	0.05	0.61
Midwest	0.63	0.56	0.72	0.69	0.71	0.73	0.71	0.65	-0.04	0.62	0.08	0.09	0.53
South	0.20	0.23	0.03	0.17	0.07	0.12	0.08	-0.17	-0.01	0.25	0.12	0.07	0.81
West	0.19	0.18	0.18	0.35	0.17	0.22	0.17	0.07	0.05	0.30	0.05	0.13	0.75
Canada	0.25	0.17	0.27	0.34	0.51	0.54	0.43	-0.67	-0.12	0.59	0.03	-0.09	0.45
GDSTRD	-0.89	-0.82	-0.94	-0.94	-0.95	-0.96	-0.96	-0.12	0.13	-0.95	-0.18	0.06	-0.97
TTLTRD	-0.82	-0.75	-0.89	-0.91	-0.95	-0.95	-0.93	0.14	0.14	-0.96	-0.17	0.14	-0.94
TTLINV	0.91	0.81	0.95	0.92	0.81	0.79	0.88	0.23	-0.18	0.71	0.18	0.01	0.86
RTLSLS	0.89	0.76	0.98	0.98	0.99	0.98	1.00	-0.02	-0.20	0.94	0.20	-0.08	0.99
SP		0.95	0.93	0.93	0.91	0.93	0.93	0.70	-0.13	0.87	0.22	0.06	0.91
NSDQ			0.84	0.86	0.80	0.83	0.83	0.62	-0.06	0.80	0.25	0.06	0.77
EMPLY				0.94	0.98	0.98	0.99	0.86	-0.14	0.87	0.14	0.05	0.98
EMPLC					0.89	0.92	0.92	0.68	-0.16	0.90	0.15	0.02	0.98
ECICOMP						0.99	1.00	0.83	-0.18	0.89	0.13	0.03	0.99
OUTHR							0.99	0.79	-0.17	0.92	0.14	0.02	0.98
GDP								0.82	-0.18	0.90	0.14	0.03	0.99
CNSCRNF									0.02	0.57	0.13	0.09	0.01
CNSCR										-0.20	-0.08	0.03	-0.18
SVGS											0.23	-0.03	0.95
SVGS2												-0.02	0.16
CHCK													-0.07

Appendix F: Auction Records

Appendix F.1: List of Datasets with Outliers

Equipment Type	Number	Size from	Size to	Unit	Size Parameter	Entries from each Manufacturer				Total
						Caterpillar	Deere	Komatsu	Volvo	
Track Excavators	1	0	24,999	lbs	Standard Operating Weight	77	8	22	0	107
	2	25,000	49,999			590	218	1093	0	1901
	3	50,000	74,999			289	87	55	0	431
	4	75,000	99,999			398	28	44	0	470
	5	100,000	Open			0	5	58	0	63
Wheel Excavators	6	All	All	lbs	Standard Operating Weight	114	129	25	0	268
Wheel Loaders	7	0	1.9	CY	General Purpose Bucket Size	68	240	132	55	495
	8	2	3.9			236	2211	1002	444	3893
	9	4	5.9			372	106	1021	219	1718
	10	6	Open			214	0	142	88	444
Track Loaders	11	0	1.9	CY	General Purpose Bucket Size	45	461	62	0	568
	12	2	Open			138	251	270	0	659
Backhoe Loaders	13	0	0.9	CY	General Purpose Bucket Size (of backhoe)	0	230	0	0	230
	14	1	Open			186	7359	45	0	7590
Integrated Toolcarriers	15	All	All	HP	Net HP (flywheel)	289	48	0	0	337
Rigid Frame Trucks	16	0	99,999	lbs	Standard Operating Weight (empty)	332	0	21	0	353
	17	100,000	Open			105	0	2	0	107
Articulated Trucks	18	0	49,999	lbs	Standard Operating Weight (empty)	652	0	69	947	1668
	19	50,000	Open			404	0	0	573	977
Track Dozers	20	0	99	HP	Net HP (flywheel)	0	3652	1723	0	5375
	21	100	199			1904	1259	1491	0	4654
	22	200	299			52	0	240	0	292
	23	300	399			235	0	130	0	365
	24	400	Open			49	0	77	0	126
Motor Graders	25	0	149	HP	Net HP (flywheel)	333	367	0	0	700
	26	150	Open			321	478	0	0	799
Wheel Tractor Scrapers	27	0	74,999	lbs	Standard Operating Weight (empty)	623	164	0	0	787
	28	75,000	Open			165	0	0	0	165
Sum	N/A	N/A	N/A	N/A	N/A	8191	17301	7724	2326	35542

Appendix F.2: List of Datasets without Outliers

Equipment Type	Number	Size from	Size to	Unit	Size Parameter	Entries from each Manufacturer				Total
						Caterpillar	Deere	Komatsu	Volvo	
Track Excavators	1	0	24,999	lbs	Standard Operating Weight	76	8	22	0	106
	2	25,000	49,999			584	216	1088	0	1888
	3	50,000	74,999			286	87	54	0	427
	4	75,000	99,999			395	28	42	0	465
	5	100,000	Open			0	5	58	0	63
Wheel Excavators	6	All	All	lbs	Standard Operating Weight	114	129	25	0	268
Wheel Loaders	7	0	1.9	CY	General Purpose Bucket Size	68	238	131	53	490
	8	2	3.9			233	2195	996	433	3857
	9	4	5.9			364	104	1009	218	1695
	10	6	Open			210	0	142	88	440
Track Loaders	11	0	1.9	CY	General Purpose Bucket Size	44	456	62	0	562
	12	2	Open			130	245	270	0	645
Backhoe Loaders	13	0	0.9	CY	General Purpose Bucket Size (of backhoe)	0	226	0	0	226
	14	1	Open			176	7311	43	0	7530
Integrated Toolcarriers	15	All	All	HP	Net HP (flywheel)	286	47	0	0	333
Rigid Frame Trucks	16	0	99,999	lbs	Standard Operating Weight (empty)	329	0	21	0	350
	17	100,000	Open			104	0	2	0	106
Articulated Trucks	18	0	49,999	lbs	Standard Operating Weight (empty)	648	0	69	941	1658
	19	50,000	Open			403	0	0	567	970
Track Dozers	20	0	99	HP	Net HP (flywheel)	0	3610	1710	0	5320
	21	100	199			1868	1250	1476	0	4594
	22	200	299			51	0	239	0	290
	23	300	399			233	0	130	0	363
	24	400	Open			48	0	77	0	125
Motor Graders	25	0	149	HP	Net HP (flywheel)	333	364	0	0	697
	26	150	Open			317	473	0	0	790
Wheel Tractor Scrapers	27	0	74,999	lbs	Standard Operating Weight (empty)	618	163	0	0	781
	28	75,000	Open			163	0	0	0	163
Sum	N/A	N/A	N/A	N/A	N/A	8081	17155	7666	2300	35202

Appendix G: Coefficients and Statistics

Appendix G.1: Statistics for Regression Models

Number	Regression Model 1 age				Regression Model 2 age^2				Regression Model 3 age^2, age				Regression Model 4 age^3			
	R^2	R^2_{adj}	Root MSE	PRESS	R^2	R^2_{adj}	Root MSE	PRESS	R^2	R^2_{adj}	Root MSE	PRESS	R^2	R^2_{adj}	Root MSE	PRESS
1	0.7334	0.7084	0.0826	0.975	0.6252	0.5901	0.0980	2.345	0.7934	0.7717	0.0731	28.774	0.5716	0.5315	0.1048	11.412
2	0.6502	0.6485	0.0753	8.802	0.5800	0.5780	0.0825	9.710	0.6892	0.6875	0.0710	8.695	0.5350	0.5328	0.0868	10.994
3	0.6034	0.5947	0.0699	2.101	0.5321	0.5219	0.0759	2.269	0.6191	0.6099	0.0686	2.212	0.4494	0.4374	0.0823	4.106
4	0.6177	0.6101	0.0728	2.319	0.5261	0.5167	0.0811	2.633	0.6427	0.6348	0.0705	2.440	0.4452	0.4341	0.0877	3.547
5	0.7259	0.6853	0.0580	0.548	0.6757	0.6276	0.0631	0.894	0.7500	0.7075	0.0559	0.711	0.6292	0.5743	0.0675	1.917
6	0.6971	0.6865	0.0928	2.161	0.6383	0.6257	0.1014	2.335	0.7495	0.7398	0.0846	2.151	0.6129	0.5994	0.1049	2.577
7	0.6155	0.6074	0.0814	3.629	0.5746	0.5657	0.0856	3.816	0.6286	0.6201	0.0800	3.501	0.5366	0.5269	0.0893	4.072
8	0.6745	0.6736	0.0916	26.991	0.5995	0.5985	0.1016	31.797	0.7163	0.7155	0.0855	25.832	0.5455	0.5443	0.1082	36.736
9	0.8052	0.8039	0.0721	6.344	0.7564	0.7549	0.0807	8.137	0.8455	0.8444	0.0643	6.021	0.7253	0.7235	0.0857	10.514
10	0.8427	0.8393	0.0767	1.690	0.7967	0.7923	0.0872	2.238	0.8957	0.8932	0.0625	1.653	0.7765	0.7717	0.0914	2.782
11	0.6798	0.6747	0.0645	2.184	0.6281	0.6221	0.0696	2.428	0.7111	0.7059	0.0614	2.231	0.5891	0.5824	0.0731	2.766
12	0.8650	0.8631	0.0684	1.970	0.8563	0.8542	0.0706	2.110	0.8861	0.8843	0.0629	1.968	0.8535	0.8514	0.0713	2.330
13	0.1754	0.1494	0.0546	0.718	0.1549	0.1282	0.0552	0.708	0.2053	0.1765	0.0537	0.788	0.1423	0.1152	0.0557	0.696
14	0.6098	0.6093	0.0900	48.578	0.5206	0.5200	0.0997	58.330	0.6630	0.6626	0.0836	45.278	0.4566	0.4559	0.1062	67.502
15	0.7114	0.7042	0.0886	2.482	0.6183	0.6088	0.1018	2.997	0.7731	0.7667	0.0787	2.656	0.5472	0.5360	0.1109	3.641
16	0.4977	0.4860	0.0929	2.882	0.4500	0.4372	0.0972	3.073	0.5239	0.5114	0.0906	2.910	0.4133	0.3997	0.1004	3.254
17	0.7159	0.6927	0.0579	0.329	0.6577	0.6298	0.0636	0.386	0.7244	0.6989	0.0573	0.295	0.5906	0.5572	0.0695	0.446
18	0.5352	0.5326	0.0947	11.956	0.4444	0.4413	0.1035	13.947	0.5926	0.5901	0.0886	11.646	0.3767	0.3732	0.1096	16.265
19	0.4291	0.4243	0.0984	7.330	0.3625	0.3572	0.1040	7.961	0.4836	0.4788	0.0936	7.198	0.3114	0.3056	0.1081	8.926
20	0.6118	0.6112	0.0770	27.000	0.5344	0.5337	0.0843	31.790	0.6593	0.6587	0.0721	25.152	0.4785	0.4777	0.0892	36.100
21	0.7339	0.7333	0.0944	31.545	0.6815	0.6809	0.1033	38.605	0.7819	0.7814	0.0855	30.559	0.6520	0.6513	0.1080	46.557
22	0.8328	0.8280	0.0834	1.575	0.8199	0.8148	0.0865	1.709	0.8465	0.8416	0.0800	1.670	0.8124	0.8071	0.0883	1.915
23	0.8566	0.8534	0.0794	1.698	0.8162	0.8121	0.0899	1.919	0.8942	0.8916	0.0683	1.812	0.7989	0.7944	0.0940	2.173
24	0.8438	0.8331	0.0661	0.503	0.8208	0.8086	0.0708	0.744	0.8922	0.8838	0.0551	0.463	0.8107	0.7977	0.0728	1.103
25	0.8198	0.8177	0.0693	2.635	0.7721	0.7694	0.0779	2.947	0.8564	0.8545	0.0619	2.631	0.7418	0.7388	0.0829	3.390
26	0.8737	0.8724	0.0687	2.902	0.8349	0.8332	0.0785	3.263	0.9044	0.9033	0.0598	2.743	0.8113	0.8094	0.0840	3.758
27	0.7256	0.7228	0.0945	5.541	0.6442	0.6406	0.1076	6.733	0.7766	0.7740	0.0853	5.459	0.5772	0.5729	0.1173	8.138
28	0.7078	0.6967	0.0709	0.789	0.6583	0.6453	0.0767	0.926	0.7154	0.7028	0.0702	1.401	0.6070	0.5920	0.0823	1.056

Appendix G.1 (continued): Statistics for Regression Models

Number	Regression Model 5 age^3, age				Regression Model 6 age^3, age^2				Regression Model 7 age^3, age^2, age				Regression Model 8 e^{-age}			
	R^2	R^2_{adj}	Root MSE	PRESS	R^2	R^2_{adj}	Root MSE	PRESS	R^2	R^2_{adj}	Root MSE	PRESS	R^2	R^2_{adj}	Root MSE	PRESS
1	0.7826	0.7597	0.0750	85.616	0.7321	0.7039	0.0833	111.040	0.8081	0.7856	0.0709	24709.945	0.7386	0.7141	0.0818	7.506
2	0.6816	0.6799	0.0719	8.718	0.6475	0.6456	0.0756	8.763	0.6981	0.6963	0.0700	8.648	0.5990	0.5970	0.0807	10.332
3	0.6178	0.6085	0.0687	2.215	0.6005	0.5909	0.0702	3.101	0.6192	0.6091	0.0686	2.610	0.5036	0.4928	0.0782	2.401
4	0.6426	0.6347	0.0705	2.441	0.6270	0.6188	0.0720	2.502	0.6429	0.6342	0.0705	3.418	0.5234	0.5139	0.0813	5.037
5	0.7493	0.7067	0.0560	1.302	0.7383	0.6938	0.0572	1.921	0.7500	0.7019	0.0565	2.288	0.5063	0.4331	0.0779	0.423
6	0.7413	0.7312	0.0859	2.176	0.7029	0.6913	0.0921	2.233	0.7560	0.7455	0.0836	2.704	0.6707	0.6592	0.0968	2.987
7	0.6271	0.6185	0.0802	3.515	0.6165	0.6077	0.0813	3.600	0.6298	0.6204	0.0800	3.857	0.4798	0.4690	0.0946	9.814
8	0.7079	0.7071	0.0868	25.771	0.6729	0.6720	0.0918	25.703	0.7282	0.7273	0.0837	25.720	0.5509	0.5497	0.1076	34.604
9	0.8377	0.8366	0.0659	6.097	0.8110	0.8097	0.0711	6.836	0.8555	0.8544	0.0622	12.218	0.7530	0.7515	0.0812	8.058
10	0.8869	0.8842	0.0651	1.627	0.8555	0.8520	0.0736	1.621	0.9049	0.9024	0.0598	1.585	0.8491	0.8459	0.0751	2.442
11	0.7030	0.6977	0.0622	2.328	0.6764	0.6706	0.0649	2.341	0.7336	0.7283	0.0590	2.316	0.5652	0.5582	0.0752	2.937
12	0.8800	0.8781	0.0646	1.931	0.8668	0.8647	0.0680	1.922	0.9000	0.8982	0.0590	1.988	0.8927	0.8912	0.0610	2.223
13	0.2006	0.1716	0.0539	0.902	0.1895	0.1601	0.0542	0.767	0.2246	0.1929	0.0532	18.168	0.2164	0.1917	0.0532	136.313
14	0.6509	0.6504	0.0851	45.314	0.6065	0.6059	0.0903	45.389	0.6854	0.6849	0.0808	45.061	0.5125	0.5119	0.1005	60.448
15	0.7697	0.7632	0.0792	2.933	0.7405	0.7332	0.0841	3.659	0.7734	0.7662	0.0787	2.551	0.3794	0.3639	0.1299	3.744
16	0.5202	0.5076	0.0909	2.955	0.5035	0.4905	0.0925	2.979	0.5285	0.5147	0.0903	3.146	0.3723	0.3577	0.1039	6.439
17	0.7216	0.6957	0.0576	0.359	0.7037	0.6762	0.0594	0.396	0.7493	0.7232	0.0550	0.394	0.4649	0.4212	0.0795	0.397
18	0.5823	0.5797	0.0898	11.647	0.5417	0.5389	0.0940	11.587	0.6033	0.6006	0.0875	11.559	0.4296	0.4265	0.1049	26.978
19	0.4755	0.4706	0.0944	7.255	0.4474	0.4422	0.0969	7.317	0.4909	0.4856	0.0930	6.942	0.3724	0.3671	0.1032	7.963
20	0.6486	0.6480	0.0733	25.155	0.6106	0.6100	0.0771	25.103	0.6814	0.6808	0.0698	24.768	0.5113	0.5106	0.0864	38.563
21	0.7734	0.7730	0.0871	30.926	0.7428	0.7422	0.0928	31.397	0.7911	0.7906	0.0837	30.978	0.7094	0.7089	0.0986	36.602
22	0.8437	0.8387	0.0807	1.670	0.8353	0.8300	0.0829	1.739	0.8509	0.8456	0.0790	2.894	0.8252	0.8203	0.0852	7.625
23	0.8882	0.8854	0.0702	1.816	0.8624	0.8589	0.0779	1.805	0.8996	0.8968	0.0666	2.060	0.8562	0.8530	0.0795	2.049
24	0.8817	0.8725	0.0578	0.512	0.8588	0.8478	0.0631	0.596	0.9139	0.9064	0.0495	1.824	0.8823	0.8742	0.0574	4.824
25	0.8538	0.8519	0.0624	2.652	0.8391	0.8370	0.0655	2.643	0.8575	0.8554	0.0617	2.761	0.7338	0.7307	0.0842	3.776
26	0.9015	0.9003	0.0607	2.809	0.8861	0.8848	0.0653	2.949	0.9060	0.9048	0.0593	2.967	0.8211	0.8193	0.0817	4.568
27	0.7715	0.7689	0.0863	5.412	0.7474	0.7445	0.0907	5.415	0.7797	0.7769	0.0848	5.587	0.5568	0.5523	0.1201	9.243
28	0.7123	0.6995	0.0706	1.464	0.6904	0.6766	0.0733	1.211	0.7285	0.7146	0.0688	1.781	0.3642	0.3401	0.1046	2.448

Appendix G.1 (continued): Statistics for Regression Models

Number	Regression Model 9 $\log_e(\text{age})$				Regression Model 10 age^{-1}				Regression Model 11 $\text{age}^{-1/2}$			
	R^2	R^2_{adj}	Root MSE	PRESS	R^2	R^2_{adj}	Root MSE	PRESS	R^2	R^2_{adj}	Root MSE	PRESS
1	0.8055	0.7873	0.0706	0.987	0.7600	0.7375	0.0784	2.129	0.7894	0.7697	0.0734	1.439
2	0.7005	0.6991	0.0697	8.709	0.6450	0.6433	0.0759	8.950	0.6836	0.6821	0.0716	8.737
3	0.6067	0.5982	0.0696	2.140	0.5331	0.5230	0.0758	2.173	0.5759	0.5667	0.0723	2.126
4	0.6274	0.6200	0.0719	2.366	0.5523	0.5434	0.0788	2.764	0.5948	0.5867	0.0750	2.409
5	0.7481	0.7107	0.0556	0.431	0.6246	0.5690	0.0679	0.362	0.7074	0.6641	0.0599	0.395
6	0.7517	0.7431	0.0840	2.175	0.7002	0.6897	0.0923	2.241	0.7317	0.7224	0.0873	2.158
7	0.6307	0.6230	0.0797	3.580	0.5645	0.5554	0.0866	4.385	0.6088	0.6006	0.0821	3.758
8	0.7263	0.7256	0.0840	26.127	0.6365	0.6355	0.0968	26.803	0.6991	0.6983	0.0880	26.151
9	0.8543	0.8534	0.0624	5.933	0.8043	0.8030	0.0723	6.066	0.8431	0.8421	0.0647	5.954
10	0.8965	0.8943	0.0622	1.711	0.8709	0.8681	0.0695	1.549	0.8921	0.8898	0.0635	1.632
11	0.7309	0.7265	0.0592	2.136	0.6768	0.6716	0.0648	2.353	0.7261	0.7217	0.0597	2.216
12	0.8897	0.8881	0.0619	1.993	0.8985	0.8970	0.0594	2.019	0.8995	0.8981	0.0590	1.981
13	0.2033	0.1781	0.0536	0.733	0.2238	0.1993	0.0529	0.787	0.2157	0.1910	0.0532	0.753
14	0.6855	0.6851	0.0808	45.865	0.6107	0.6102	0.0899	47.058	0.6703	0.6699	0.0827	45.944
15	0.7449	0.7385	0.0833	2.415	0.5298	0.5181	0.1130	2.219	0.6662	0.6579	0.0952	2.215
16	0.5237	0.5127	0.0905	2.806	0.4449	0.4320	0.0977	2.841	0.4955	0.4838	0.0931	2.796
17	0.7285	0.7064	0.0566	0.282	0.6796	0.6534	0.0615	0.277	0.7108	0.6872	0.0584	0.273
18	0.5975	0.5953	0.0880	11.963	0.5198	0.5171	0.09607	11.848	0.5772	0.5748	0.0902	11.896
19	0.4826	0.4783	0.0937	7.272	0.4463	0.4417	0.0969	7.030	0.4795	0.4752	0.0940	7.110
20	0.6775	0.6770	0.0701	25.520	0.6119	0.6113	0.0769	25.461	0.6659	0.6654	0.0714	25.373
21	0.7894	0.7890	0.0840	30.820	0.7531	0.7526	0.0909	30.658	0.7840	0.7836	0.0851	30.494
22	0.8511	0.8468	0.0787	1.668	0.8446	0.8401	0.0804	1.892	0.8531	0.8490	0.0781	1.802
23	0.8971	0.8948	0.0672	1.731	0.8735	0.8707	0.0745	1.728	0.8910	0.8885	0.0692	1.710
24	0.8872	0.8795	0.0562	0.517	0.9047	0.8982	0.0516	0.823	0.9049	0.8984	0.0516	0.667
25	0.8500	0.8483	0.0632	2.711	0.7938	0.7914	0.0741	2.738	0.8321	0.8301	0.0669	2.639
26	0.9028	0.9018	0.0603	2.930	0.8613	0.8599	0.0720	3.068	0.8895	0.8884	0.0642	2.899
27	0.7749	0.7726	0.0856	5.496	0.6824	0.6791	0.1016	5.735	0.7495	0.7469	0.7469	5.480
28	0.7066	0.6954	0.0711	0.759	0.5345	0.5169	0.0895	0.859	0.6402	0.6265	0.0787	0.793

Appendix G.2: Coefficients for Plain Models

Equipment Type	Number	β_0 (Intercept)	β_2 (Age^2)	β_1 (Age)	M_1	M_2	M_3
Track Excavators	1	0.58972	0.00374	-0.08322	0.0	-0.00512	0.02017
	2	0.59899	0.00201	-0.05154	0.0	-0.07731	-0.04378
	3	0.58169	0.00324	-0.06997	0.0	-0.04967	-0.06366
	4	0.53428	0.00368	-0.08194	0.0	-0.03735	0.04646
	5	0.43101	0.00153	-0.04581	0.0	0.0	0.04545
Wheel Excavators	6	0.73563	0.00302	-0.07393	0.0	-0.10738	-0.07523
Wheel Loaders	7	0.59698	0.001	-0.03594	-0.06025	-0.09599	-0.09104
	8	0.73678	0.00243	-0.06494	-0.13094	-0.09149	-0.08869
	9	0.61938	0.00254	-0.0636	-0.14158	-0.12428	-0.00769
	10	0.64439	0.0034	-0.07782	-0.1204	-0.12773	0.0
Track Loaders	11	0.55178	0.00143	-0.04143	0.0	-0.07294	-0.04785
	12	0.67103	0.00247	-0.05819	0.0	-0.25069	-0.03541
Backhoe Loaders	13	0.48797	0.0014	-0.04106	0.0	0.0	0.0
	14	0.76828	0.00247	-0.06437	0.0	-0.14843	-0.14246
Integrated Toolcarriers	15	0.72345	0.00329	-0.08468	0.0	0.01375	0.0
Rigid Frame Trucks	16	0.55324	0.00143	-0.04361	0.0	-0.1056	0.0
	17	0.56302	0.0011	-0.04817	0.0	-0.19434	0.0
Articulated Trucks	18	0.53409	0.00289	-0.06904	0.06272	-0.03535	0.0
	19	0.51316	0.003	-0.06846	0.07011	0.0	0.0
Track Dozers	20	0.58368	0.00204	-0.05323	0.0	0.0	-0.04005
	21	0.66202	0.0031	-0.07476	0.0	-0.10034	-0.02558
	22	0.64456	0.00249	-0.06027	0.0	-0.27136	0.0
	23	0.62065	0.00327	-0.0776	0.0	-0.16817	0.0
	24	0.5974	0.00341	-0.07417	0.0	-0.15175	0.0
Motor Graders	25	0.74453	0.00252	-0.06769	0.0	-0.0682	0.0
	26	0.78837	0.00258	-0.06825	0.0	-0.1452	0.0
Wheel Tractor Scrapers	27	0.77399	0.00302	-0.08271	0.0	-0.15315	0.0
	28	0.65732	0.00117	-0.05152	0.0	0.0	0.0

Appendix G.2 (Continued): Coefficients for Plain Models

Equipment Type	Number	C_1	C_2	C_3	R_1	R_2	R_3	E_1	E_2
Track Excavators	1	0.05172	0.02018	0.01955	-0.05078	-0.00194	-0.00921	N/A	N/A
	2	0.02271	-0.01197	0.01249	-0.03289	-0.00638	-0.00266	N/A	N/A
	3	0.03313	-0.02371	0.03859	-0.03064	-0.01408	0.00981	N/A	N/A
	4	0.03666	-0.03699	0.03172	-0.02806	0.00648	-0.00422	N/A	N/A
	5	0.058	-0.06932	0.03829	-0.07249	-0.04234	0.01024	N/A	N/A
Wheel Excavators	6	0.0116	-0.00855	0.02573	-0.01576	-0.04085	-0.02678	N/A	N/A
Wheel Loaders	7	0.07465	0.00137	0.01192	0.01102	0.00563	0.01904	N/A	N/A
	8	0.02927	-0.02013	0.02033	0.00681	0.00816	0.02213	N/A	N/A
	9	0.0373	0.00944	-0.00155	6.044E-4	0.0074	0.00996	N/A	N/A
	10	0.0303	-0.01601	-6.839E-4	-0.01499	-0.01704	-0.00672	N/A	N/A
Track Loaders	11	0.06268	-0.02097	0.01679	-0.01908	0.02701	-0.00689	N/A	N/A
	12	0.07781	0.01531	0.01232	-0.04705	0.00712	0.00935	N/A	N/A
Backhoe Loaders	13	0.01216	-0.02069	0.01562	0.01173	-0.00315	0.00175	N/A	N/A
	14	0.04734	-0.02229	0.02465	-0.02278	-0.00867	0.03171	N/A	N/A
Integrated Toolcarriers	15	0.01594	-0.0292	0.0119	-0.00466	0.00563	-0.00644	N/A	N/A
Rigid Frame Trucks	16	0.04822	-0.05813	0.04115	0.0066	0.01488	-0.05843	N/A	N/A
	17	-0.06657	0.03599	0.01547	-0.07538	-0.00918	-0.05791	N/A	N/A
Articulated Trucks	18	0.02996	-0.02999	0.03019	0.00632	0.01014	0.01387	N/A	N/A
	19	0.02073	-0.00651	-7.099E-4	-0.02958	0.01453	0.0151	N/A	N/A
Track Dozers	20	0.04288	-0.01667	0.01827	-0.00337	0.00845	0.00987	N/A	N/A
	21	0.04668	-0.02164	0.01716	0.02785	0.01804	0.02694	N/A	N/A
	22	0.09273	-0.00575	0.01425	0.07471	0.05529	0.01704	N/A	N/A
	23	0.06846	0.03169	0.01569	0.03076	0.02929	0.02749	N/A	N/A
	24	0.08504	0.00173	0.0158	-0.00625	-0.01886	-0.01768	N/A	N/A
Motor Graders	25	0.02908	-0.01366	0.01699	-0.05193	-0.02501	-0.0401	N/A	N/A
	26	-0.00589	-0.03832	0.0168	-0.0284	-0.02609	-0.04169	N/A	N/A
Wheel Tractor Scrapers	27	0.03741	-0.0187	0.02634	0.05958	0.0303	-4.672E-4	N/A	N/A
	28	0.08594	0.01942	0.03347	6.6336E-4	0.0	0.00423	N/A	N/A

Appendix G.3: Statistics for Plain Models

Equipment Type	Number	R^2	Adjusted R^2	Root MSE	Economic Indicator e_1	Economic Indicator e_2	Complete Observations	Average Age
Track Excavators	1	0.8290	0.8110	0.0640	N/A	N/A	82	3.46
	2	0.7168	0.7153	0.0676	N/A	N/A	1426	4.97
	3	0.7097	0.7027	0.0574	N/A	N/A	357	3.61
	4	0.7233	0.7172	0.0629	N/A	N/A	409	3.47
	5	0.7500	0.7075	0.0559	N/A	N/A	51	7.13
Wheel Excavators	6	0.7495	0.7398	0.0846	N/A	N/A	209	6.54
Wheel Loaders	7	0.6560	0.6481	0.0756	N/A	N/A	374	6.99
	8	0.7438	0.7431	0.0807	N/A	N/A	2961	6.77
	9	0.9137	0.9132	0.0547	N/A	N/A	1368	6.65
	10	0.9147	0.9127	0.0592	N/A	N/A	375	5.99
Track Loaders	11	0.7273	0.7223	0.0575	N/A	N/A	418	8.46
	12	0.9253	0.9241	0.0519	N/A	N/A	471	8.97
Backhoe Loaders	13	0.4130	0.3914	0.0369	N/A	N/A	128	12.56
	14	0.6913	0.6909	0.0800	N/A	N/A	5554	6.97
Integrated Toolcarriers	15	0.8437	0.8393	0.0661	N/A	N/A	253	5.19
Rigid Frame Trucks	16	0.5634	0.5519	0.0860	N/A	N/A	250	9.43
	17	0.7634	0.7412	0.0527	N/A	N/A	55	8.05
Articulated Trucks	18	0.6715	0.6695	0.0800	N/A	N/A	1146	5.84
	19	0.5891	0.5853	0.0799	N/A	N/A	677	5.87
Track Dozers	20	0.7132	0.7127	0.0673	N/A	N/A	3968	7.48
	21	0.8065	0.8061	0.0788	N/A	N/A	3754	5.86
	22	0.8711	0.8670	0.0751	N/A	N/A	250	7.86
	23	0.9008	0.8983	0.0658	N/A	N/A	308	5.08
	24	0.9064	0.8991	0.0516	N/A	N/A	105	7.00
Motor Graders	25	0.8668	0.8651	0.0601	N/A	N/A	575	7.19
	26	0.9162	0.9152	0.0561	N/A	N/A	679	7.15
Wheel Tractor Scrapers	27	0.8002	0.7978	0.0799	N/A	N/A	626	7.93
	28	0.7307	0.7185	0.0663	N/A	N/A	147	8.79

Appendix G.3 (Continued): Statistics for Plain Models

Equipment Type	Number	S_{xx}	$t_{0.95,\ n-p}$	Degrees of Freedom n-p	Standard Deviation	Minimum Age	Maximum Age	Total Observations
Track Excavators	1	789.0345	1.6669	70	3.1020	0	13	106
	2	15883.3074	1.6459	1414	3.3374	0	15	1888
	3	948.5654	1.6493	345	1.6300	0	12	427
	4	1191.6655	1.6487	397	1.7069	0	13	465
	5	538.7773	1.6849	39	3.2503	1	15	63
Wheel Excavators	6	2999.9427	1.6526	197	3.7886	1	15	268
Wheel Loaders	7	4998.1001	1.6491	362	3.6557	0	15	490
	8	46192.6167	1.6454	2949	3.9497	0	15	3857
	9	23938.1661	1.6460	1356	4.1831	0	15	1695
	10	5855.6204	1.6491	363	3.9516	0	15	440
Track Loaders	11	7376.0795	1.6486	406	4.2007	1	15	562
	12	7712.4420	1.6482	459	4.0466	0	15	645
Backhoe Loaders	13	626.7067	1.6581	116	2.2127	3	15	226
	14	83448.7988	1.6451	5542	3.8762	0	15	7530
Integrated Toolcarriers	15	4157.0346	1.6512	241	4.0535	0	15	333
Rigid Frame Trucks	16	4072.7569	1.6513	238	4.0362	1	15	350
	17	686.5908	1.6811	43	3.5332	3	15	106
Articulated Trucks	18	11761.0754	1.6462	1134	3.2035	0	15	1658
	19	5393.5342	1.6471	665	2.8226	0	15	970
Track Dozers	20	65865.8687	1.6452	3956	4.0742	0	15	5320
	21	57373.4953	1.6453	3742	3.9094	0	15	4594
	22	3287.1256	1.6513	238	3.6261	0	15	290
	23	3685.3821	1.6500	296	3.4591	1	15	363
	24	1232.9032	1.6614	93	3.4267	1	15	125
Motor Graders	25	10820.7013	1.6476	563	4.3380	0	15	697
	26	12231.6035	1.6471	667	4.2443	0	15	790
Wheel Tractor Scrapers	27	9230.3913	1.6473	614	3.8399	1	15	781
	28	1438.1572	1.6562	135	3.1278	1	15	163

Appendix G.4: Coefficients for Best Models

Equipment Type	Number	β_0 (Intercept)	β_2 (Age^2)	β_1 (Age)	M_1	M_2	M_3
Track Excavators	1	1.35942	0.0043	-0.08702	0.0	-0.06232	-0.08506
	2	0.9968	0.0018	-0.04744	0.0	-0.11137	-0.08277
	3	1.3416	0.00211	-0.05675	0.0	-0.05546	-0.07983
	4	0.74753	0.00305	-0.07163	0.0	-0.08455	-0.01504
	5	0.46816	0.00197	-0.05423	0.0	0.0	0.07347
Wheel Excavators	6	2.43388	0.00365	-0.07646	0.0	-0.19249	-0.06808
Wheel Loaders	7	1.19577	0.00107	-0.03626	-0.084	-0.12296	-0.09382
	8	0.85117	0.00254	-0.06718	-0.15049	-0.11851	-0.09084
	9	0.87161	0.00278	-0.06652	-0.17026	-0.14402	-0.01911
	10	0.75371	0.00351	-0.07844	-0.13163	-0.15887	0.0
Track Loaders	11	0.13399	0.00139	-0.0413	0.0	-0.0954	-0.04843
	12	0.77776	0.00246	-0.05741	0.0	-0.27287	-0.03713
Backhoe Loaders	13	0.83953	0.00159	-0.04514	0.0	0.0	0.0
	14	1.12429	0.00249	-0.06562	0.0	-0.14822	-0.1355
Integrated Toolcarriers	15	0.44283	0.00324	-0.08444	0.0	0.01499	0.0
Rigid Frame Trucks	16	0.36468	0.00156	-0.04519	0.0	-0.1416	0.0
	17	1.22834	7.1514E-4	-0.0419	0.0	-0.20181	0.0
Articulated Trucks	18	0.63519	0.00348	-0.0752	0.05059	-0.08786	0.0
	19	1.18674	0.0033	-0.06959	0.06195	0.0	0.0
Track Dozers	20	0.55133	0.00211	-0.05484	0.0	0.0	-0.04026
	21	0.63403	0.003	-0.07445	0.0	-0.1253	-0.02741
	22	1.00144	0.00246	-0.05947	0.0	-0.31246	0.0
	23	0.25529	0.00295	-0.0715	0.0	-0.18127	0.0
	24	0.44866	0.00329	-0.07109	0.0	-0.17398	0.0
Motor Graders	25	0.34036	0.00215	-0.06074	0.0	-0.09028	0.0
	26	0.65632	0.00254	-0.06769	0.0	-0.15219	0.0
Wheel Tractor Scrapers	27	-0.4796	0.00326	-0.08678	0.0	-0.16752	0.0
	28	0.0302	0.00191	-0.06272	0.0	0.0	0.0

Appendix G.4 (Continued): Coefficients for Best Models

Equipment Type	Number	C_1	C_2	C_3	R_1	R_2	R_3	E_1	E_2
Track Excavators	1	0.05109	0.0357	0.01443	-0.02871	-0.00368	0.01775	-1.0273E-4	1.65E-6
	2	0.02325	4.8753E-4	0.00466	-0.034	-0.0055	-0.0017	0.00128	-9.562E-4
	3	0.0323	-0.00941	0.03168	-0.02941	-0.02024	0.00669	-0.00548	0.00116
	4	0.02636	-0.01733	0.01709	-0.0256	-9.273E-4	-0.00318	6.470124E-7	-9.5897E-4
	5	0.07075	-0.0406	0.02717	-0.06532	-0.02734	0.02137	-5.148E-5	-4.35515E-7
Wheel Excavators	6	-0.00451	-0.02137	0.01977	0.00302	-0.03601	-0.02525	0.00629	-0.01646
Wheel Loaders	7	0.07233	0.00486	0.01065	0.02048	0.01443	0.02692	-9.69E-5	7.122597E-7
	8	0.02309	-0.00904	0.00988	0.0105	0.00603	0.02317	5.273183E-7	-5.4864E-7
	9	0.03231	0.01009	-0.00326	2.2418E-4	0.00314	0.00831	-0.00153	3.65478E-7
	10	0.01984	-0.00885	-0.00551	-0.00268	-0.00765	-3.6162E-4	5.437066E-7	-6.6142E-4
Track Loaders	11	0.06192	-0.00839	0.01376	-0.02583	0.02543	-0.00195	0.00651	-0.00370
	12	0.07757	0.02146	0.0099	-0.04724	0.00667	0.01095	0.00171	-0.0018
Backhoe Loaders	13	0.01385	-0.01766	0.01541	0.0112	0.00119	0.0014	-6.688E-5	-0.00161
	14	0.04583	-0.01122	0.01784	-0.02037	-0.00681	0.03309	-0.00181	-0.00147
Integrated Toolcarriers	15	0.01633	-0.03101	0.01362	0.00328	0.00656	-0.00157	0.0033	2.457E-4
Rigid Frame Trucks	16	0.05729	0.00259	0.00555	-0.01059	-0.0057	-0.03462	0.00846	-1.3485E-4
	17	-0.02352	0.02841	0.02659	-0.05788	-0.00361	-0.06046	-0.01056	0.00378
Articulated Trucks	18	0.01293	-4.1702E-4	0.00536	0.00515	0.00629	0.00896	0.01779	-0.0012
	19	0.01343	-0.00111	-0.00273	-0.01332	0.01255	-1.2061E-4	-2.49E-6	-9.4423E-4
Track Dozers	20	0.03577	-0.00754	0.01224	-0.00158	0.00904	0.00916	9.1614E-4	-7.1848E-4
	21	0.04011	-0.00537	0.00589	0.03263	0.01896	0.02629	0.00133	-0.00104
	22	0.07194	-0.00112	0.00419	0.09273	0.0661	0.02542	0.00355	-0.0051
	23	0.0765	0.04325	0.01875	0.02932	0.03116	0.02381	0.00561	-5.247E-5
	24	0.07463	0.01001	-9.6283E-4	-0.00882	-0.02195	-0.01883	0.01735	3.368385E-7
Motor Graders	25	0.0214	0.00169	0.00678	-0.06202	-0.03329	-0.0373	0.0075	-0.00496
	26	-0.00255	-0.03045	0.01612	-0.03283	-0.029	-0.03603	2.4033E-4	4.512954E-7
Wheel Tractor Scrapers	27	0.02691	-0.00319	0.00516	0.08673	0.04652	0.00162	0.01043	-0.00184
	28	0.08227	0.03829	0.04168	0.00216	0.0	1.5119E-4	5.5674E-4	-0.00917

Appendix G.5: Statistics for Best Models

Equipment Type	Number	R^2	Adjusted R^2	Root MSE	Economic Indicator e_1	Economic Indicator e_2	Complete Observations	Average Age
Track Excavators	1	0.8813	0.8656	0.0542	EMPLC	CNSCR	82	3.46
	2	0.7569	0.7553	0.0630	STLPRD	TNR	1426	4.97
	3	0.7421	0.7344	0.0540	CPI	STLPRD	357	3.61
	4	0.7707	0.7644	0.0573	CNSCR	SVGS	409	3.47
	5	0.7924	0.7468	0.0524	SP	SVGS2	51	7.13
Wheel Excavators	6	0.8054	0.7961	0.0749	LEADG	PPIME	209	6.54
Wheel Loaders	7	0.7185	0.7106	0.0691	CCI	CNSCR	374	6.99
	8	0.7676	0.7668	0.0772	CNSCR	SVGS	2961	6.77
	9	0.9233	0.9226	0.0519	ECICOMP	CNSCR	1368	6.65
	10	0.9316	0.9296	0.0539	CNSCR	SVGS	375	5.99
Track Loaders	11	0.7612	0.7559	0.0542	PPIME	ECICOMP	418	8.46
	12	0.9280	0.9266	0.0512	LEADG	CPI	471	8.97
Backhoe Loaders	13	0.4559	0.4306	0.0357	BCI	CNSCRNF	128	12.56
	14	0.7081	0.7076	0.0780	ECICOMP	CNSCRNF	5554	6.97
Integrated Toolcarriers	15	0.8552	0.8501	0.0646	HWY	ATSLS	253	5.19
Rigid Frame Trucks	16	0.6722	0.6614	0.0749	LEADG	EMPLC	250	9.43
	17	0.8318	0.8121	0.0449	LEADG	STLPRD	55	8.05
Articulated Trucks	18	0.7903	0.7888	0.0641	INTRST	SVGS	1146	5.84
	19	0.7864	0.7839	0.0576	RTLSLS	CNSCRNF	677	5.87
Track Dozers	20	0.7397	0.7392	0.0639	STLPRD	SVGS	3968	7.48
	21	0.8336	0.8331	0.0737	STLPRD	SVGS	3754	5.86
	22	0.8933	0.8890	0.0690	INDPRD	PPIMIN	250	7.86
	23	0.9096	0.9067	0.0630	LEADG	EMPLC	308	5.08
	24	0.9160	0.9076	0.0497	SWR	SVGS2	105	7.00
Motor Graders	25	0.8891	0.8873	0.0550	PPIME	ECICOMP	575	7.19
	26	0.9220	0.9208	0.0543	ATSLS	CNSCR	679	7.15
Wheel Tractor Scrapers	27	0.8472	0.8450	0.0699	PPIME	SVGS	626	7.93
	28	0.7934	0.7813	0.0585	BCI	ECICOMP	147	8.79

Appendix G.5 (Continued): Statistics for Best Models

Equipment Type	Number	S_{xx}	$t_{0.95,\ n-p}$	Degrees of Freedom n-p	Standard Deviation	Minimum Age	Maximum Age	Total Observations
Track Excavators	1	789.0345	1.6676	68	3.1020	0	13	106
	2	15883.3074	1.6459	1412	3.3374	0	15	1888
	3	948.5654	1.6493	343	1.6300	0	12	427
	4	1191.6655	1.6487	395	1.7069	0	13	465
	5	538.7773	1.6871	37	3.2503	1	15	63
Wheel Excavators	6	2999.9427	1.6527	195	3.7886	1	15	268
Wheel Loaders	7	4998.1001	1.6491	360	3.6557	0	15	490
	8	46192.6167	1.6454	2947	3.9497	0	15	3857
	9	23938.1661	1.6460	1354	4.1831	0	15	1695
	10	5855.6204	1.6491	361	3.9516	0	15	440
Track Loaders	11	7376.0795	1.6486	404	4.2007	1	15	562
	12	7712.4420	1.6482	457	4.0466	0	15	645
Backhoe Loaders	13	626.7067	1.6583	114	2.2127	3	15	226
	14	83448.7988	1.6451	5540	3.8762	0	15	7530
Integrated Toolcarriers	15	4157.0346	1.6513	239	4.0535	0	15	333
Rigid Frame Trucks	16	4072.7569	1.6513	236	4.0362	1	15	350
	17	686.5908	1.6829	41	3.5332	3	15	106
Articulated Trucks	18	11761.0754	1.6462	1132	3.2035	0	15	1658
	19	5393.5342	1.6472	663	2.8226	0	15	970
Track Dozers	20	65865.8687	1.6452	3954	4.0742	0	15	5320
	21	57373.4953	1.6453	3740	3.9094	0	15	4594
	22	3287.1256	1.6513	236	3.6261	0	15	290
	23	3685.3821	1.6501	294	3.4591	1	15	363
	24	1232.9032	1.6618	91	3.4267	1	15	125
Motor Graders	25	10820.7013	1.6476	561	4.3380	0	15	697
	26	12231.6035	1.6471	665	4.2443	0	15	790
Wheel Tractor Scrapers	27	9230.3913	1.6473	612	3.8399	1	15	781
	28	1438.1572	1.6564	133	3.1278	1	15	163

Appendix G.6: Coefficients for Trade Journal Models

Equipment Type	Number	β_0 (Intercept)	β_2 (Age^2)	β_1 (Age)	M_1	M_2	M_3
Track Excavators	1	0.79677	0.00393	-0.08606	0.0	-0.03649	-0.02967
	2	0.74335	0.00195	-0.05008	0.0	-0.10486	-0.0745
	3	0.25704	0.00211	-0.05785	0.0	-0.05431	-0.07771
	4	0.89535	0.00304	-0.07267	0.0	-0.08572	-0.01501
	5	0.49556	0.00189	-0.04947	0.0	0.0	0.0358
Wheel Excavators	6	0.99272	0.00358	-0.07536	0.0	-0.18192	-0.06167
Wheel Loaders	7	0.72284	9.7051E-4	-0.03517	-0.07784	-0.11789	-0.08922
	8	0.87404	0.00254	-0.0671	-0.14816	-0.1145	-0.09023
	9	0.69706	0.00273	-0.06554	-0.16866	-0.14253	-0.01859
	10	0.88322	0.00355	-0.07887	-0.1329	-0.15856	0.0
Track Loaders	11	0.4638	0.00148	-0.04287	0.0	-0.09042	-0.0469
	12	0.6688	0.0025	-0.05856	0.0	-0.26362	-0.03603
Backhoe Loaders	13	0.61258	0.00164	-0.04589	0.0	0.0	0.0
	14	0.84294	0.0025	-0.06562	0.0	-0.14785	-0.13428
Integrated Toolcarriers	15	0.70137	0.00334	-0.08617	0.0	0.01193	0.0
Rigid Frame Trucks	16	0.7753	0.00143	-0.04316	0.0	-0.12567	0.0
	17	0.93508	8.5851E-4	-0.04268	0.0	-0.16153	0.0
Articulated Trucks	18	0.86178	0.0035	-0.07511	0.05533	-0.08667	0.0
	19	1.11318	0.00333	-0.06979	0.06377	0.0	0.0
Track Dozers	20	0.57207	0.00208	-0.05414	0.0	0.0	-0.04021
	21	0.74821	0.00305	-0.0751	0.0	-0.11932	-0.02755
	22	0.88429	0.00255	-0.06085	0.0	-0.30717	0.0
	23	0.4916	0.00307	-0.07475	0.0	-0.17985	0.0
	24	0.91872	0.00345	-0.07397	0.0	-0.16261	0.0
Motor Graders	25	0.8306	0.00221	-0.06271	0.0	-0.08524	0.0
	26	0.58248	0.00259	-0.06877	0.0	-0.1484	0.0
Wheel Tractor Scrapers	27	0.66746	0.00335	-0.08735	0.0	-0.16492	0.0
	28	-0.07134	0.00126	-0.05312	0.0	0.0	0.0

Appendix G.6 (Continued): Coefficients for Trade Journal Models

Equipment Type	Number	C_1	C_2	C_3	R_1	R_2	R_3	E_1	E_2
Track Excavators	1	0.04677	0.01391	0.03151	-0.05247	-0.0111	-0.0112	2.7396E-4	-5.945E-5
	2	0.02209	-0.00184	0.00512	-0.03705	-0.00851	-0.00465	0.02331	-3.604E-5
	3	0.03367	-0.01516	0.0353	-0.03555	-0.02388	0.00687	0.02529	0.02086
	4	0.02751	-0.01882	0.01764	-0.03174	-0.0016	-0.00347	1.4644E-4	-5.542E-5
	5	0.06463	-0.04977	0.03466	-0.058	-0.02099	0.01529	1.6876E-4	-5.711E-5
Wheel Excavators	6	-0.0083	-0.0249	0.02077	0.00619	-0.02961	-0.0275	0.02159	-3.758E-5
Wheel Loaders	7	0.07171	0.00623	0.00894	0.01827	0.01498	0.02432	0.01599	-2.315E-5
	8	0.02694	-0.00764	0.01235	0.00599	0.00491	0.02199	8.454E-5	-2.627E-5
	9	0.0337	0.01092	-0.00313	-0.00197	0.00456	0.00631	0.0106	-1.139E-5
	10	0.02467	-0.01056	-0.00339	-0.00902	-0.01047	-0.00535	0.00743	-2.889E-5
Track Loaders	11	0.06232	-0.00803	0.01268	-0.02623	0.02967	-7.4849E-4	-0.00661	0.01614
	12	0.0764	0.02137	0.00976	-0.04474	0.00813	0.01107	7.694E-5	-1.23E-5
Backhoe Loaders	13	0.0172	-0.01715	0.01506	0.01183	9.1043E-4	0.00246	0.00539	-9.8777E-4
	14	0.04623	-0.01322	0.01851	-0.01985	-0.00646	0.03187	0.005	-1.905E-5
Integrated Toolcarriers	15	0.018	-0.02826	0.01064	0.00166	0.0063	-0.00526	0.00471	-0.00114
Rigid Frame Trucks	16	0.04803	-0.03816	0.02647	0.00385	0.01224	-0.04951	0.02777	-3.0685E-4
	17	-0.0527	0.03272	0.00385	-0.07988	-0.02926	-0.04454	-0.01413	-4.161E-5
Articulated Trucks	18	0.01351	-0.00881	0.01231	0.00308	0.00682	0.00726	0.01265	-4.49E-5
	19	0.01457	-0.00207	-0.00187	-0.01511	0.01211	-5.7094E-4	0.00941	-6.945E-5
Track Dozers	20	0.0366	-0.00977	0.01417	-0.00361	0.00808	0.00643	0.01357	-6.8574E-4
	21	0.04547	-0.00709	0.00862	0.03196	0.0204	0.02774	1.4661E-4	-3.258E-5
	22	0.07334	0.00345	0.0013	0.08919	0.06539	0.0221	0.02263	-0.00233
	23	0.06919	0.03329	0.01669	0.02934	0.02709	0.02581	0.01049	0.00642
	24	0.09543	0.01192	0.01762	-0.01262	-0.02692	-0.01158	-0.02228	-2.138E-5
Motor Graders	25	0.02516	-0.00322	0.01005	-0.05512	-0.02571	-0.03368	0.00359	-2.651E-5
	26	-0.0014	-0.03434	0.02028	-0.03213	-0.0283	-0.03835	0.02074	5.765E-5
Wheel Tractor Scrapers	27	0.03406	-0.00763	0.01446	0.07859	0.04782	0.00185	0.02323	-6.7331E-4
	28	0.08042	0.01792	0.0343	0.00125	0.0	-2.5605E-4	0.02734	0.0034

Appendix G.7: Statistics for Trade Journal Models

Equipment Type	Number	R^2	Adjusted R^2	Root MSE	Economic Indicator e_1	Economic Indicator e_2	Complete Observations	Average Age
Track Excavators	1	0.8588	0.8402	0.0591	HMSTS	GDP	82	3.46
	2	0.7542	0.7526	0.0633	INTRST	EMPLC	1426	4.97
	3	0.7356	0.7277	0.0547	SWR	INTRST	357	3.61
	4	0.7558	0.7490	0.0592	HMSTS	GDP	409	3.47
	5	0.7825	0.7346	0.0537	HMSTS	EMPLC	51	7.13
Wheel Excavators	6	0.7990	0.7893	0.0761	INTRST	GDP	209	6.54
Wheel Loaders	7	0.7109	0.7028	0.0700	INTRST	GDP	374	6.99
	8	0.7626	0.7618	0.0780	HMSTS	GDP	2961	6.77
	9	0.9216	0.9210	0.0524	INTRST	GDP	1368	6.65
	10	0.9275	0.9253	0.0555	WTR	GDP	375	5.99
Track Loaders	11	0.7534	0.7480	0.0551	WTR	SWR	418	8.46
	12	0.9272	0.9258	0.0514	HMSTS	GDP	471	8.97
Backhoe Loaders	13	0.4314	0.4050	0.0365	WTR	TTLCNST	128	12.56
	14	0.7046	0.7041	0.0785	SWR	EMPLC	5554	6.97
Integrated Toolcarriers	15	0.8524	0.8472	0.0653	HWY	TTLCNST	253	5.19
Rigid Frame Trucks	16	0.6703	0.6595	0.0751	SWR	HMSTS	250	9.43
	17	0.7924	0.7682	0.0499	SWR	EMPLC	55	8.05
Articulated Trucks	18	0.7782	0.7766	0.0659	SWR	GDP	1146	5.84
	19	0.7768	0.7742	0.0589	WTR	GDP	677	5.87
Track Dozers	20	0.7326	0.7320	0.0647	SWR	TTLCNST	3968	7.48
	21	0.8246	0.8241	0.0757	HMSTS	GDP	3754	5.86
	22	0.8916	0.8872	0.0696	WTR	TTLCNST	250	7.86
	23	0.9037	0.9006	0.0651	SWR	INTRST	308	5.08
	24	0.9131	0.9045	0.0506	INTRST	GDP	105	7.00
Motor Graders	25	0.8813	0.8794	0.0569	HWY	GDP	575	7.19
	26	0.9198	0.9186	0.0550	INTRST	HMSTS	679	7.15
Wheel Tractor Scrapers	27	0.8228	0.8202	0.0753	SWR	TTLCNST	626	7.93
	28	0.7790	0.7661	0.0605	SWR	PPIME	147	8.79

Appendix G.7 (Continued): Statistics for Trade Journal Models

Equipment Type	Number	S_{xx}	$t_{0.95, n-p}$	Degrees of Freedom n-p	Standard Deviation	Minimum Age	Maximum Age	Total Observations
Track Excavators	1	789.0345	1.6676	68	3.1020	0	13	106
	2	15883.3074	1.6459	1412	3.3374	0	15	1888
	3	948.5654	1.6493	343	1.6300	0	12	427
	4	1191.6655	1.6487	395	1.7069	0	13	465
	5	538.7773	1.6871	37	3.2503	1	15	63
Wheel Excavators	6	2999.9427	1.6527	195	3.7886	1	15	268
Wheel Loaders	7	4998.1001	1.6491	360	3.6557	0	15	490
	8	46192.6167	1.6454	2947	3.9497	0	15	3857
	9	23938.1661	1.6460	1354	4.1831	0	15	1695
	10	5855.6204	1.6491	361	3.9516	0	15	440
Track Loaders	11	7376.0795	1.6486	404	4.2007	1	15	562
	12	7712.4420	1.6482	457	4.0466	0	15	645
Backhoe Loaders	13	626.7067	1.6583	114	2.2127	3	15	226
	14	83448.7988	1.6451	5540	3.8762	0	15	7530
Integrated Toolcarriers	15	4157.0346	1.6513	239	4.0535	0	15	333
Rigid Frame Trucks	16	4072.7569	1.6513	236	4.0362	1	15	350
	17	686.5908	1.6829	41	3.5332	3	15	106
Articulated Trucks	18	11761.0754	1.6462	1132	3.2035	0	15	1658
	19	5393.5342	1.6472	663	2.8226	0	15	970
Track Dozers	20	65865.8687	1.6452	3954	4.0742	0	15	5320
	21	57373.4953	1.6453	3740	3.9094	0	15	4594
	22	3287.1256	1.6513	236	3.6261	0	15	290
	23	3685.3821	1.6501	294	3.4591	1	15	363
	24	1232.9032	1.6618	91	3.4267	1	15	125
Motor Graders	25	10820.7013	1.6476	561	4.3380	0	15	697
	26	12231.6035	1.6471	665	4.2443	0	15	790
Wheel Tractor Scrapers	27	9230.3913	1.6473	612	3.8399	1	15	781
	28	1438.1572	1.6564	133	3.1278	1	15	163

Appendix G.8: Statistics for Comparison of Nested Models

Equipment Type	Number	Degrees of Freedom n-p	Plain Model	Best Model		Trade Journal Model	
			SS_{err}	SS_{err}	MS_{err}	SS_{err}	MS_{err}
Track Excavators	1	68	0.38913	0.26696	0.00293	0.31755	0.00349
	2	1412	8.57883	7.23122	0.00397	7.31294	0.00401
	3	343	1.37178	1.16523	0.00291	1.19471	0.00299
	4	395	1.79429	1.43626	0.00329	1.53008	0.0035
	5	37	0.16575	0.13732	0.00275	0.1439	0.00288
Wheel Excavators	6	195	1.83731	1.39549	0.0056	1.4415	0.00579
Wheel Loaders	7	360	2.73198	2.22316	0.00477	2.28312	0.0049
	8	2947	25.06661	22.30387	0.00596	22.78267	0.00609
	9	1354	5.03045	4.36661	0.00269	4.45809	0.00275
	10	361	1.50325	1.17565	0.0029	1.24713	0.00308
Track Loaders	11	404	1.81975	1.58833	0.00294	1.6402	0.00303
	12	457	1.70437	1.60616	0.00262	1.62365	0.00264
Backhoe Loaders	13	114	0.29495	0.27343	0.00127	0.28571	0.00133
	14	5540	48.07086	44.56098	0.00609	45.08989	0.00616
Integrated Toolcarriers	15	239	1.41205	1.29954	0.00418	1.32475	0.00426
Rigid Frame Trucks	16	236	2.5172	1.87183	0.0056	1.88259	0.00564
	17	41	0.26657	0.18948	0.00202	0.23383	0.00249
Articulated Trucks	18	1132	10.55043	6.68499	0.00411	7.07618	0.00435
	19	663	6.13419	3.09731	0.00332	3.23718	0.00347
Track Dozers	20	3954	24.05194	21.27702	0.00408	21.86147	0.00419
	21	3740	28.43003	23.99071	0.00543	25.28568	0.00573
	22	236	1.57896	1.29959	0.00476	1.32111	0.00484
	23	294	1.52615	1.37523	0.00397	1.46444	0.00423
	24	91	0.30597	0.27214	0.00247	0.28133	0.00256
Motor Graders	25	561	2.48159	2.0205	0.00302	2.16286	0.00323
	26	665	2.45024	2.22125	0.00295	2.28382	0.00303
Wheel Tractor Scrapers	27	612	4.92593	3.71465	0.00488	4.30956	0.00566
	28	133	0.68138	0.52268	0.00342	0.55903	0.00365

Appendix G.8 (continued): Statistics for Comparison of Nested Models

Equipment Type	Number	Comparison Plain Model and Best Model			Comparison Plain Model and Trade Journal Model		
		F_{obs}	$F_{0.9, 2, n-p}$	p-Value	F_{obs}	$F_{0.9, 2, n-p}$	p-Value
Track Excavators	1	20.8481	2.3823	<0.00001	10.2550	2.3823	0.00012
	2	169.7242	2.3063	<0.00001	157.8416	2.3063	<0.00001
	3	35.4897	2.3181	<0.00001	29.6104	2.3181	<0.00001
	4	54.4119	2.3161	<0.00001	37.7443	2.3161	<0.00001
	5	5.1691	2.4520	0.01020	3.7934	2.4520	0.03123
Wheel Excavators	6	39.4482	2.3300	<0.00001	34.1805	2.3300	<0.00001
Wheel Loaders	7	53.3354	2.3174	<0.00001	45.8020	2.3174	<0.00001
	8	231.7735	2.3044	<0.00001	187.5156	2.3044	<0.00001
	9	123.3903	2.3065	<0.00001	104.0655	2.3065	<0.00001
	10	56.4828	2.3173	<0.00001	41.5779	2.3173	<0.00001
Track Loaders	11	39.3571	2.3158	<0.00001	29.6287	2.3158	<0.00001
	12	18.7424	2.3142	<0.00001	15.2879	2.3142	<0.00001
Backhoe Loaders	13	8.4724	2.3497	0.00037	3.4737	2.3497	0.03426
	14	288.1675	2.3035	<0.00001	241.9619	2.3035	<0.00001
Integrated Toolcarriers	15	13.4581	2.3249	<0.00001	10.2465	2.3249	0.00005
Rigid Frame Trucks	16	57.6223	2.3252	<0.00001	56.2598	2.3252	<0.00001
	17	19.0817	2.4369	<0.00001	6.5743	2.4369	0.00334
Articulated Trucks	18	470.2482	2.3073	<0.00001	399.3391	2.3073	<0.00001
	19	457.3614	2.3106	<0.00001	417.4366	2.3106	<0.00001
Track Dozers	20	340.0637	2.3039	<0.00001	261.3926	2.3039	<0.00001
	21	408.7772	2.3040	<0.00001	274.3761	2.3040	<0.00001
	22	29.3456	2.3252	<0.00001	26.6374	2.3252	<0.00001
	23	19.0076	2.3207	<0.00001	7.2943	2.3207	0.00081
	24	6.8482	2.3618	0.00168	4.8125	2.3618	0.01026
Motor Graders	25	76.3394	2.3121	<0.00001	49.3390	2.3121	<0.00001
	26	38.8119	2.3106	<0.00001	27.4620	2.3106	<0.00001
Wheel Tractor Scrapers	27	124.1066	2.3113	<0.00001	54.4496	2.3113	<0.00001
	28	23.2018	2.3429	<0.00001	16.7603	2.3429	<0.00001

Appendix G.9: Coefficients for Validation of Plain Models

Equipment Type	Number	β_0 (Intercept)	β_2 (Age^2)	β_1 (Age)	M_1	M_2	M_3
Track Excavators	1	0.62568	0.00445	-0.08718	0.0	-0.03019	-0.00596
	2	0.60955	0.00212	-0.05341	0.0	-0.08117	-0.04704
	3	0.59048	0.00415	-0.07706	0.0	-0.05392	-0.06758
	4	0.49441	0.00398	-0.08715	0.0	-0.01796	0.0884
	5	0.45456	0.00189	-0.05	0.0	0.0	0.03529
Wheel Excavators	6	0.70508	0.00322	-0.07723	0.0	-0.09487	-0.05415
Wheel Loaders	7	0.5821	0.00056461	-0.02853	-0.03494	-0.09966	-0.07923
	8	0.74117	0.0025	-0.06626	-0.12594	-0.08779	-0.08547
	9	0.6244	0.00259	-0.064	-0.1393	-0.12727	-0.00517
	10	0.60081	0.0032	-0.07462	-0.13157	-0.13373	0.0
Track Loaders	11	0.55056	0.00141	-0.04093	0.0	-0.07379	-0.04923
	12	0.63895	0.00228	-0.05383	0.0	-0.24743	-0.02833
Backhoe Loaders	13	0.46866	0.00125	-0.03708	0.0	0.0	0.0
	14	0.78371	0.00251	-0.06527	0.0	-0.15472	-0.1489
Integrated Toolcarriers	15	0.70842	0.00332	-0.08521	0.0	0.03724	0.0
Rigid Frame Trucks	16	0.53849	0.00165	-0.04801	0.0	-0.1077	0.0
	17	0.58213	0.00149	-0.05331	0.0	-0.16972	0.0
Articulated Trucks	18	0.53798	0.00286	-0.06962	0.06062	-0.03993	0.0
	19	0.51681	0.003	-0.06899	0.06985	0.0	0.0
Track Dozers	20	0.58599	0.00205	-0.05358	0.0	0.0	-0.03946
	21	0.65364	0.00302	-0.07304	0.0	-0.10279	-0.02197
	22	0.67107	0.00252	-0.06255	0.0	-0.28272	0.0
	23	0.60533	0.00301	-0.07217	0.0	-0.17749	0.0
	24	0.53707	0.00294	-0.06562	0.0	-0.13524	0.0
Motor Graders	25	0.75161	0.00233	-0.06516	0.0	-0.05494	0.0
	26	0.84626	0.00292	-0.07572	0.0	-0.13383	0.0
Wheel Tractor Scrapers	27	0.73125	0.00307	-0.08247	0.0	-0.15477	0.0
	28	0.68022	0.00148	-0.05543	0.0	0.0	0.0

Appendix G.9 (Continued): Coefficients for Validation of Plain Models

Equipment Type	Number	C_1	C_2	C_3	R_1	R_2	R_3	E_1	E_2
Track Excavators	1	0.07408	0.01133	0.02661	-0.05195	-0.00285	-0.02754	N/A	N/A
	2	0.01875	-0.01477	0.01303	-0.0347	-0.00814	0.00251	N/A	N/A
	3	0.01512	-0.02385	0.02882	-0.02165	2.428E-5	0.02792	N/A	N/A
	4	0.03174	-0.03712	0.02921	-0.02013	0.01726	-0.00404	N/A	N/A
	5	0.05617	-0.06742	0.02999	-0.07843	-0.05216	0.00694	N/A	N/A
Wheel Excavators	6	0.02642	0.02462	0.00306	-0.02819	-0.03436	-0.01617	N/A	N/A
Wheel Loaders	7	0.0938	0.00859	0.00345	0.0107	-0.01016	0.00564	N/A	N/A
	8	0.02563	-0.01524	0.0117	0.00368	0.0053	0.02249	N/A	N/A
	9	0.03425	-3.3621E-4	5.7201E-4	0.00516	0.00487	0.00926	N/A	N/A
	10	0.04944	0.00955	-6.7288E-4	-0.00451	-2.9735E-4	0.00429	N/A	N/A
Track Loaders	11	0.06659	-0.02616	0.01506	-0.01197	0.03261	-0.01615	N/A	N/A
	12	0.0928	0.01511	0.01866	-0.05539	0.00375	0.01417	N/A	N/A
Backhoe Loaders	13	-0.01029	-0.03835	0.0215	0.0242	0.00131	0.00389	N/A	N/A
	14	0.04476	-0.02828	0.02652	-0.01902	-0.00921	0.02719	N/A	N/A
Integrated Toolcarriers	15	0.00953	-0.03188	9.7635E-4	0.02241	0.02778	-0.00398	N/A	N/A
Rigid Frame Trucks	16	0.05589	-0.04649	0.02517	0.04405	0.05304	-0.05931	N/A	N/A
	17	-0.067	0.03238	0.0029	-0.07296	-0.02055	-0.05059	N/A	N/A
Articulated Trucks	18	0.03687	-0.02692	0.03135	0.0104	0.01434	0.01396	N/A	N/A
	19	0.02126	-0.01982	0.01353	-0.02318	0.01519	0.00635	N/A	N/A
Track Dozers	20	0.04373	-0.01199	0.01592	-0.0077	0.00502	0.01132	N/A	N/A
	21	0.04006	-0.02981	0.02261	0.03492	0.02039	0.02758	N/A	N/A
	22	0.077	0.01455	-1.2729E-4	0.08715	0.06459	2.0459E-4	N/A	N/A
	23	0.08009	0.02443	0.02782	0.01886	0.02609	0.03136	N/A	N/A
	24	0.12449	0.02071	0.00542	-0.0138	-0.00632	-0.01894	N/A	N/A
Motor Graders	25	0.01259	-0.01274	0.00783	-0.07362	-0.03581	-0.03368	N/A	N/A
	26	-0.01608	-0.04337	0.01662	-0.05533	-0.05789	-0.03813	N/A	N/A
Wheel Tractor Scrapers	27	0.04327	-0.01687	0.02413	0.08309	0.06605	-0.00211	N/A	N/A
	28	0.05806	-0.00227	0.03327	-0.01495	0.0	0.0346	N/A	N/A

Appendix G.10: Statistics for Validation of Plain Models

Equipment Type	Number	R^2	Adjusted R^2	Root MSE	Correlation R_{corr}	Correlation R_{corr}^2	Complete Observations	Average Age
Track Excavators	1	0.8297	0.7927	0.0707	0.8931	0.7977	82	3.46
	2	0.7276	0.7246	0.0685	0.8341	0.6957	1426	4.97
	3	0.7435	0.7302	0.0563	0.8119	0.6593	357	3.61
	4	0.7698	0.7594	0.0585	0.8176	0.6685	409	3.47
	5	0.8369	0.7805	0.0500	0.7921	0.6273	51	7.13
Wheel Excavators	6	0.8201	0.8038	0.0748	0.8466	0.7168	209	6.54
Wheel Loaders	7	0.6338	0.6159	0.0822	0.8370	0.7006	374	6.99
	8	0.7473	0.7459	0.0808	0.8582	0.7365	2961	6.77
	9	0.9085	0.9072	0.0560	0.9604	0.9225	1368	6.65
	10	0.9201	0.9163	0.0575	0.9606	0.9228	375	5.99
Track Loaders	11	0.7408	0.7315	0.0559	0.8489	0.7206	418	8.46
	12	0.9213	0.9189	0.0528	0.9658	0.9327	471	8.97
Backhoe Loaders	13	0.4548	0.4140	0.0369	0.6441	0.4149	128	12.56
	14	0.6965	0.6957	0.0796	0.8274	0.6846	5554	6.97
Integrated Toolcarriers	15	0.8580	0.8491	0.0666	0.9041	0.8174	253	5.19
Rigid Frame Trucks	16	0.5725	0.5508	0.0844	0.7435	0.5527	250	9.43
	17	0.7642	0.6978	0.0579	0.9028	0.8151	55	8.05
Articulated Trucks	18	0.6765	0.6726	0.0815	0.8213	0.6745	1146	5.84
	19	0.5907	0.5829	0.0803	0.7674	0.5889	677	5.87
Track Dozers	20	0.7144	0.7134	0.0676	0.8464	0.7164	3968	7.48
	21	0.8056	0.8047	0.0786	0.8959	0.8027	3754	5.86
	22	0.8843	0.8770	0.0708	0.9287	0.8625	250	7.86
	23	0.8993	0.8940	0.0649	0.9469	0.8966	308	5.08
	24	0.9230	0.9101	0.0482	0.9355	0.8751	105	7.00
Motor Graders	25	0.8608	0.8571	0.0595	0.9344	0.8732	575	7.19
	26	0.9214	0.9196	0.0550	0.9522	0.9068	679	7.15
Wheel Tractor Scrapers	27	0.7965	0.7918	0.0789	0.8989	0.8079	626	7.93
	28	0.7140	0.6880	0.0670	0.8827	0.7791	147	8.79

Appendix G.10 (Continued): Statistics for Validation of Plain Models

Equipment Type	Number	Complete Observations	Adjusted R	Correlation R_{corr}	t_{obs}	$t_{0.95,\, n-2}$	p-Value (t-Test)	z_{obs}	$z_{0.95,\, n-2}$	p-Value (z-Test)
Track Excavators	1	82	0.9526	0.8931	4.1290	1.6849	0.00009	2.7754	1.6449	0.00276
	2	1426	0.8557	0.8341	19.1385	1.6470	<0.00001	0.6836	1.6449	0.24711
	3	357	0.8545	0.8119	9.0780	1.6530	<0.00001	1.1038	1.6449	0.13483
	4	409	0.8727	0.8176	9.4558	1.6524	<0.00001	1.9186	1.6449	0.02752
	5	51	0.9173	0.7921	2.7565	1.7139	0.00562	1.6981	1.6449	0.04475
Wheel Excavators	6	209	0.8889	0.8466	7.4190	1.6585	<0.00001	1.2646	1.6449	0.10300
Wheel Loaders	7	374	0.8275	0.8370	9.7611	1.6528	<0.00001	-0.5150	1.6449	0.30327
	8	2961	0.8655	0.8582	28.6403	1.6459	<0.00001	0.3989	1.6449	0.34497
	9	1368	0.9554	0.9604	23.7766	1.6471	<0.00001	-1.3887	1.6449	0.08246
	10	375	0.9593	0.9606	11.6388	1.6532	<0.00001	-0.3671	1.6449	0.35677
Track Loaders	11	418	0.8562	0.8489	9.7288	1.6530	<0.00001	0.2963	1.6449	0.38350
	12	471	0.9713	0.9658	13.2605	1.6515	<0.00001	0.6381	1.6449	0.26170
Backhoe Loaders	13	128	0.6259	0.6441	4.1820	1.6711	0.00005	-1.2631	1.6449	0.10327
	14	5554	0.8386	0.8274	36.1069	1.6454	<0.00001	0.9713	1.6449	0.16570
Integrated Toolcarriers	15	253	0.9276	0.9041	9.1687	1.6561	<0.00001	1.2633	1.6449	0.10323
Rigid Frame Trucks	16	250	0.7511	0.7435	5.9716	1.6579	<0.00001	0.1001	1.6449	0.46012
	17	55	0.9220	0.9028	3.9524	1.6924	0.00019	0.7783	1.6449	0.21820
Articulated Trucks	18	1146	0.8242	0.8213	16.2256	1.6475	<0.00001	-0.0730	1.6449	0.47089
	19	677	0.7775	0.7674	11.0744	1.6492	<0.00001	0.1918	1.6449	0.42394
Track Dozers	20	3968	0.8546	0.8464	31.7923	1.6456	<0.00001	0.2921	1.6449	0.38510
	21	3754	0.8969	0.8959	34.9998	1.6457	<0.00001	0.0015	1.6449	0.49939
	22	250	0.9385	0.9287	8.6258	1.6586	<0.00001	0.4504	1.6449	0.32622
	23	308	0.9502	0.9469	10.4499	1.6549	<0.00001	0.2107	1.6449	0.41658
	24	105	0.9519	0.9355	5.3689	1.6747	<0.00001	0.6017	1.6449	0.27367
Motor Graders	25	575	0.9260	0.9344	14.4682	1.6502	<0.00001	-0.9875	1.6449	0.16169
	26	679	0.9583	0.9522	15.6939	1.6496	<0.00001	0.8944	1.6449	0.18555
Wheel Tractor Scrapers	27	626	0.8918	0.8989	13.9952	1.6498	<0.00001	-0.5207	1.6449	0.30130
	28	147	0.8169	0.8827	6.0608	1.6676	<0.00001	-1.3682	1.6449	0.08563

Appendix H: Box Plots of Residual Value Percent over Age with Sample Curves

The following box plots are overlaid with sample curves of the fitted regression model that were calculated using the Equation H.1 for the trade journal models.

$$RVP = \beta_0 + \beta_1 \cdot age^2 + \beta_2 \cdot age + M_1 \cdot m_1 + M_2 \cdot m_2 + M_3 \cdot m_3 + C_1 \cdot c_1 + C_2 \cdot c_2 + C_3 \cdot c_3 + R_1 \cdot r_1 + R_2 \cdot r_2 + R_3 \cdot r_3 + E_{1t} \cdot e_{1t} + E_{2t} \cdot e_{2t}$$

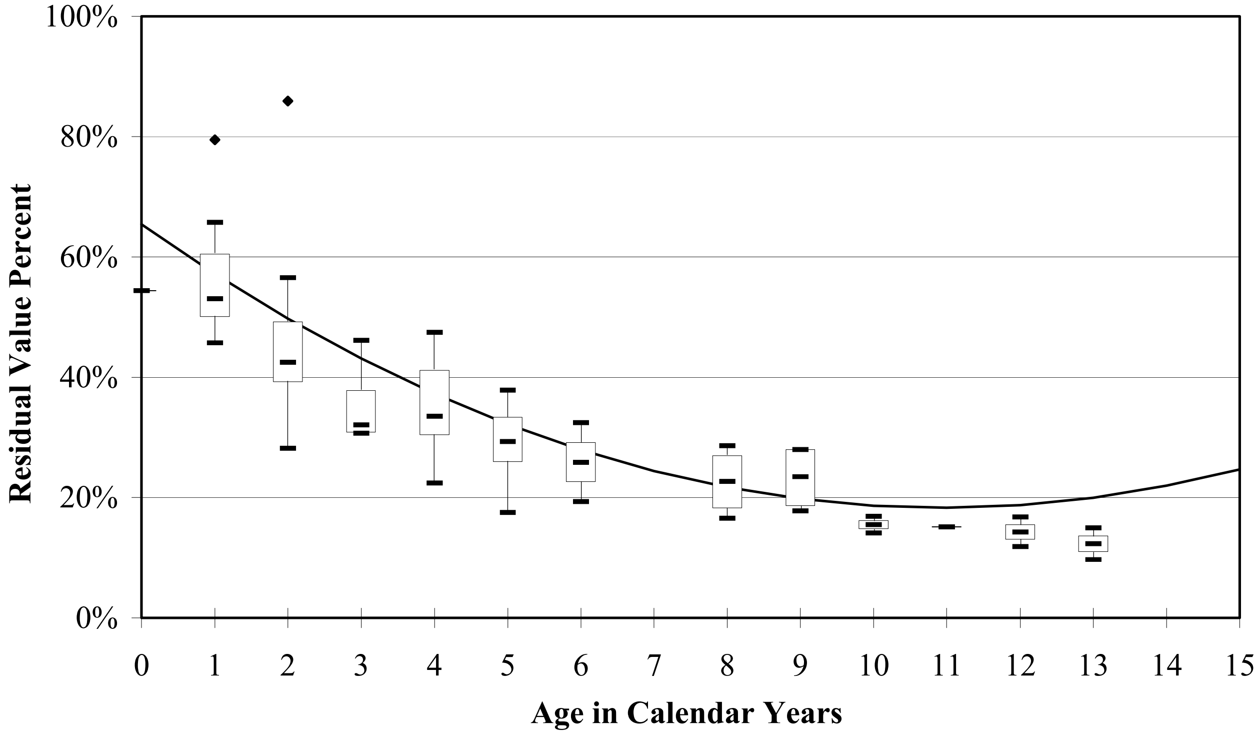
Equation H.1

where RVP is the residual value percent, β_0 through β_2 are regression coefficients (β_0 being the intercept), *age* is the age in calendar years, M_i, C_i, and R_i are the regression coefficients for the manufacturer, condition rating, and auction region indicator variables, respectively, m_i, c_i, and r_i are the manufacturer, condition rating, and auction region indicator variables, respectively, E_{it} are the regression coefficients for the economic indicators from the trade journal models, and e_{it} are the economic indicator values from the trade journal models.

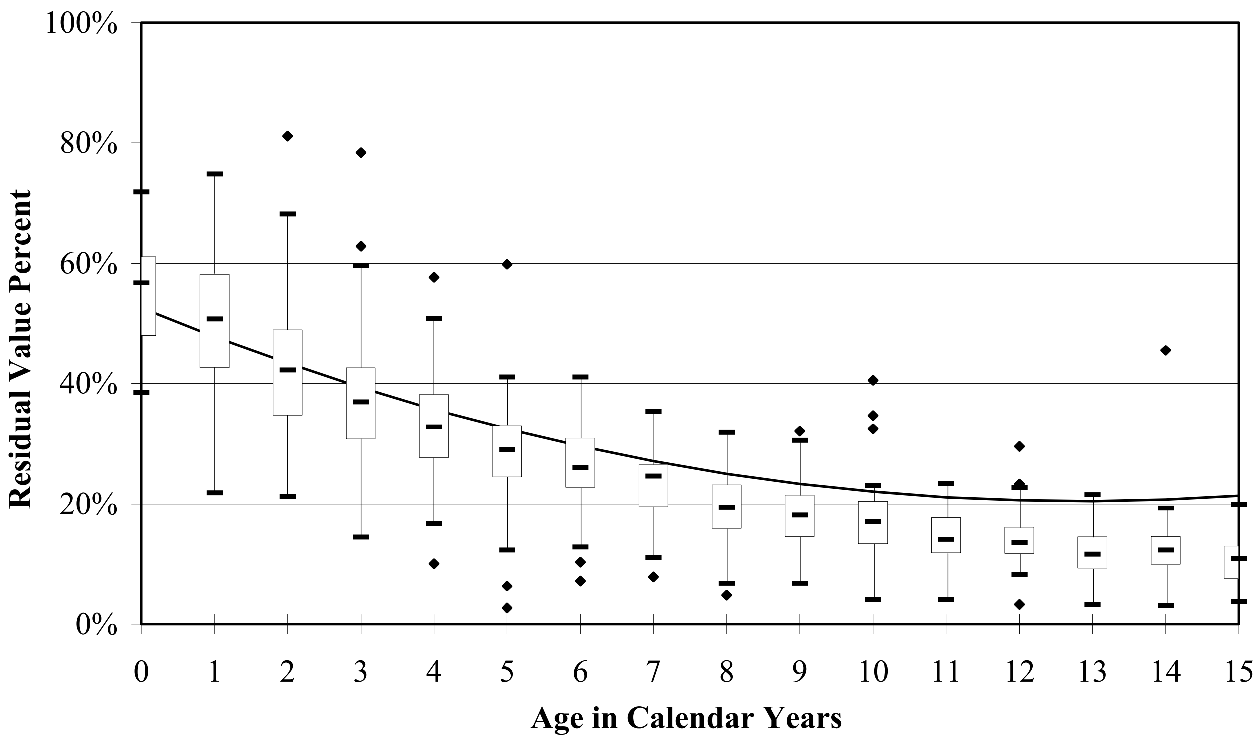
In order to generate these curves it was necessary to assume values for the explanatory variables that are not displayed in the plots. Caterpillar was chosen as manufacturer for all plots except in Appendices H5, H13, and H20, where no data points from Caterpillar were available. Deere was chosen as the manufacturer in these cases. Condition rating was assumed as good. Economic indicator values from November 31, 2002 were used. The auction region was Northeast. Since the diagrams display residual value percent, an inflation correction was not necessary.

It is noted that the diagrams in this appendix display only one facet of a multidimensional model and that their curves depend not only on age in calendar years but also on the remaining explanatory variables. Varying these input values would shift the curves in the diagrams.

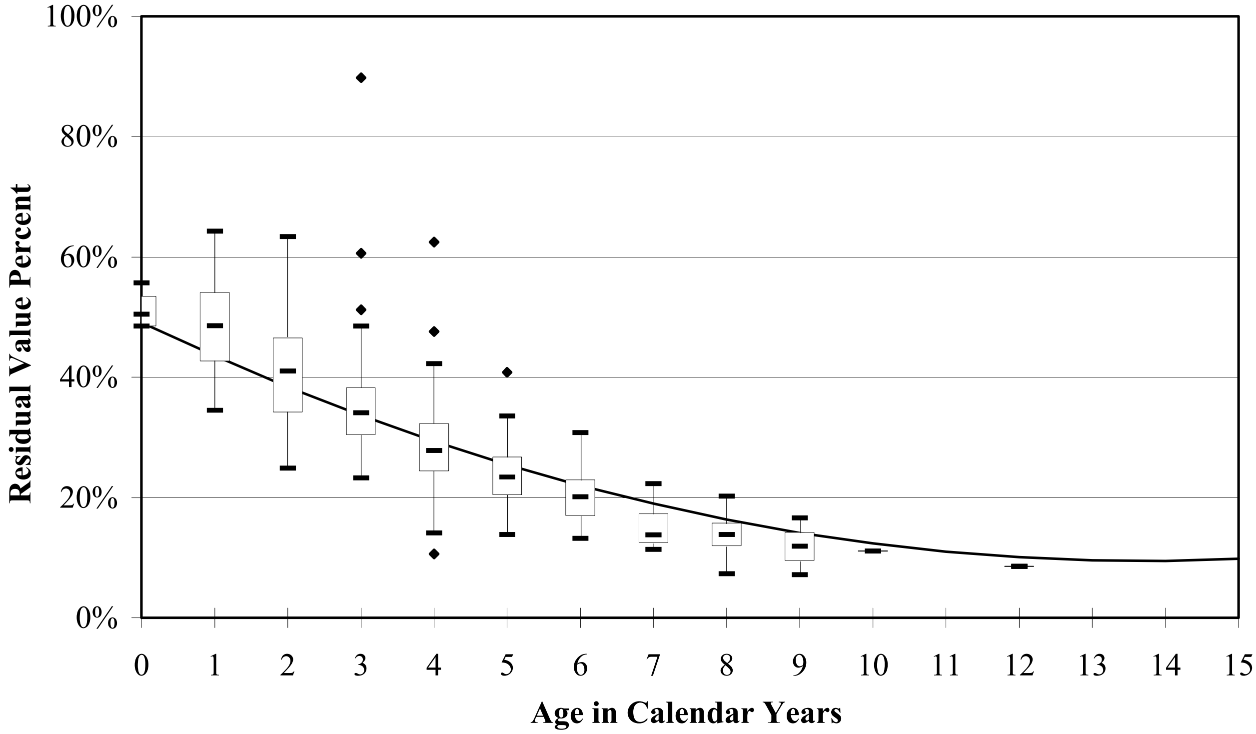
Appendix H.1: **Track Excavators (0-24,999 lbs)**



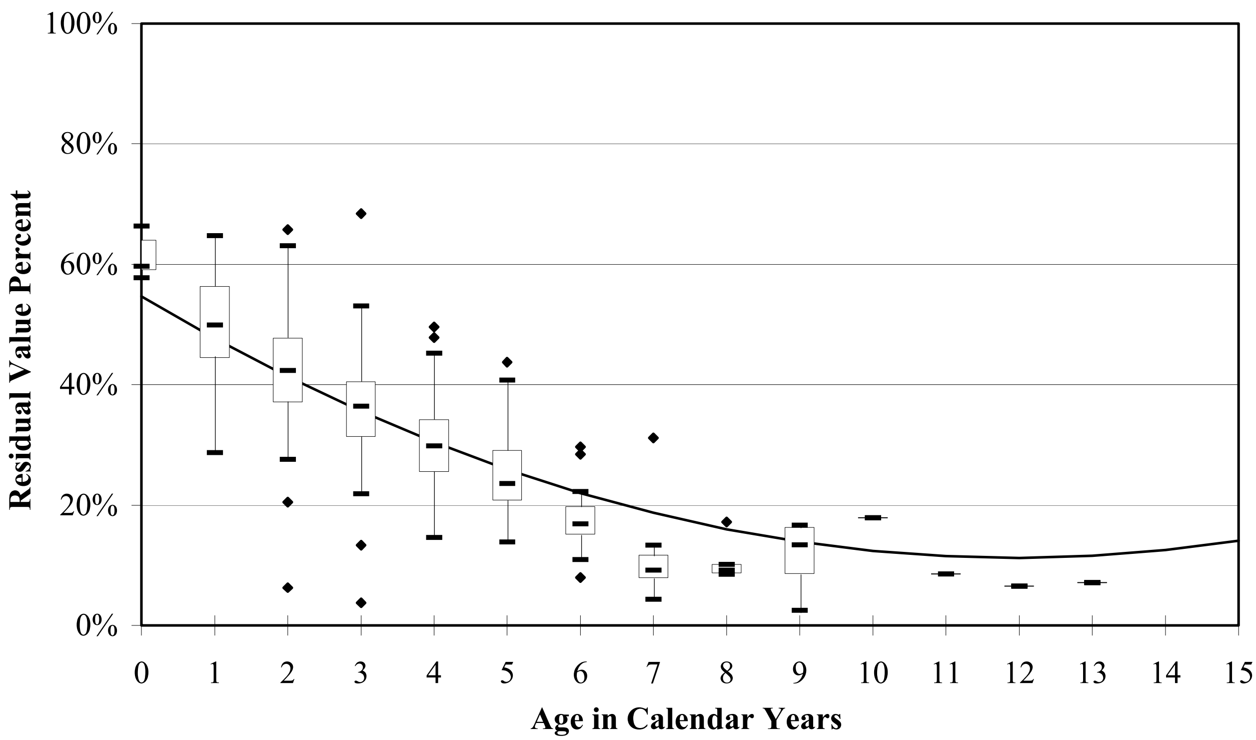
Appendix H.2: **Track Excavators (25,000-49,999 lbs)**



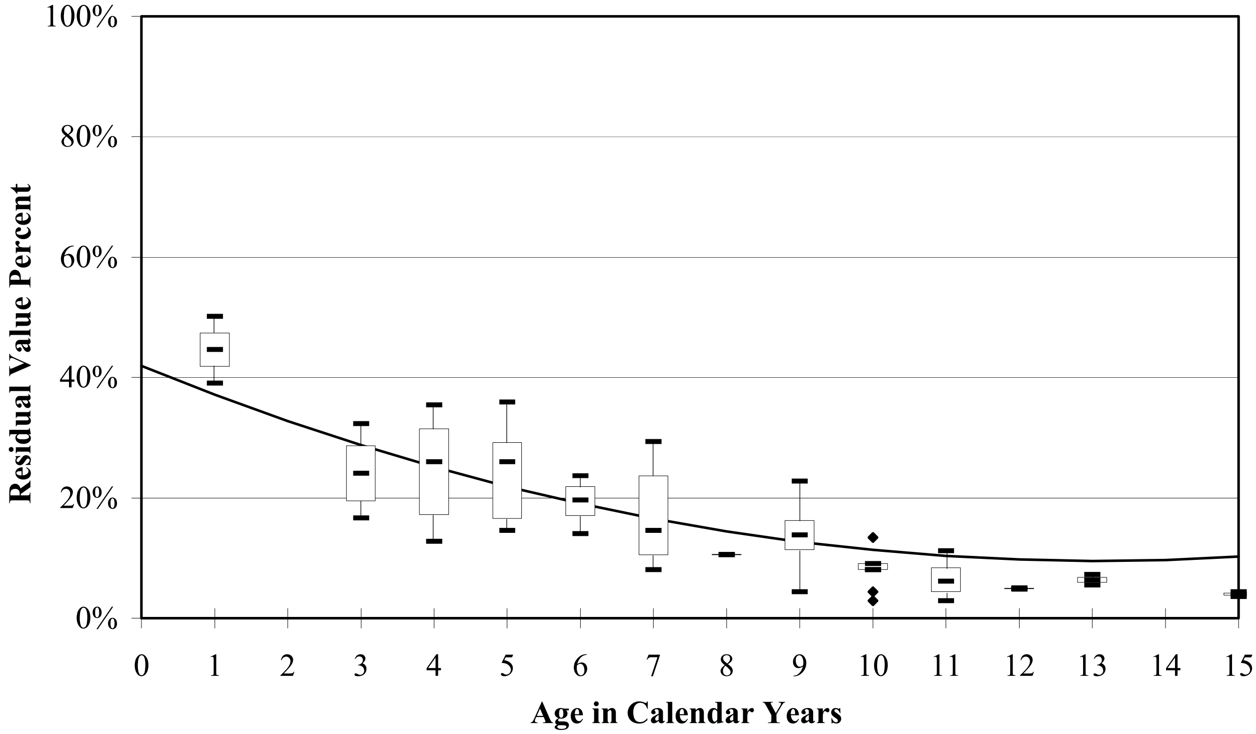
Appendix H.3: Track Excavators (50,000-74,999 lbs)



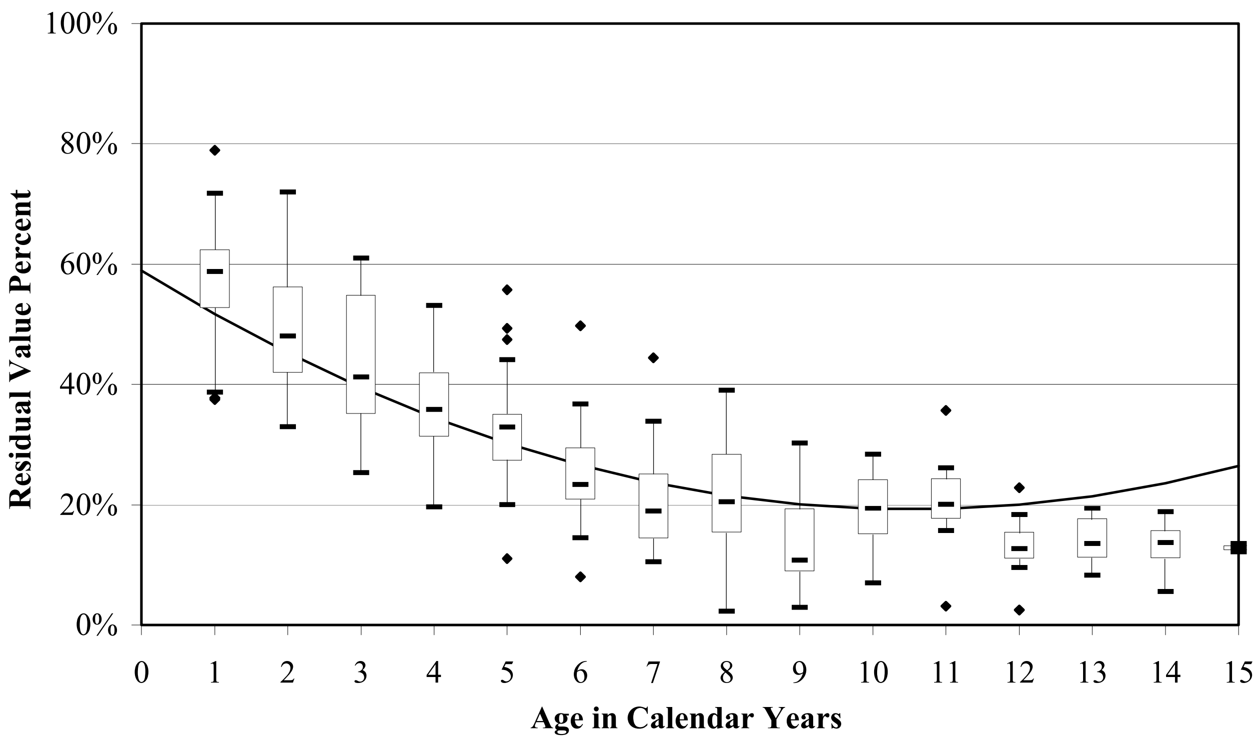
Appendix H.4: Track Excavators (75,000-99,999 lbs)



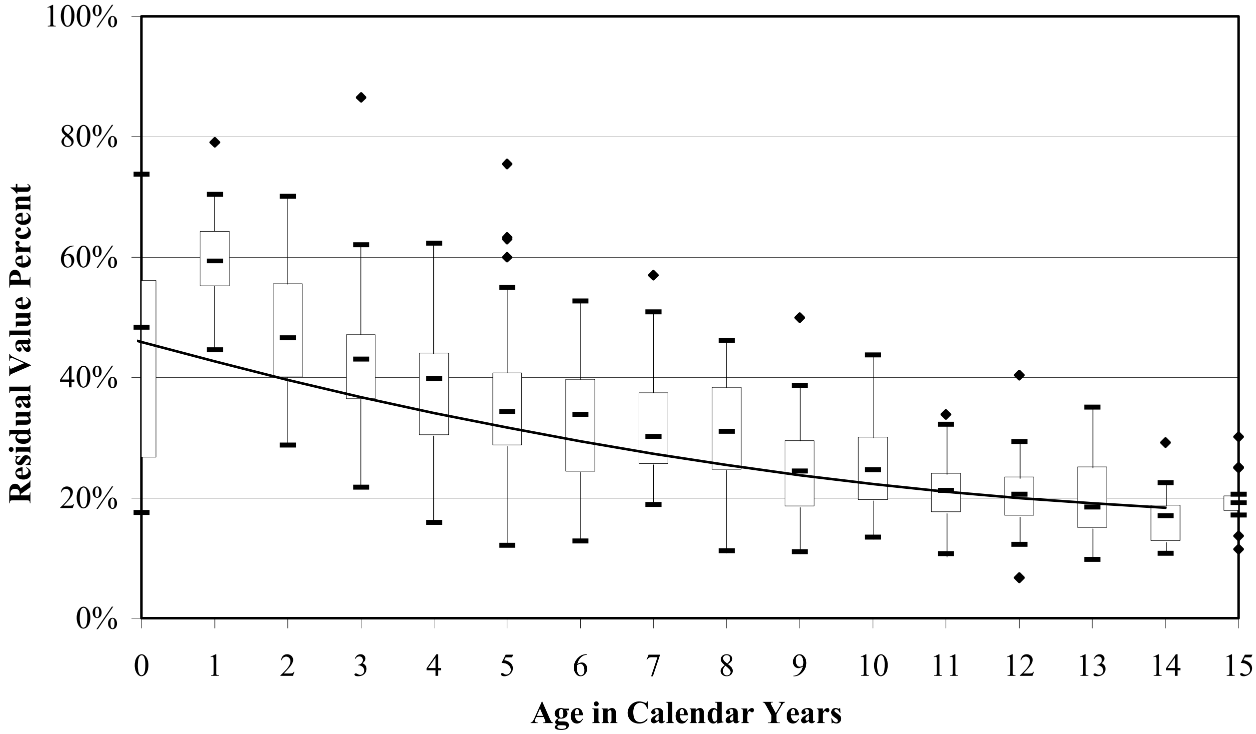
Appendix H.5: Track Excavators (100,000+ lbs)



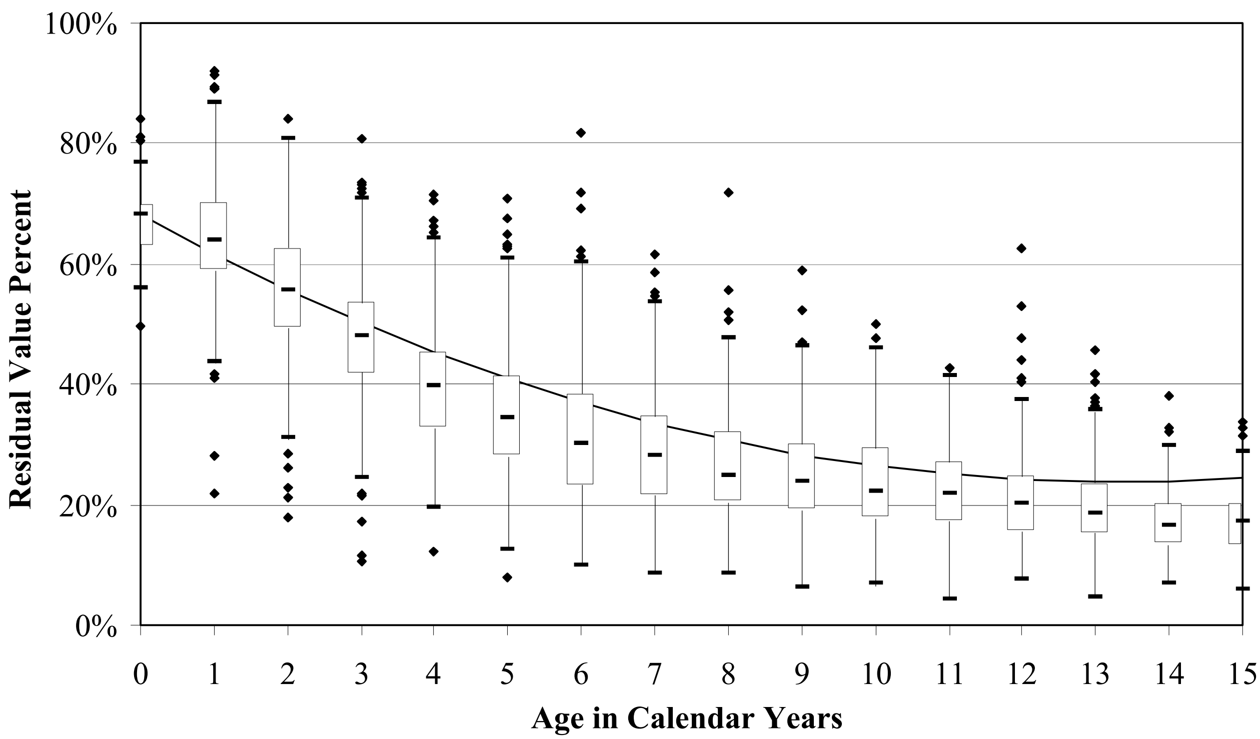
Appendix H.6: Wheel Excavators (All Sizes)



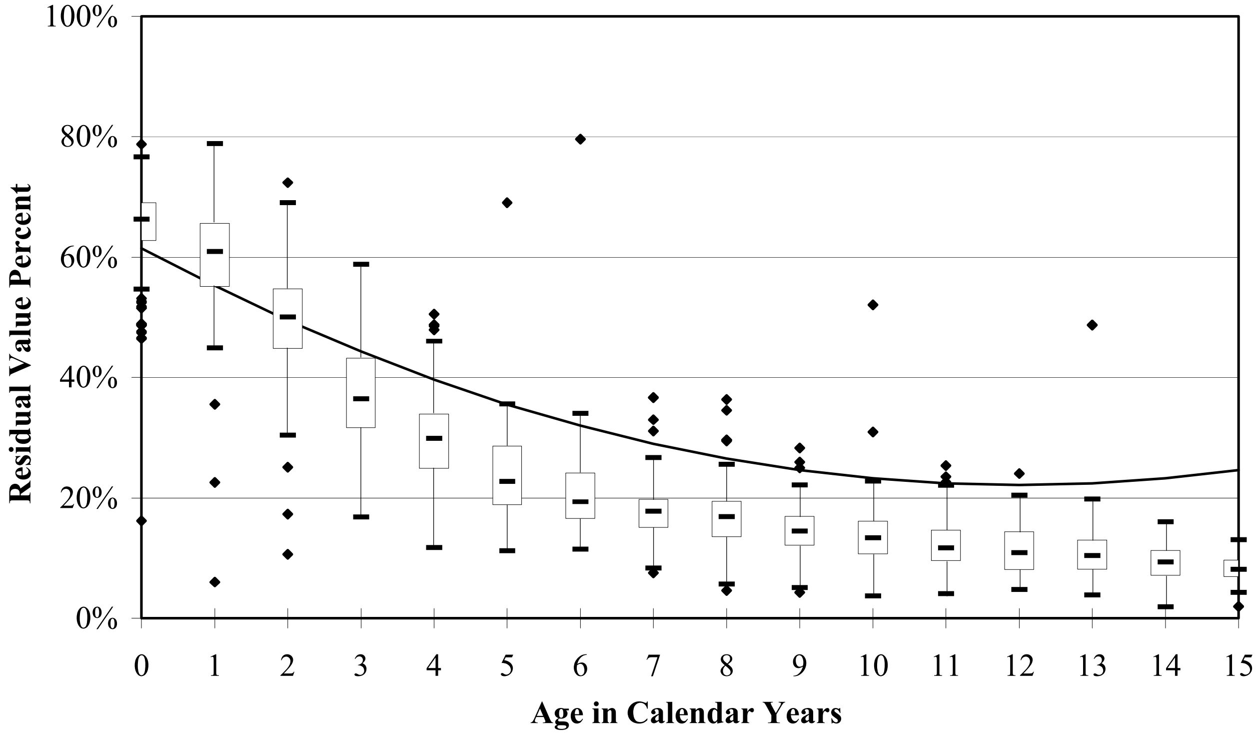
Appendix H.7: Wheel Loaders (0-1.9 CY)



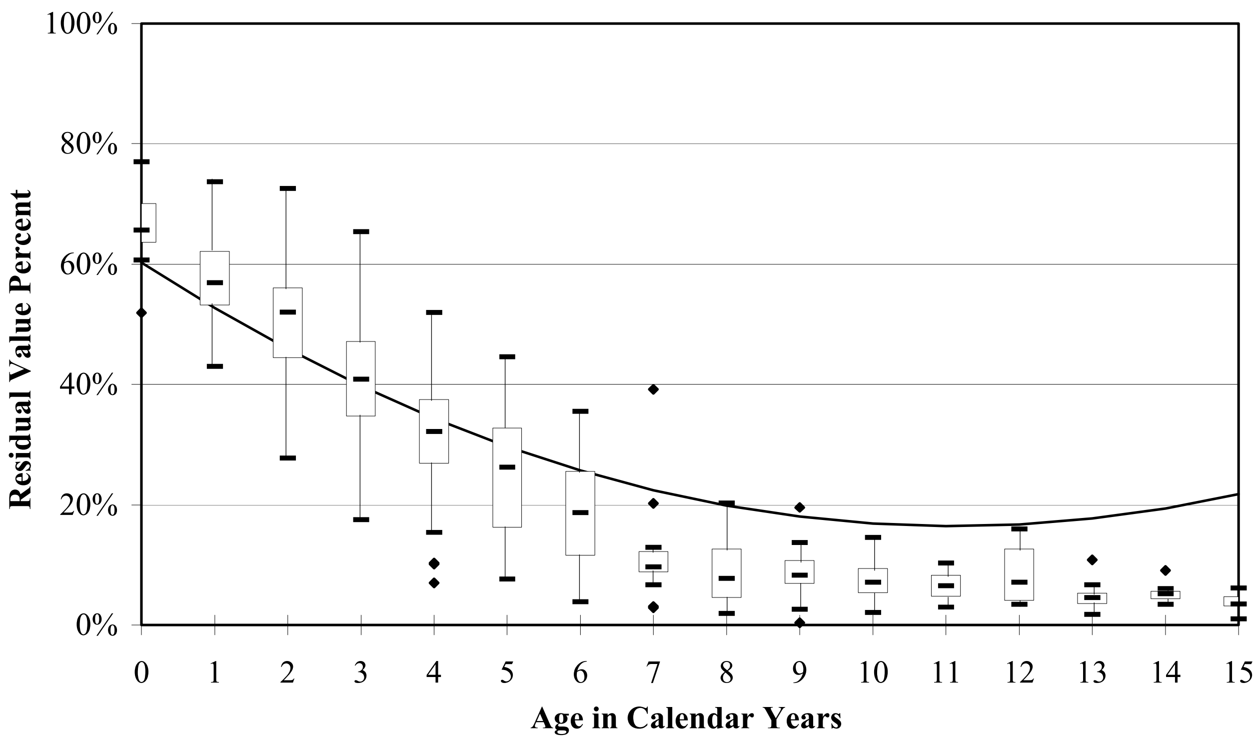
Appendix H.8: Wheel Loaders (2-3.9 CY)



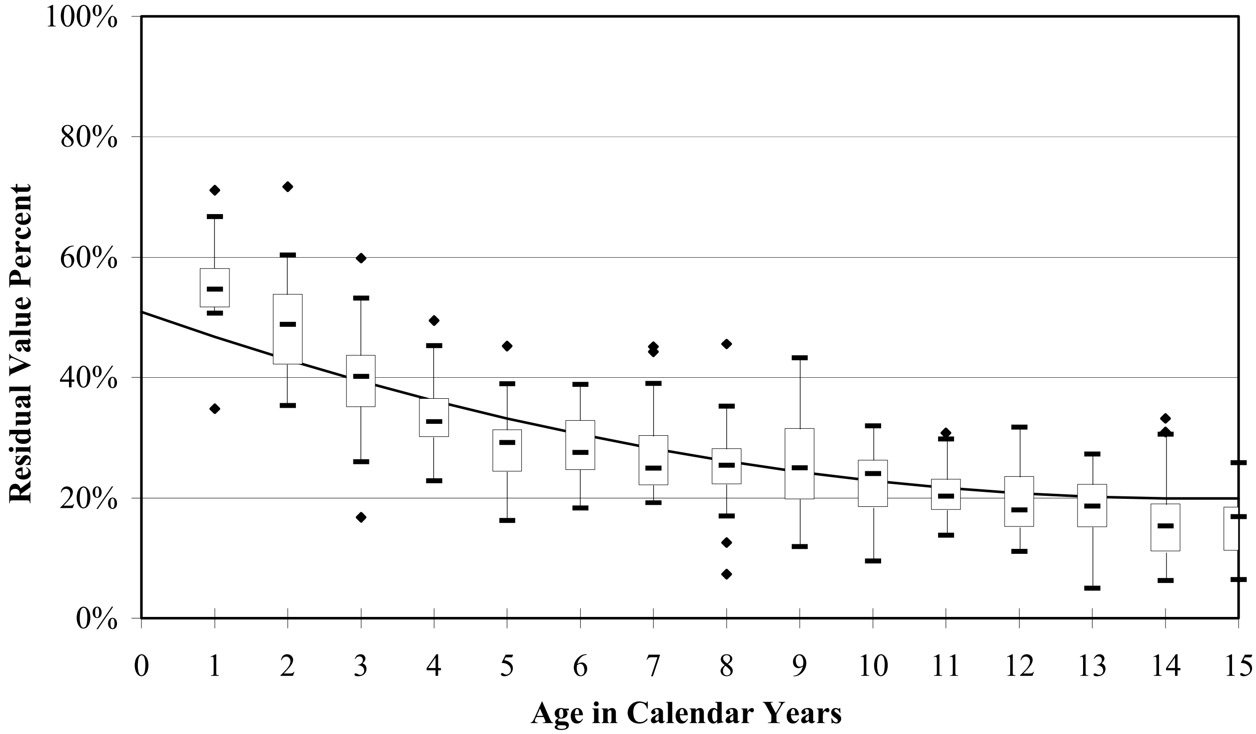
Appendix H.9: Wheel Loaders (4-5.9 CY)



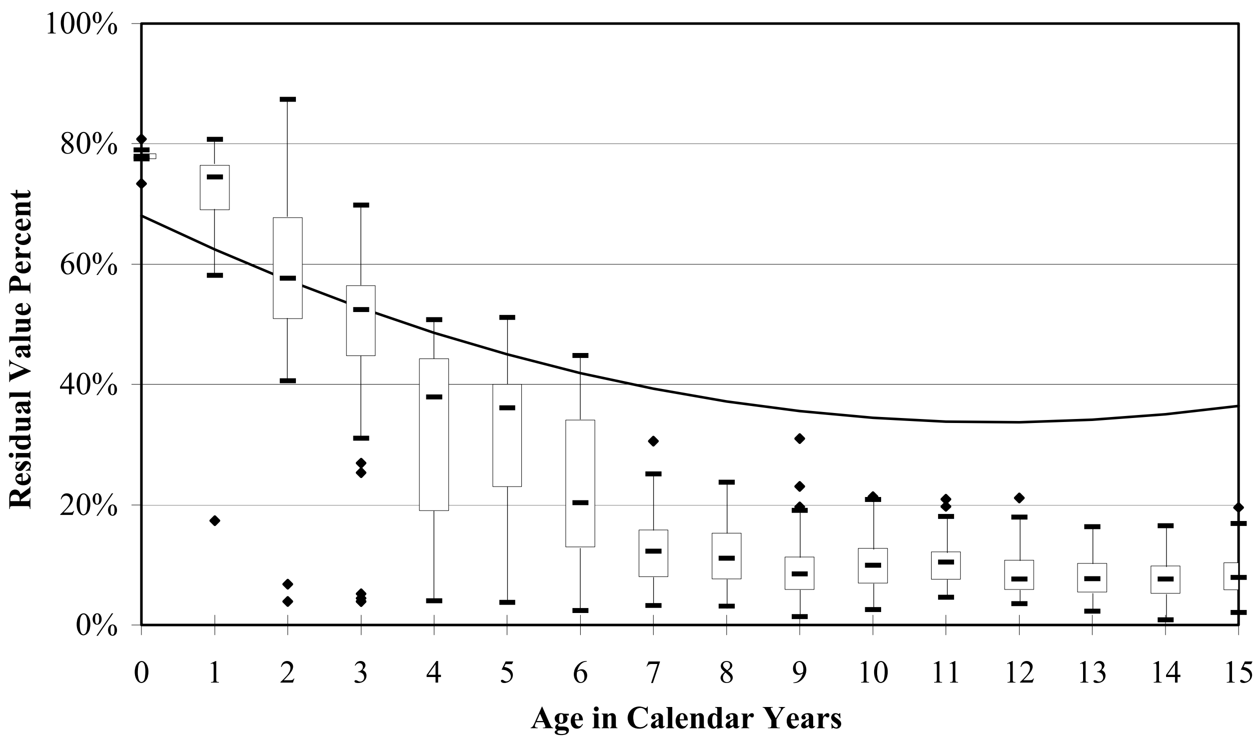
Appendix H.10: Wheel Loaders (6+ CY)



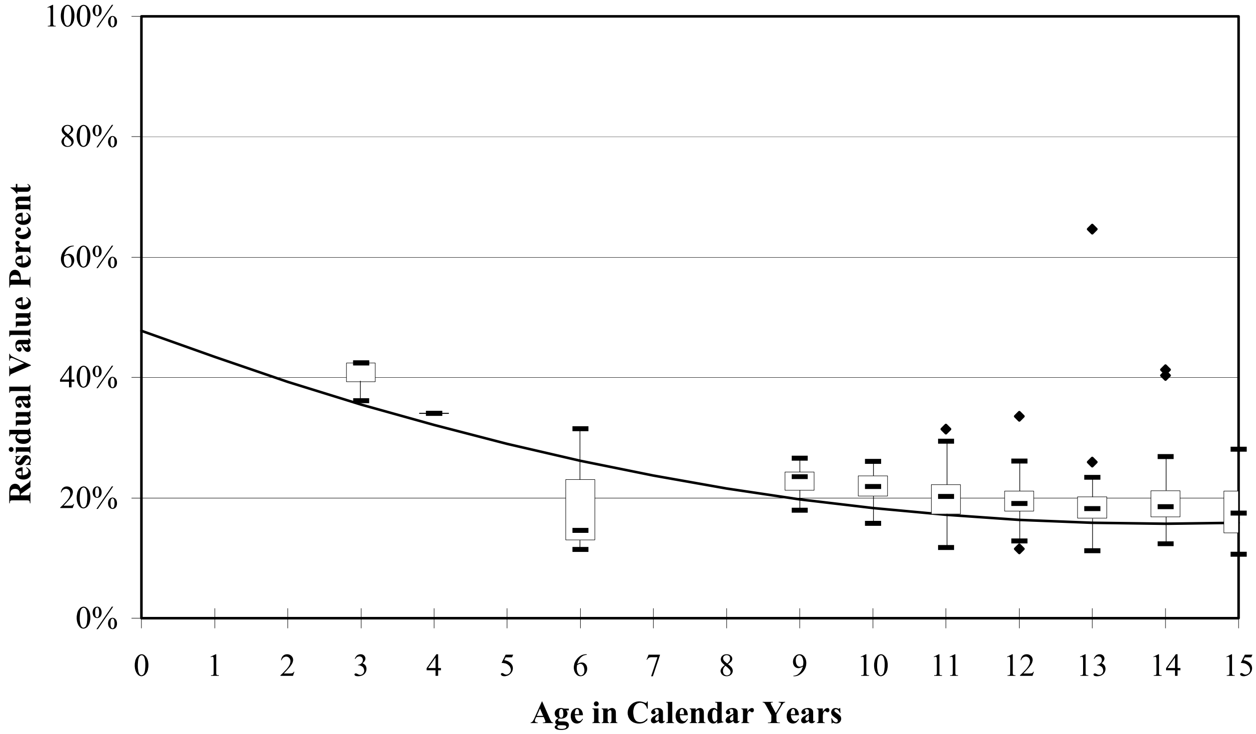
Appendix H.11: Track Loaders (0-1.9 CY)



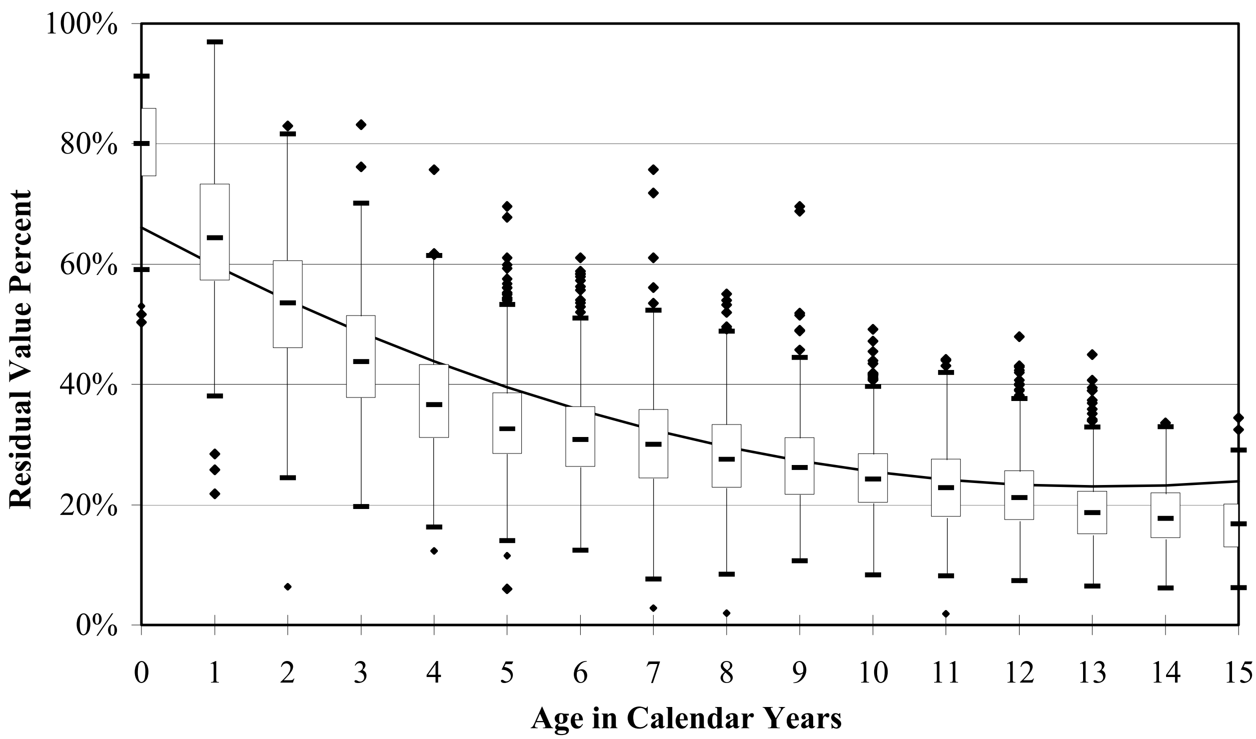
Appendix H.12: Track Loaders (2+ CY)



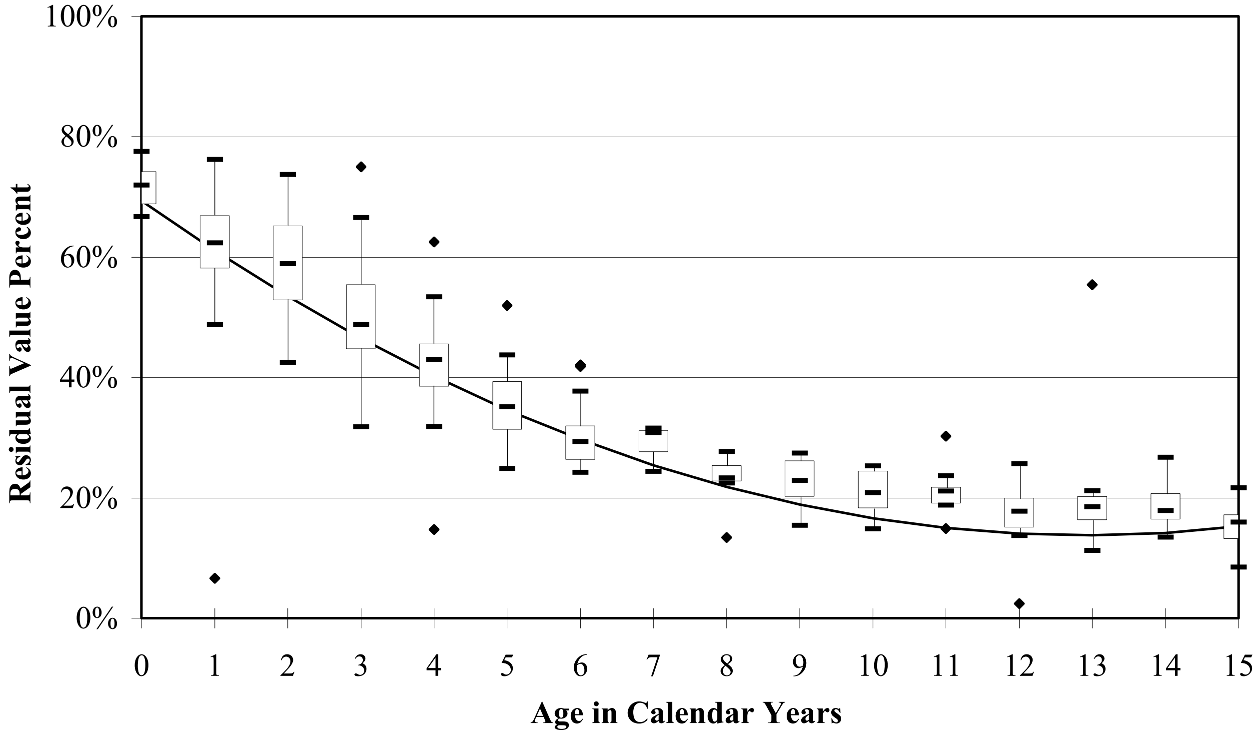
Appendix H.13: Backhoe Loaders (0-0.9 CY)



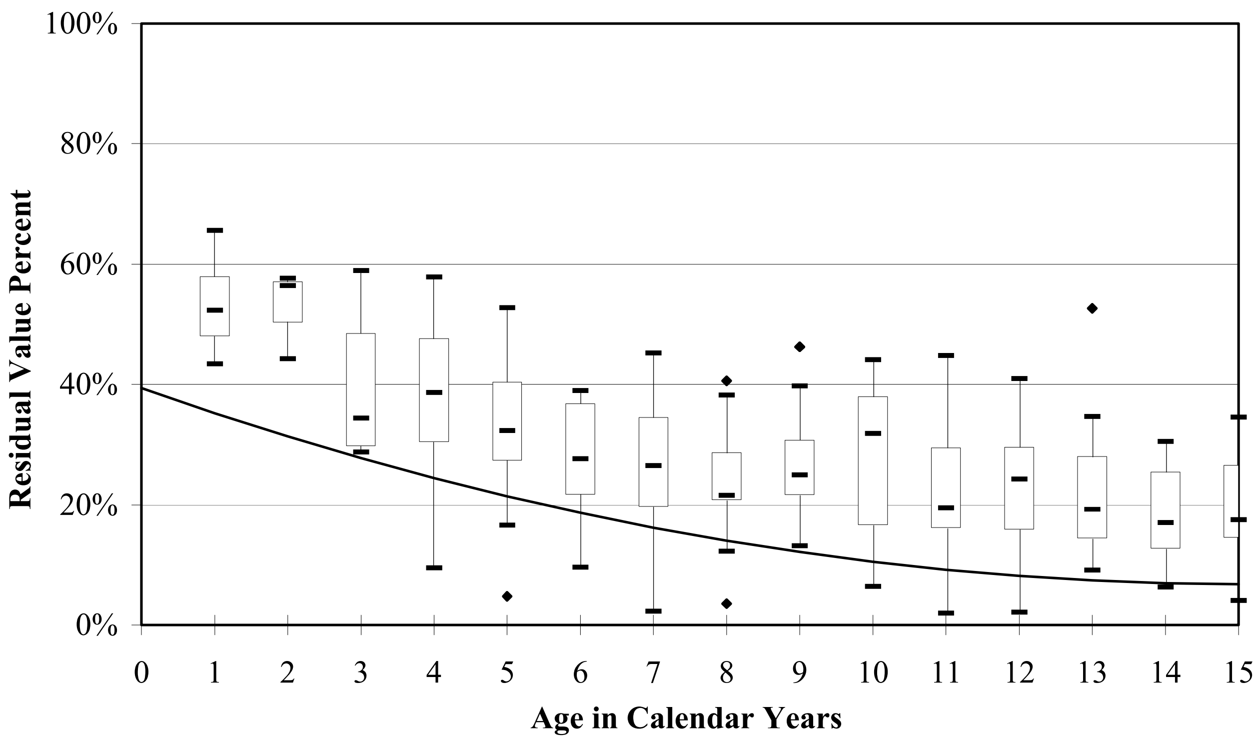
Appendix H.14: Backhoe Loaders (1+ CY)



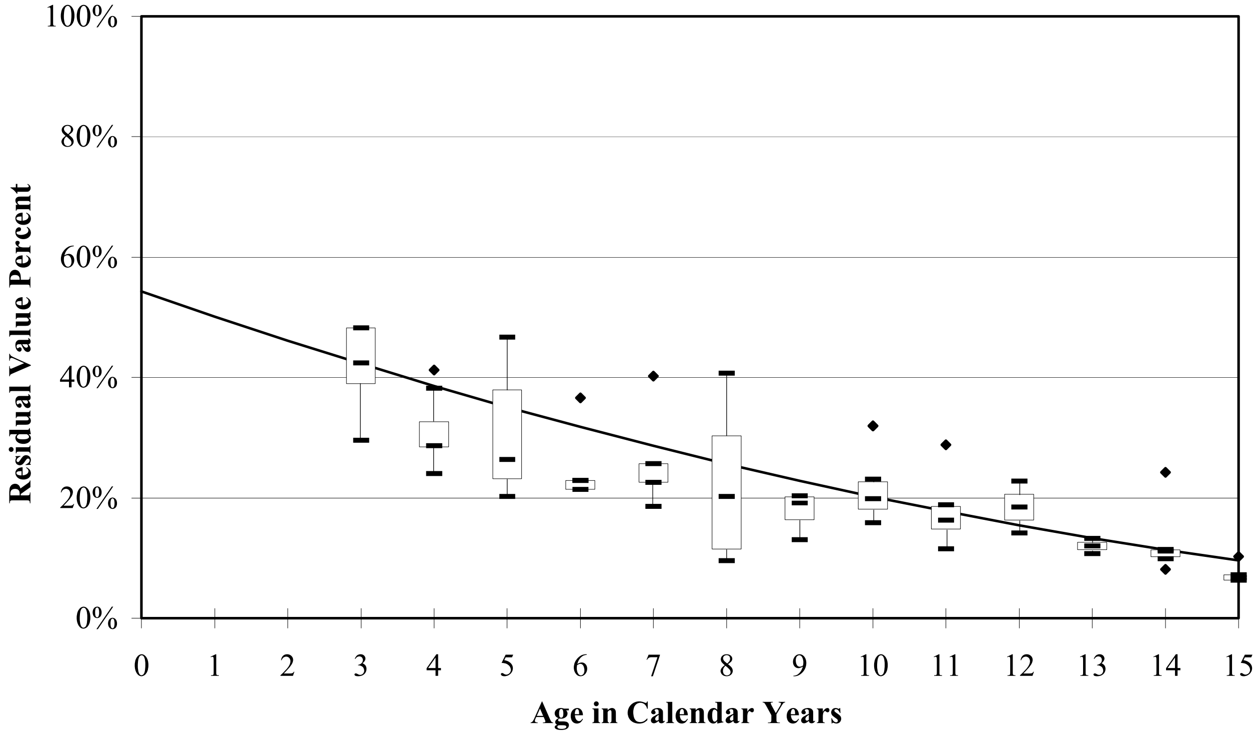
Appendix H.15: Integrated Toolcarriers (All Sizes)



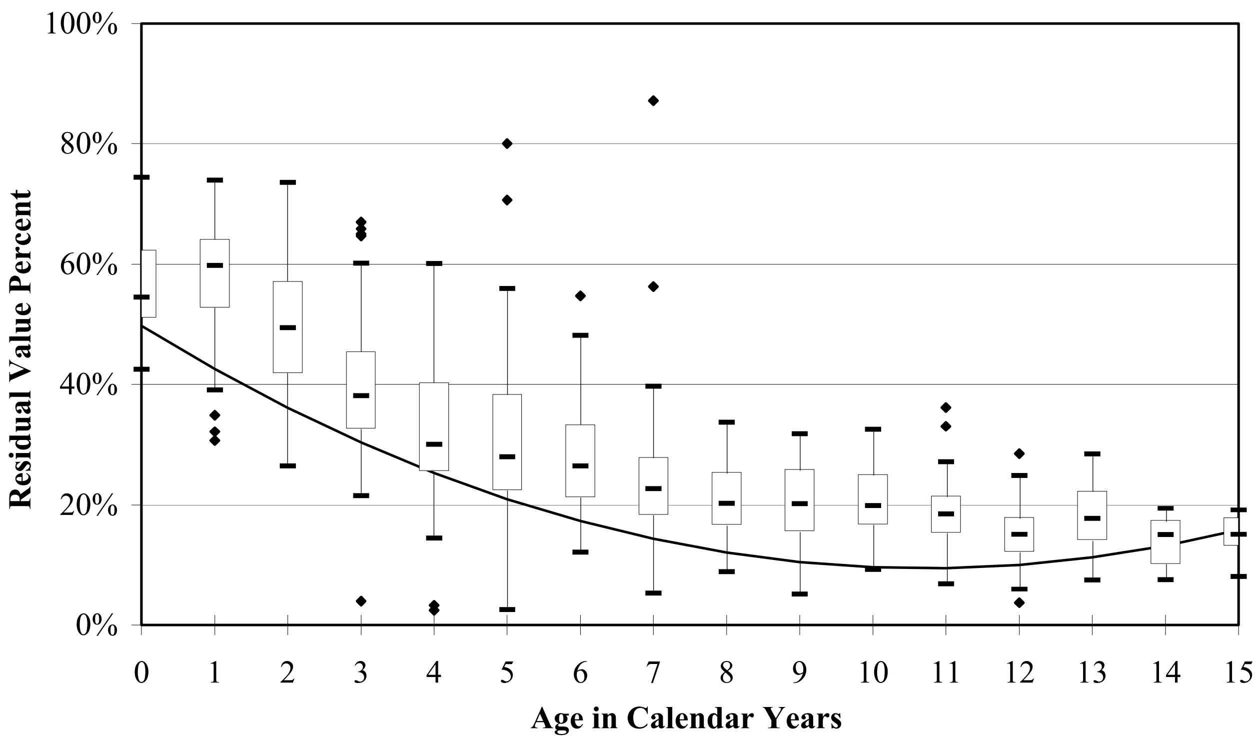
Appendix H.16: Rigid Frame Trucks (0-99,999 lbs)



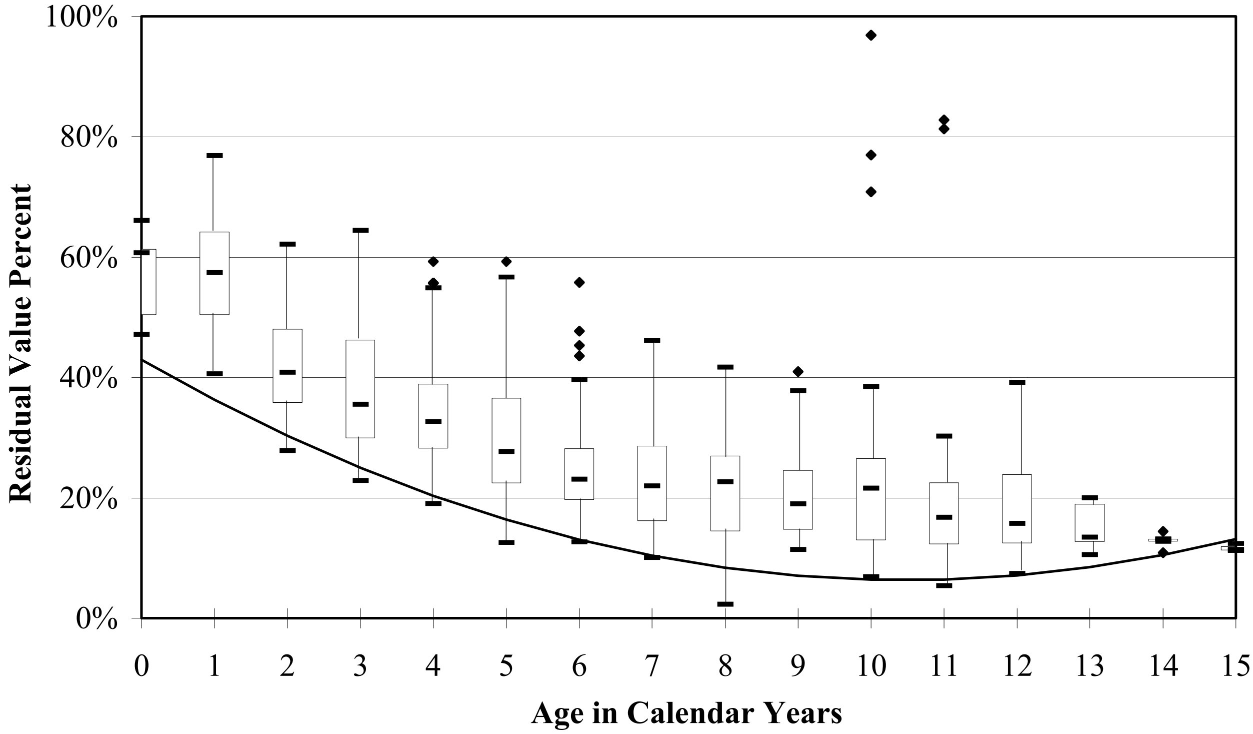
Appendix H.17: Rigid Frame Trucks (100,000+ lbs)



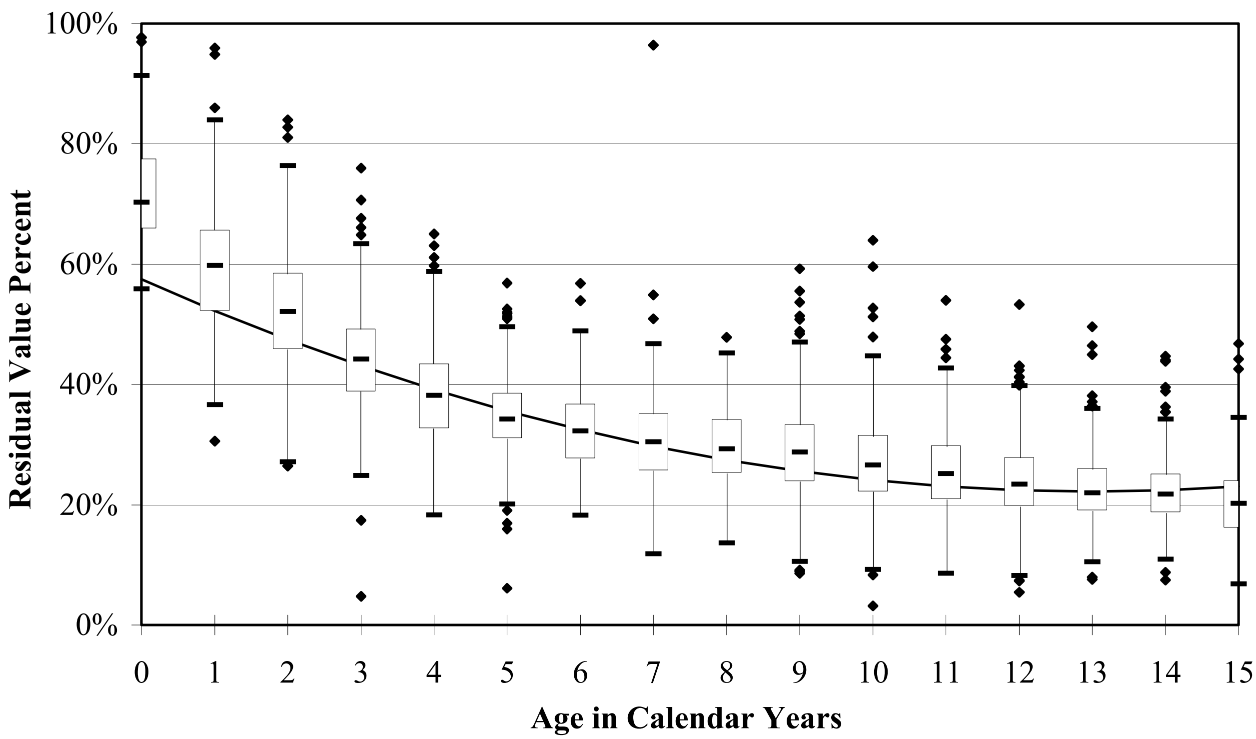
Appendix H.18: Articulated Trucks (0-49,999 lbs)



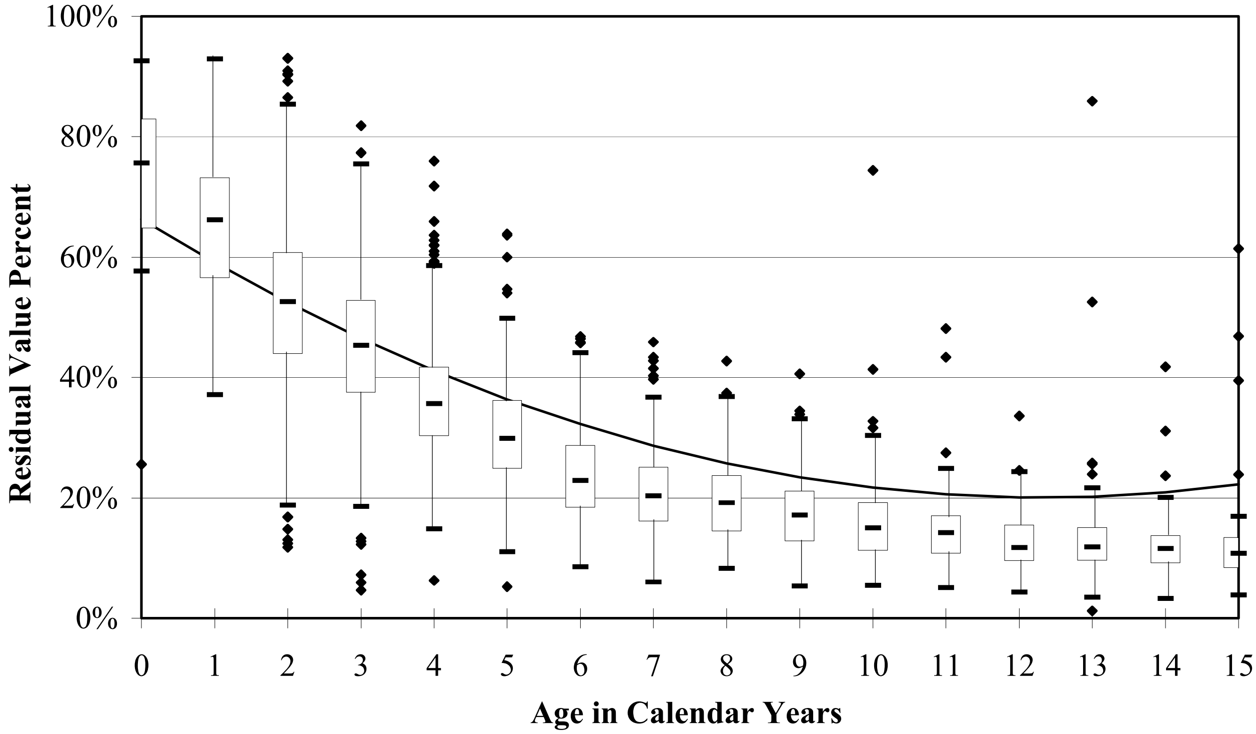
Appendix H.19: Articulated Trucks (50,000+ lbs)



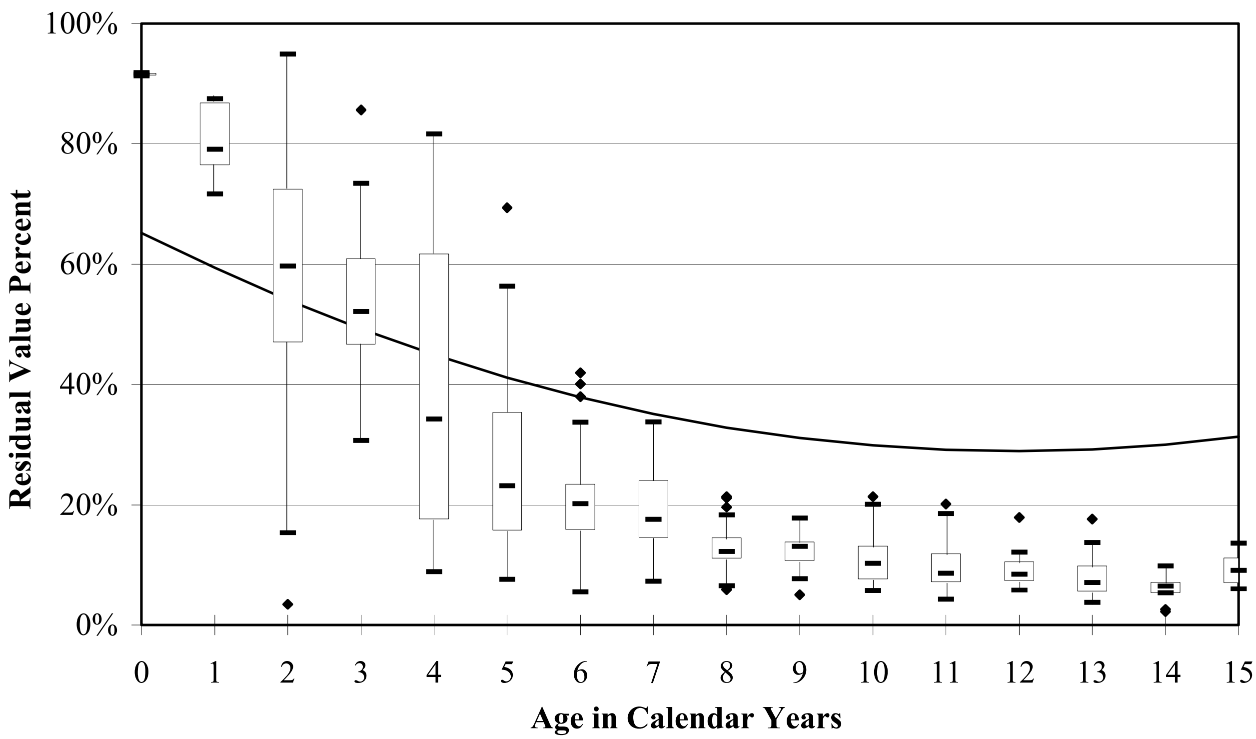
Appendix H.20: Track Dozers (0-99 HP)



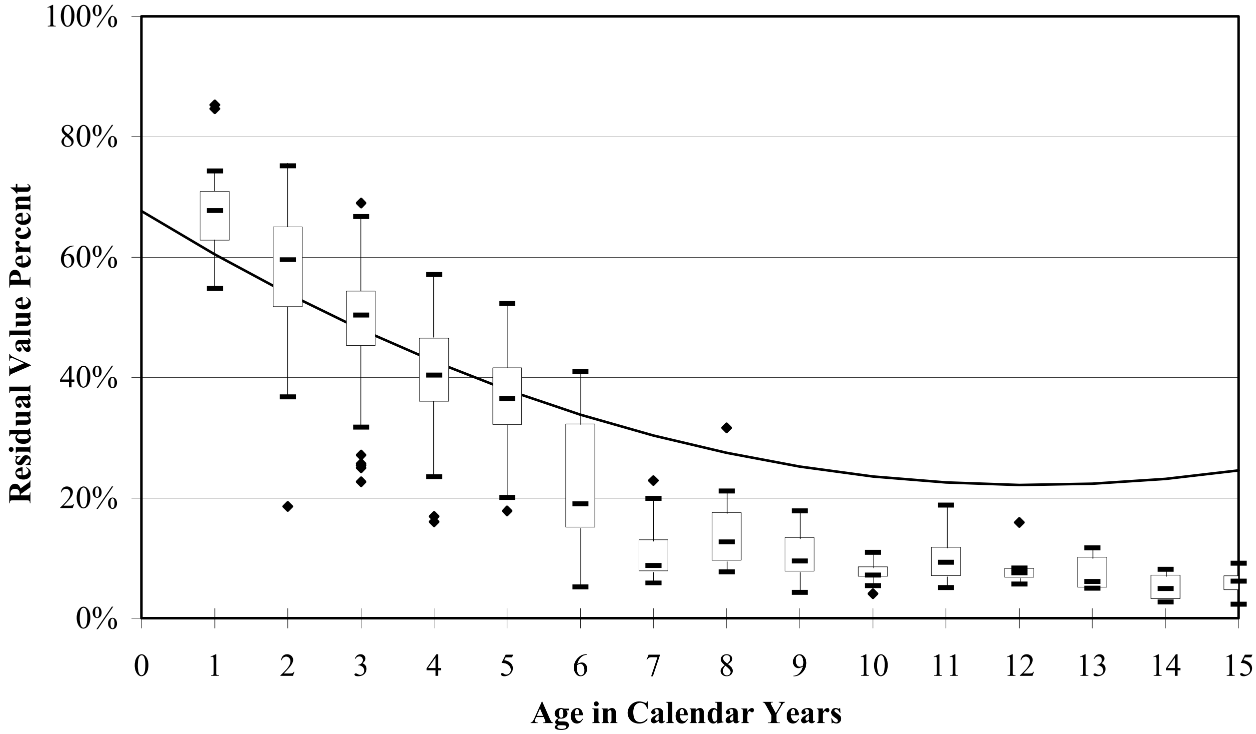
Appendix H.21: Track Dozers (100-199 HP)



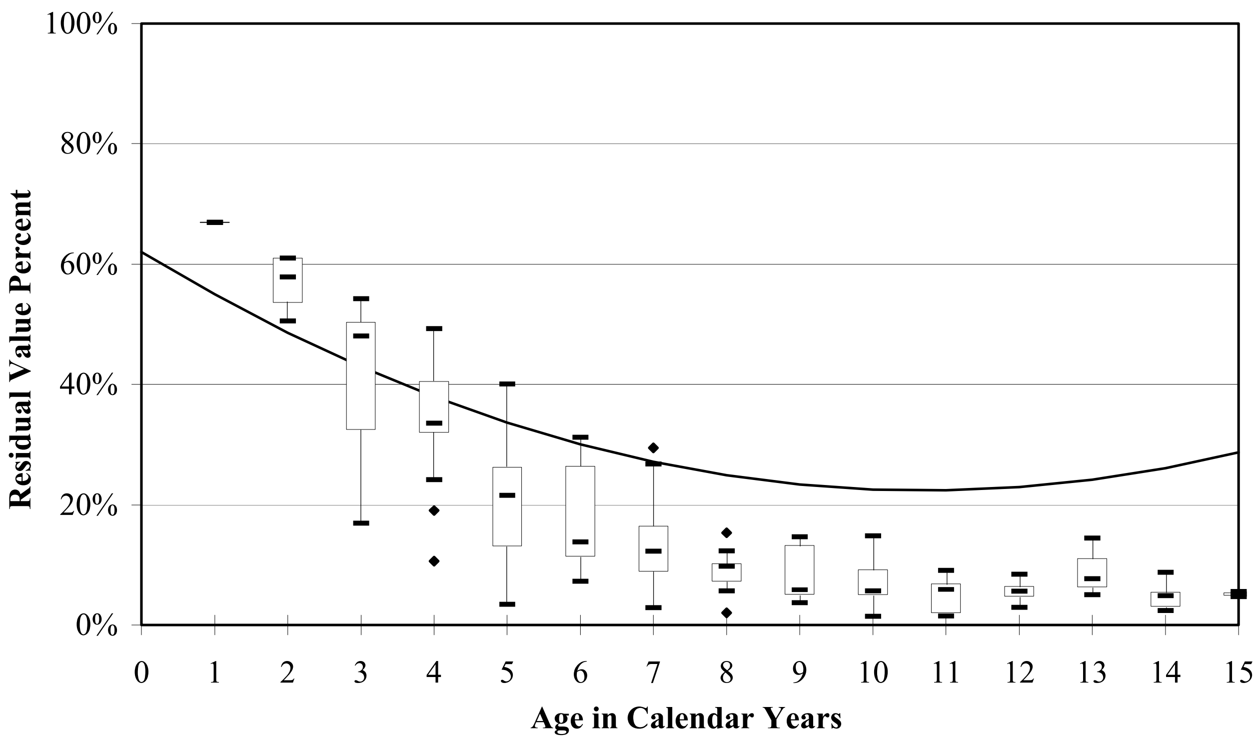
Appendix H.22: Track Dozers (200-299 HP)



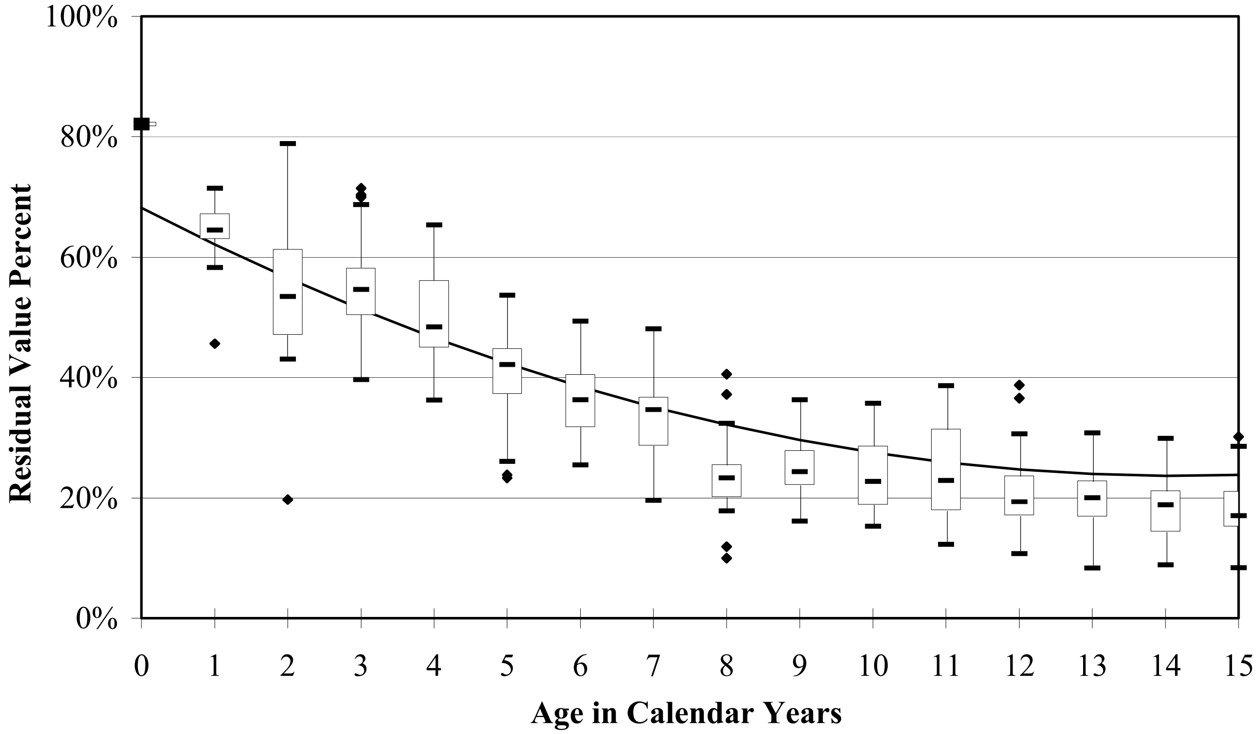
Appendix H.23: Track Dozers (300-399 HP)



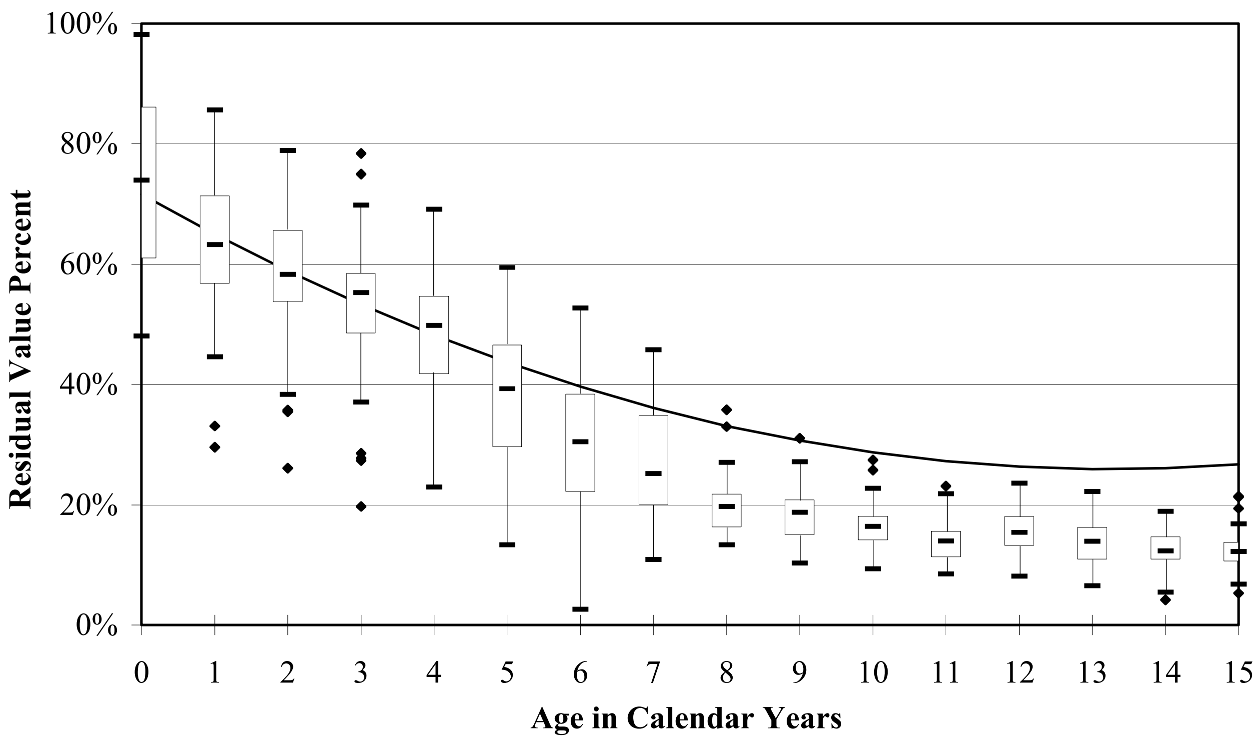
Appendix H.24: Track Dozers (400+ HP)



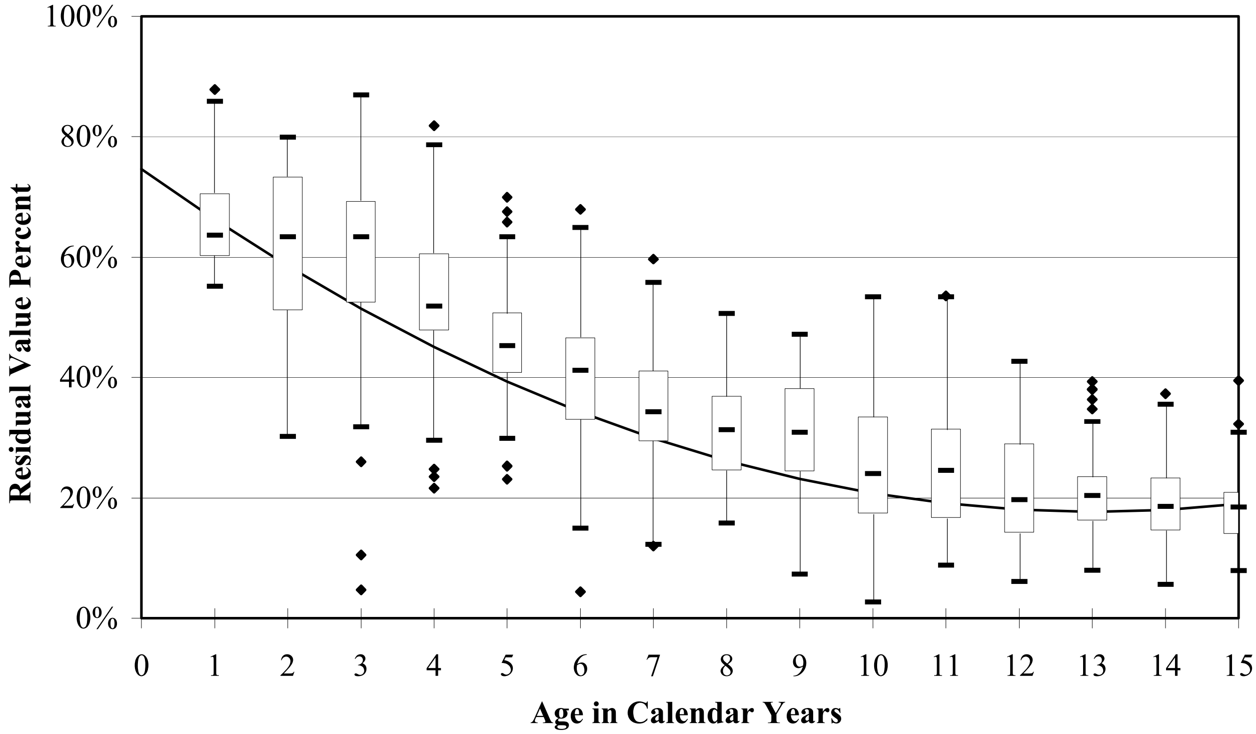
Appendix H.25: Motor Graders (0-149 HP)



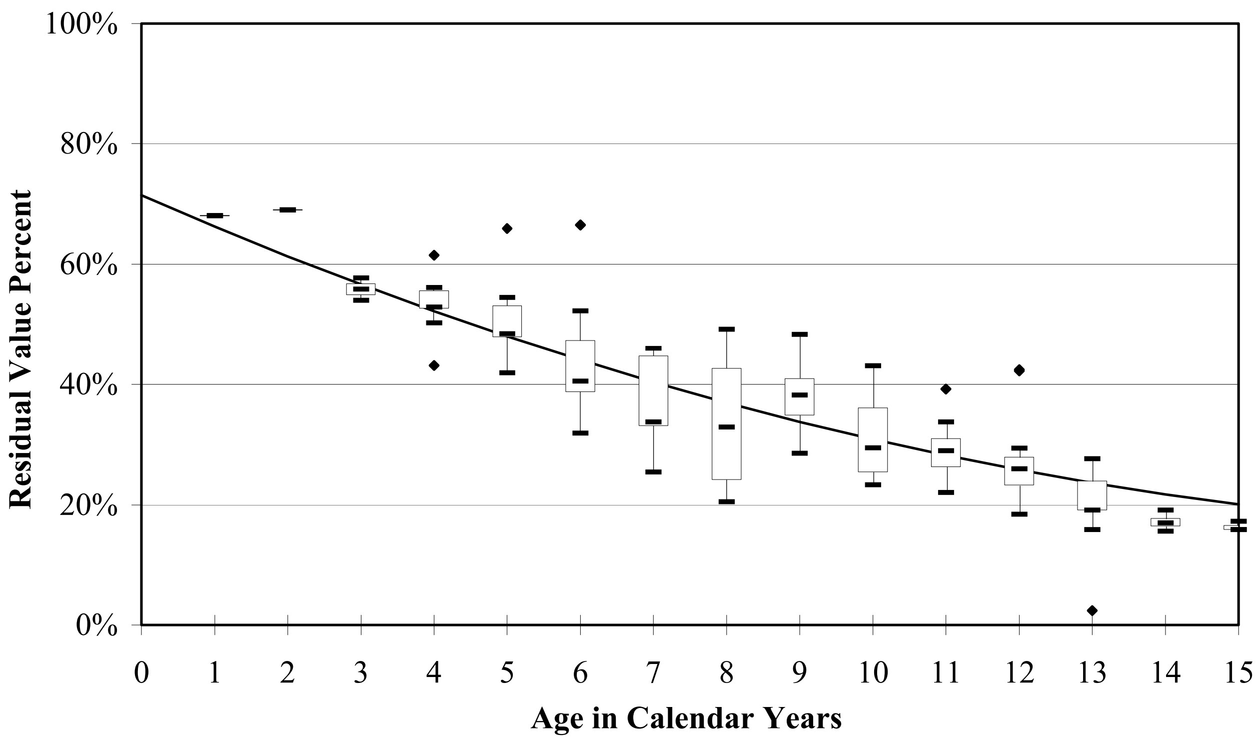
Appendix H.26: Motor Graders (150+ HP)



Appendix H.27: Wheel Tractor Scrapers (0-74,999 lbs)



Appendix H.28: Wheel Tractor Scrapers (75,000+ lbs)



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Vita

Gunnar Lucko, son of Dr. med. Manfred Lucko and Dr. med. Karin Lucko, was born on January 13, 1976 in Hamburg, Germany, where he also grew up. After graduating from Charlotte-Paulsen-Gymnasium in 1994 he entered the Civil Engineering and Environmental Technology Program at the Technical University of Hamburg-Harburg, where he earned his Intermediate Diploma in Civil Engineering in 1996, completed coursework requirements, and worked with major German construction companies during two internships. He entered the Vecellio Construction Engineering and Management Program at Virginia Polytechnic Institute and State University in August of 1998 and earned the degree of Master of Science in Civil Engineering in December of 1999. In summer of 2000 he completed the requirements for the German Diploma in Civil Engineering and returned to Virginia Tech to pursue his doctoral studies. Upon completion of his degree Gunnar intends to begin a career in the Construction Engineering and Management area of the Construction Industry.