Cost and Quality Drivers in Printed Circuit Board Assembly

by

Elizabeth Jane Altman

B.S., Mechanical Engineering
Cornell University, 1988

Submitted to the Sloan School of Management and
the Department of Mechanical Engineering
in Partial Fulfillment of the Requirements for the Degrees of

Master of Science in Management
and
Master of Science in Mechanical Engineering

in conjunction with the

Leaders for Manufacturing Program

at the

Massachusetts Institute of Technology
June, 1992

© Massachusetts Institute of Technology 1992 (all rights reserved)

Signature of Author _____
Department of Mechanical Engineering
Sloan School of Management
8 May 1992

Certified by _____
Thomas W. Eagar, Thesis Supervisor
Professor of Materials Science & Engineering

Certified by _____
Charles H. Fine, Thesis Supervisor
Associate Professor of Management

Certified by _____
Ain Sonin, Thesis Reader
Professor of Mechanical Engineering

Accepted by _____
Jeffrey Barks
Associate Dean, Sloan Master's & Bachelor's Programs

ARCHIVES
MASS. INST. TECH.
JUN 30 1992

Cost and Quality Drivers in Printed Circuit Board Assembly

by

Elizabeth Jane Altman

Submitted to the Sloan School of Management and
the Department of Mechanical Engineering
in Partial Fulfillment of the Requirements for the Degrees of

Master of Science in Management
and
Master of Science in Mechanical Engineering

ABSTRACT

Activity-based costing (ABC) systems are beginning to gain widespread acceptance as tools for determining costs of products and processes. Similarly, continuous process improvement is becoming an essential activity in world class manufacturing organizations. To determine costs accurately with an ABC system, the cost drivers must reflect the critical activities of a process. To rationally approach process improvement efforts, personnel must understand the factors affecting the quality of the output of their system. Both types of information, cost drivers and quality drivers, can also be used to facilitate better interaction between design and production personnel by providing an objective language with which to discuss the effects of design on production.

This thesis presents a methodology to determine the significant cost and quality drivers in the surface mount area of a printed circuit board assembly process. Multiple regression techniques are used to determine the significance of potential drivers to factors that reflect cost and quality. The techniques presented here can be applied to other areas of a production process as well.

The research was performed at Digital Equipment Corporation's Albuquerque, New Mexico plant between June and December 1991 in conjunction with MIT's Leaders for Manufacturing Program. The Assembly Engineering department and Finance organization at the plant were key resources for data for this research.

Four drivers are presented in the thesis as recommendations for new drivers for Albuquerque's ABC system. They are: 1) Number of fine pitch components on a board, 2) Number of passive devices on a board, 3) Number of chips on a board, and 4) Number of greater than 44 pin, non-fine pitch, components on a board. Additionally, it is recommended that a fifth new driver also be explored: 5) Number of components hand placed in the surface mount area. The four recommended drivers have been adopted by the Albuquerque plant, and the fifth is under investigation.

In addition to the example of the methodology, and specific recommendations, this thesis discusses issues relating to data collection and presents other applications for driver selection techniques.

Thesis Advisors:
Professor Thomas W. Eagar, Richard P. Simmons Professor of Metallurgy
Professor Charles H. Fine, Associate Professor of Management

The author gratefully acknowledges the support and resources made available to her through the Leaders for Manufacturing Program, a partnership between MIT and major U.S. manufacturing companies.

Acknowledgements

While this thesis bears the name of one author, it is truly the combined effort of many. Because it is impossible to acknowledge all by name, I would like to say a huge thank you to everyone who contributed to this work. Additionally, I would like to recognize the following people to whom I am especially grateful.

To everyone at Digital's Albuquerque plant who made this project not only possible, but also a lot of fun! With special thanks to Greg Durfee, Ted Jameson, and Assembly Engineering. Also, to Mike Langone, Peg Pacheco, and the rest of the Thursday morning ABC crew.

To Pam, Tanya, Bettie, and the others in the SMT area - yes, I am done collecting data - Thanks!

To Linda, your questions, comments, and laughs added a great deal to this research.

To my advisors, Professors Charlie Fine and Tom Eagar, your direction and guidance was always a great help. Thanks for keeping this project on track, even long distance. Also, thank you to Professor Roy Welsch, for providing the sanity check on my statistics.

To Anne, Tara, Nancy, Jon, Jim, and my other friends and classmates who have heard more about this thesis, and New Mexico, than they ever bargained for - Thank you! And may the ruckusing continue...

To my family, especially my parents, for everything.

You only live once, but if you do it right, once is enough...

- Explained to me by my grandmother, Estelle Michaels, to whom I dedicate this thesis.

Biographical Note on the Author

Elizabeth Altman, of Weston, CT, graduated from Cornell University, Ithaca, NY, in 1988 with a Bachelor of Science degree in Mechanical Engineering. From 1988 to 1990, she worked in research and development of electronic imaging systems for the Polaroid Corporation in Cambridge, MA.

Liz is a member of Pi Tau Sigma, the National Mechanical Engineering Honor Society, and in 1991 was elected an Associate Member of Sigma Xi, the National Scientific Research Society. As a fellow in MIT's Leaders for Manufacturing Program, she is working towards masters degrees in mechanical engineering and management and expects to graduate in June 1992.

Table of Contents

Abstract iii

Acknowledgements v

Biographical Note on the Author vi

Table of Contents vii

List of Figures viii

Section 1 • Introduction 9
- Project Overview 10
- Major Results 11
- Outline of the Thesis 12

Section 2 • Overview of Multiple Regression and This Application 13
- An Application of Multiple Regression 13

Section 3 • Generating the Variable Lists 17
- Generating the Independent Variable List 17
- Generating the Dependent Variable List 20
- Determining Which Products to Use 21

Section 4 • Data Collection and Verification 23
- Quality Data (Defects Attributable to Surface Mount) 23
- Total Test Time and Total Diagnose & Repair Time 24
- Surface Mount Area Set-Up Time 25
- Surface Mount Equipment Run Time 27
- Surface Mount Area Throughput Time 27

Section 5 • Statistical Analysis 29
- Some A Priori Hypotheses 30
- Correlation Analysis for Independent Variables 30
- Correlation Analysis for Independent and Dependent Variables 34
- Regression Analysis Results 35

Section 6 • Applications of this Research and Cautions 47
- Applications of This Research 47
- Cautions for Use of This Methodology 49

Section 7 • Recommendations and Conclusions 53

Bibliography 55

Appendix A • Component Class Definitions 57

Appendix B • Independent Variables: Long List 59

Appendix C • Effects of Independent Variables on Defect Rate 61

Appendix D • Dependent Variables: Long List 63

Appendix E • Gathering Variable Data 65

Appendix F • Set-Up and Run Time Data Collection Form 67

Appendix G • Correlation Matrix 69

Appendix H • Full Regression Results 71

List of Figures

Figure 2.1 Simplified Multiple Regression Matrix
Figure 3.1 Independent Variables: The Short List
Figure 3.2 Dependent Variables: The Short List
Figure 5.1 Pearson Product-Moment Correlation Matrix
Figure 5.2 Pearson Product-Moment Correlation Matrix
Figure 5.3 Summary of *Defects per Board* Regression
Figure 5.4 Summary of *Test Time* Regression
Figure 5.5 Summary of *Diagnose & Repair Time* Regression
Figure 5.6 J-Lead vs. Gull Wing Lead Geometries
Figure 5.7 Summary of *Set-Up Time* Regression
Figure 5.8 Summary of *Number of Process Steps* Regression
Figure 5.9 Significant Independent Variables for Each Dependent Variable
Figure E.1 Abridged Process Complexity Matrix
Figure G.1 Pearson Product-Moment Correlation Matrix

"Not everything that counts can be counted, and not everything that can be counted counts."

- Albert Einstein

Section 1 • Introduction

Digital Equipment Corporation (DEC) is the leading worldwide supplier of networked computer systems, software, and services. In Albuquerque, New Mexico, DEC has a 406,000 square foot manufacturing facility which produces primarily high volume printed circuit boards and workstation systems. The plant assembles a wide range of boards with varying complexity and volume levels, and receives workstation designs from teams on both the East and West coasts. A significant question facing DEC, and other large corporations, is how to increase the communication between manufacturing facilities and design teams, especially when they are not co-located.

One of the goals of this research was to improve the relationship between manufacturing facilities and designers, in this case, the Albuquerque plant and the workstation design groups in Palo Alto, California. We looked at what we could do in the plant to improve the link between manufacturing and design to smooth the process of introducing new products. Specifically, we explored what information plants could provide to design groups to help this effort. We questioned what type of feedback was appropriate to help designers as they resolved their trade-offs. For example, if a workstation CPU designer was about to choose one type of capacitor over another, what information about manufacturing, in addition to the component cost, should the designer consider during the decision-making process?

After initial study of the problem, we realized that the primary issue was how to help designers understand what affected a plant's cost and quality levels.[1] We wanted to tell them how much their designs would cost to build, and what quality levels they could reasonably expect. While the Albuquerque plant could estimate these quantities, they needed a more accurate way to determine them. They required a method to better understand what was driving their cost and their quality levels.

This thesis presents a methodology to determine whether proposed cost and quality drivers are significant. The research was performed in conjunction with MIT's Leaders for Manufacturing program and two departments at DEC's Albuquerque plant: the Assembly Engineering department and the Finance organization.

Project Overview

In June 1991, at the start of this work, the plant was adopting an activity based costing (ABC) system to measure costs, and they were still in the beginning stages of formulating a methodology to determine cost drivers. This project was developed to provide recommendations for new cost drivers for the surface mount (SMT) area of the module assembly process, and to present a methodology for the plant to use in the future to choose drivers. In SMT, the drivers that had been previously chosen were known to be too coarse to accurately reflect the complexity differences between products. One product might be much more difficult to produce than another, but the drivers would show that the costs to produce them were the same.

---

[1] In this thesis, the term "quality" refers to the first pass assembly quality of a board. It does not account for quality measures such as meeting a customer's functional requirements, or performing reliably over time. Additionally, the defects discussed are not defects that leave the plant, but ones that are detected and fixed.

DEC's plan was that once the ABC system was refined, the cost information would be provided to designers to incorporate into their design decisions. They would be able to determine how their design decisions affected the cost to assemble a particular board. While this would be an improvement over the current system, where manufacturing personnel discuss issues with designers but do not have specific quantitative cost information to provide them, it still would not address the issue of the lack of quality data for designers. Designers still would not know how their designs would fare, in terms of expected production quality, once they were running in the plant.

In this research, I used multiple regression techniques to determine cost and quality drivers in the SMT area. I focused on the surface mount process so the project would be of reasonable size and scope, but this methodology could be applied to other products and processes.

Major Results

In this thesis, I recommend that the Albuquerque plant adopt four new drivers for their ABC system, and that they explore a fifth driver. The four drivers I recommend they adopt are:

- Number of fine pitch components on a board
- Number of passive devices on a board
- Number of chips on a board
- Number of greater than 44 pin, non-fine pitch, components on a board.[2]

The fifth driver to explore is:

- Number of components hand placed in the surface mount area.

As of May 1992, the plant was proceeding to adopt the four primary drivers, and was exploring the use of the fifth.

---

[2]See Appendix A for explanation of these component class definitions.

Additionally, with the support of this work, the plant has changed the way they account for defect rates in their product costing system. They no longer use defects per board directly as a product cost driver, but rather incorporate the cost of reworking different types of components into their placement cost drivers. This gives them a more accurate way to determine the cost of producing new boards, and provides better differentiation by board assembly complexity.

While this project was initially targeted to help with product costing and analysis, the results of this work have also been used to assist in determining process costs. For example, observations from exploring quality data and set-up times are related to processes, and have subsequently been incorporated into the process costing system. The work done in support of this thesis, including data collection, interviews, etc., has served both to provide concrete recommendations and to foster debate and highlight areas of concern.

Outline of the Thesis

Section 2 presents an overview of multiple regression techniques and a brief explanation of their application in this research. Section 3 discusses generating the lists of possible variables to use in building a regression model. In the course of searching for the data, I realized that the major hurdle for this project was not statistical analysis, but initial data collection and verification of data integrity. Section 4 addresses the issues of data collection and verification relevant to this research. Section 5 includes the results of the regression analyses, explanations of the results, and recommendations. Applications, and cautions for the use of this work, are discussed in Section 6. Section 7 presents additional recommendations and conclusions.

Section 2 • Multiple Regression: An Application

Regression is a statistical technique to determine whether one set of variables is significantly related to another set. More specifically, it allows one to explore the relationship between independent variables and various dependent variables.

An Application of Multiple Regression

In this case, the ultimate goal was to determine what drove cost and quality in the surface mount process of a printed circuit board (PCB) assembly area. Our dependent variables had to represent, in some fashion, cost and quality, so we could test how various product attributes affected cost and quality measures.

For a quality metric, we chose defects/board.[3] Choosing a cost metric was not as straightforward. Ideally, one would want to use product cost as a dependent variable. This was impossible since the goal was to determine factors to measure product cost, thus creating a chicken and egg dilemma. To counter this, we looked at quantities which contribute to the cost of producing a product in the surface mount area.

We broke cost down into categories such as, set-up time, run time, test time, diagnose and re-work time, etc., which can be measured as dependent variables. Ultimately, one should be able to run regression analyses against all of these factors, and then combine the resulting regression models to yield a cost model based on product attributes. For this research, I generated a list of appropriate potential independent and dependent variables, and then chose a few to pursue to show an example of using regression analyses to determine drivers.

---

[3]It is important to remember that we have defined "quality" to represent the state of the product after initial assembly, therefore this does not include field reliability data.

The independent variables were product attributes, such as the number of leads on a board, number of fine pitch components on a board, etc. These were the potential drivers. If they proved to be significant in explaining the dependent variables, it would be reasonable to pursue them as potential drivers of cost or quality.

The observations, or trials, for this analysis were products. For example, Product A = observation 1, Product B = observation 2, etc. Figure 2.1 provides an example of a simplified matrix, with disguised data, showing the framework for the analysis. The actual analysis incorporated 21 modules.

Products	**Independent Variables**							**Dependent Variables**		
Product	Passives	Chips	44+	FP Comps	Total Comps	# of Part #'s	Total Leads	Defect /Board	Test Time	Set-Up Time
A	94	34	4	0	132	41	1,080	0.2	10	150
B	84	3	11	2	100	20	1,080	0.9	15	200
C	194	35	3	2	234	60	1,525	3.0	8	220

Figure 2.1 Simplified Multiple Regression Matrix

The performance of regression analysis leads to an understanding of the independent variables that are significant in explaining the variation of the dependent variables. Additionally, the correlation coefficient analysis, which accompanies the regression, shows whether the variables are associated with each other, and which of the independent variables are truly distinct.

Beyond the actual results from performing a regression, there are other benefits to using regression techniques. Regression forces us to quantify our perceptions about the system which we are studying. We must address how to determine what *really* is a dependent

variable, as well as what product attributes we should consider as independent variables. We must resolve how to gather the data, and must find out whether it already exists somewhere in a database.

Section 3 • Generating the Variable Lists

A critical aspect of this project was determining which independent and dependent variables were appropriate to explore. The task included three aspects: 1) identifying a long list of potential independent variables, 2) identifying a long list of potential dependent variables, and 3) determining the appropriate products to use as observations. This section will discuss all three areas.

Generating the Independent Variable List

The independent variables are product attributes that attempt to differentiate products by their assembly complexity. As mentioned earlier, this research focused on the surface mount area of the plant, so the product attributes are ones that affect the surface mount process.

I compiled the complete list of product attributes by obtaining information through four types of activities:

- Interviewing engineers, operators, and supervisors who work in the surface mount area,
- Meeting with designers who design boards with surface mount components,
- Reading literature from both inside and outside DEC about surface mount processes and what affects them,
- Observing the actual process.

Appendix B presents the long list of independent variables. Appendix C explains why some of the independent variables might have an effect on the defect rate. Figure 3.1 presents the short list of independent variables that I actually used for this analysis.

SHORT LIST OF INDEPENDENT VARIABLES[4]
Number of Fine Pitch Leads[5]
Number of Non-Fine Pitch SMT Leads
Total Number of SMT Leads
Number of Passive Devices
Number of Chips
Number of Greater Than 44 Pin Non-Fine Pitch Components
Number of Fine Pitch Components
Number of Non-Fine Pitch SMT Components
Total Number of SMT Components
Number of Components Placed by Hand in Surface Mount Area
Number of Part #'s
Total Number of Process Steps
Heat Sinks? (1=yes/0=No)

Figure 3.1 Independent Variables: The Short List

The short list does not represent the variables that were necessarily optimal to use, but more practically, a list of variables that were both potentially useful, and realistic to collect.

The data for the independent variables was not easy to collect. In some cases, collecting it involved printing the bill of materials for each board, and then manually counting attributes such as number of components, or number of fine pitch leads. Future information systems

[4]See Appendix A for component class definitions.
[5]Fine Pitch Leads is defined as the number of solder joints on components having less than 50 mil. pitch. Non-Fine Pitch Leads represents all surface mount connections which are not fine pitch.

should allow for easier gathering of product attribute data. There are a few systems in development at DEC which utilize group technology and advanced coding schemes to identify components. With these systems, for instance, one could automatically check a bill of materials for the number of components that were PQFP's (Plastic Quad Flat Packs), and then use this information in a regression analysis. The primary difficulty with these systems is their maintenance. They must contain all of the components which are being used on a product for them to be viable.

One variable which was not included on the lists but may prove to be important is the exact equipment on which the board is produced. For example, at the Albuquerque plant, there are a few unique surface mount lines. Each line is a combination of different types of equipment, and some boards are only run down one line, while others can be produced on more than one. If, for example, one board is assembled only on line A, and therefore only with screen printer 1, it might be useful to note this as a variable. This would allow machines to be tracked. It might be that all the boards that go through one screen printer tend to have more defects than others, and that this is entirely due to that printer. With the current proposed list, there is no way to account for this case.

Variables such as the aforementioned one, which relate to processes, might not be directly applicable to designers. Still, the possibility of tracking them should be explored since they could provide valuable information to process engineers.

If I were to continue with this project, I would look at further slicing the component classifications. For example, is there a difference between LDCC's, PQFP's, and others in the fine pitch component classifications?[6] I would also explore the issue of board density.

---

[6]LDCC = Leadless-Chip Carrier. PQFP = Plastic Quad Flat Pack.

This is a difficult problem, but it should be possible to develop a metric which accounts for the average number of solder connections per unit area, or the maximum number of solder connections per unit area. Again, it would be very useful if this could be derived directly from a design tool. The only way to explore the issue now is manually.

Generating the Dependent Variable List

The dependent variables are quantities that measure either product quality, or a subset of assembly cost (e.g. *Test Time*). They are measurable attributes which are, in essence, outputs of the process. While some of them relate to cost, they are not expressed in dollar units. If they need to be expressed in monetary values they can be multiplied by a rate.[7] They are "what happens" when you put a board into the system. For example, they include the defect rate of a board, the set-up time for a board, the test time, etc. Here again, I generated both a long list of potential variables, and a short list of variables that were used for this analysis. Appendix D includes the long list of dependent variables and figure 3.2 presents the short list.

SHORT LIST OF DEPENDENT VARIABLES
Defects Attributable to Surface Mount Per Board
Total Test Time Per Board
Total Diagnose plus Repair Time Per Board
Surface Mount Set-Up Time Per Board

Figure 3.2 Dependent Variables: The Short List

[7] For example, (cost/set-up time hour)(set-up time hours/board) = (cost/board for set-up time).

Once it was determined that the dependent variables should be both quality metrics and components of cost, generating the long list was relatively straightforward. We needed to have variables that represented how we should (and could) measure board quality and the cost of assembling a board. The difficult part was not to generate the list, but to actually find the data to support the analysis. The short list was derived primarily by deciding which variables were feasible to track within the timeframe of the project.

Determining Which Products to Use

The product mix at DEC's Albuquerque plant changes frequently. New products are introduced every few months. Old ones are phased out at a much slower rate than the new product introductions, thus the total number of products is growing. At any point in time there is a mix of new and old products on the floor. The mature ones tend to require much less set-up time, less engineering support, and have lower defect rates.

During the Summer and Fall of 1991, although DEC was introducing many new products into the Albuquerque plant, I chose to focus on a set of mature products for this analysis. I defined "mature" as products which had been in revenue production for at least six months. These products, while still representing recent technological developments, did not have the erratic nature of newer products. By and large, the programs to run the placement equipment for these products had been debugged, the thermal profiles had been set, and the process had generally been stabilized.

Section 4 • Data Collection and Verification

For both costing and process improvement efforts, it is essential to have accurate, relevant data. Personnel need to know how their processes are performing before they can focus both process and design improvement activities. While it is not trivial to determine what needs to be collected, it is much easier to discuss than to actually obtain data. This section will outline the issues related to gathering data encountered during the course of this research. The data for some variables were relatively straightforward to find. For others, the process was more complex. Where applicable, I will present recommendations for getting the data more quickly from current systems, or for changing the system.

For the purposes of this document, I will limit the discussion in this section to a general overview of those variables which were difficult, or impossible, to obtain. (Note that these were all dependent variables.) In Appendix E I present a more thorough explanation of how data for all the variables was gathered. Through other documentation, and conversations, I have provided DEC personnel with more detailed analyses and recommendations.

Quality Data (Defects Attributable to Surface Mount)

Defect data is currently collected on the floor by inspectors and technicians. It is entered into a large database system maintained by a plantwide information systems group. Whenever a defect is found on a board, the serial number of that board is entered into the system along with an explanation of the defect. Once the defect is diagnosed and repaired, a further explanation is entered into the system. The serial numbers of all boards which pass through the system are not recorded (e.g. if a board is defect free, its serial number never gets into the quality database system). Unfortunately, while it is possible to track

trends in types of defects and absolute numbers of defects, it is impossible to get an accurate measure of defects per board. Because Albuquerque runs a very high mix operation, and some boards are run infrequently, the problem is compounded. It is not just a simple matter to use the plant's other tracking systems to determine the number of boards which have passed through a series of inspection/repair stations.[8]

As an estimate, I looked at the aggregate number of boards passing through a few stations in the system over a given period of time and calculated the median. I divided the total number of defects found, which were attributable back to SMT, by this median to estimate defects per board.

For this type of analysis it is necessary to have data on a per product, per board basis. One needs to be able to determine how specific products are performing in the process. The current data collection system does not support this.

Total Test Time and Total Diagnose & Repair Time

Test, diagnose, and repair times are very difficult to measure. They vary over the life of a product as the test process matures, and they vary with product yields. The Albuquerque plant does not directly track time spent testing, diagnosing, and repairing products. They do estimate these times, and they have a Capacity Resources Planning model (CRP) in which they incorporate estimates of these times. For this project, I used the estimates developed for the CRP tool for two dependent variables: Test Time and Diagnose plus Repair Time.

---

[8]It is easy to access the number of boards which have passed through a specific station, but this is not useful if we are looking for the total defects/board attributable to an entire process, such as SMT.

The estimates in the CRP tool represent the combined wisdom of test engineers and technicians who have helped to develop the tool. They use estimates of machine test times, yields, and experience to determine their best estimate for the time required for each product. Their goal is to have the values accurately reflect the relative differences between products, even if the absolute values are not completely accurate (i.e. if one product tends to take twice as long to test than another, its estimate will be twice as large). In developing the estimates, the engineers and technicians use estimates of mature yields. So, if a product is relatively young, its actual test, diagnose, and repair time might be much higher than the estimate. Optimally, one would like to have an accurate measure of how long products are spending being tested, diagnosed, and repaired.

Surface Mount Area Set-Up Time

In the surface mount area, set-up time consists of a few sub-components. For example, screen printing machines, placement machines, and re-flow ovens all need to be set-up for each product. Some of these operations, particularly for the placement machines, are highly dependent on the order in which products are scheduled to run. For example, if two products have similar components, and are run sequentially, the set-up time between the two is minimal. If two products require mostly different components, the set-up time between the two is very long because the machine has to be entirely re-loaded. This dependence on scheduling presents a problem when one wants to measure the set-up time for a specific product.

One way to address this problem might be to figure out the set-up times for each product after each other product, and then calculate the probability distribution that one product will run after another product. For example, if Product A runs after Product B 40% of the time, and after Product C 60% of the time, then one could do a weighted average for set-up time and get an estimate. Unfortunately, with a high volume of products in the area, and a

product mix that changes frequently, this approach would be very difficult in the Albuquerque plant.

Instead, I collected data over a two month period directly from the operators in the area. Every time they set-up a machine for a new product they filled out a form and recorded the set-up time. Appendix F includes the form used for this study.

After reviewing the data, I determined that the screen print and re-flow operation have virtually constant set-up times, so I set these as fixed. The placement equipment set-ups vary significantly with product and with scheduling. Unfortunately, because of the high mix through the area, over a two month period, each product is not set-up very many times. Therefore, while the data is useful on a per machine basis - we have a lot of data about all the set-ups for a given machine - it is not as useful on a per product basis.

To estimate set-up time, I took the median of all set-up times for a given product on a given machine. If machines were set-up simultaneously for one product, I used the highest set-up time. If machines were set-up serially for a product, in sequence, I summed the set-up times.

Since this project was conducted, the Albuquerque plant has begun "off-line" set-ups where components are readied for the machine before the actual switch over, and the machine downtime in between products is reduced to a minimum. This will eliminate most of the dependence on scheduling. Additionally, the surface mount area has begun to measure set-up time as a standard process.

Surface Mount Equipment Run Time

Albuquerque does not presently measure equipment run time per product. They calculate standards by using theoretical machine capabilities, but these were not appropriate for dependent variables since they were, by definition, dependent on the product attributes used to calculate them.

While collecting set-up time data, I also recorded equipment run times. The same difficulty was apparent here as with set-up times; over the time period I studied, each product was only run a few times. After reviewing the data, I decided to eliminate it from the regression analysis. There was simply too much variability to believe that it was a true representation of a product's run time. While we used a manual method to collect the data, it should be possible in the future to use information from within the machine controllers to record run time. The Albuquerque plant is investigating the best method to do this.

Surface Mount Area Throughput Time

Under the current system, it is impossible to determine the amount of time a particular board spends in the surface mount area. Serial numbers are not recorded when boards leave surface mount. There was no way for me to track this variable.

Section 5 • Statistical Analyses

A series of multiple linear regressions were performed using DataDesk 3.0 software on an Apple Macintosh SE/30 computer.[9] These techniques require one to assume that the independent variables are related linearly to the dependent variables. If this is not the case, the regression results will be invalid. By transforming variables, the regression model can be formulated so that it is a closer representation of the true relationship among the variables. In this analysis, a transformation proved to be useful for one of the dependent variables.

The statistics alone do not point to what should be used for drivers, but rather provide us with a tool to verify or disprove hypotheses, and to explore relationships among variables. Combined with insights into the assembly process, and some of the current business practices at the plant, the statistics assisted in formulating recommendations.

Before embarking on an explanation of the statistical analysis, I present two hypotheses that I formulated prior to performing the analysis. These hypotheses are relevant because they were based on an understanding of the surface mount assembly process and the associated support systems. If the data entirely disproved these, yet everyone in the plant knowledgeable about the system agreed with them, I would be highly skeptical of the appropriateness of this model. In fact, the analyses supported the hypotheses.

---

[9] I explored a few other software packages, including SAS and FOCUS, the plant database software. None provided the ability to explore data as easily, through both quick computation and graphing, as DataDesk 3.0.

Some A Priori Hypotheses

The difference in complexity between placing fine pitch and non-fine pitch devices should be accounted for in the driver selection. In speaking to operators, supervisors, engineers, and production managers, I realized that the more fine pitch devices on a board, the harder the board is to assemble. The original cost per placement driver does not capture this distinction between boards. Even if one board has twenty resistors on it, and another board has twenty 224-pin fine pitch devices on it, both will still be priced at the same level - twenty times the cost per placement rate - under the old system. Yet, the board with the fine pitch devices is significantly more difficult, and costly, to produce. While this is an extreme situation, it illustrates that the original drivers are not adequate with regard to fine pitch components.

In addition to fine pitch components, there are other distinctions between components that influence the assembly complexity of a board. For the capacity resources planning (CRP) model in the plant, surface mount components had been broken into four categories: 1) Passive devices, 2) Chips, 3) Greater than 44 pin non-fine pitch devices, and 4) Fine pitch components.[10] These four categories were considered independent variables in this analysis. Since engineers had decided that these divisions were logical for the CRP model, I suspected that they would be reasonable for the drivers. Additionally, there was great incentive to see if they worked, because using the same breakdowns for both the CRP <u>and</u> the ABC tool would save the plant a significant amount of effort.

Correlation Analysis For Independent Variables

If, in a multiple regression analysis, the independent variables are highly correlated, the results will be difficult to interpret. The goal of a regression analysis is to explain the

---

[10]See Appendix A for more detailed definitions of component classifications.

variation in a dependent variable with independent variables, or predictor variables. If two predictors are correlated, they both account for the same variability in the dependent variable. Correlation coefficients measure the degree of some kinds of association between variables.[11] Correlated variables can be substituted for each other, but cannot both be present in the model.

I intentionally collected some variables that measured similar quantities so that I could test their correlation. By understanding the obstacles involved in obtaining them, I could determine which would be best as drivers. For example, while the total number of components on a board might be relatively simple to track, the total number of non-fine pitch components might be more difficult. If the values were highly correlated, then the easier one to collect could be used.

Figure 5.1 shows the correlation coefficients for seven of the independent variables.

---

[11] See Paul F. Velleman, Learning Data Analysis with Data Desk (New York: W.H. Freeman & Co., 1989) for a good summary explanation of correlation coefficients.

	Total Comps.						
Total Comps.	1.000	Non-FP Comps.					
Non-FP Comps.	1.000	1.000	Total Leads				
Total Leads	0.966	0.966	1.000	Non-FP Leads			
Non-FP Leads	0.957	0.957	0.997	1.000	# of Part #'s		
# of Part #'s	0.934	0.934	0.912	0.907	1.000	Passives	
Passives	0.991	0.991	0.926	0.912	0.914	1.000	Chips
Chips	0.943	0.944	0.978	0.983	0.913	0.890	1.000

Figure 5.1 Pearson Product-Moment Correlation Matrix

These seven independent variables are all very highly correlated. (The lowest value of the correlation coefficient, ρ , equals 0.890.) Therefore, no two of them can be used in a regression analysis at the same time.

Passives and *Chips* are very highly correlated ($\rho = 0.890$). This is consistent with reality because bigger boards tend to have both more passives and more chips. Smaller boards tend to have less of both. They are directly proportional to each other. Therefore, either *Passives* or *Chips* can be used as an independent variable, but they cannot both be included in an analysis. Either can be used to represent a measure of the total number of components on a board since both are highly correlated with *Total Components.*

Figure 5.2 presents the correlation matrix for *Fine Pitch Components, Greater than 44 pin Devices, Passives, and Chips,* (i.e. the four classes of components) and *Fine Pitch Leads,* and *Components Hand Placed in SMT.*

	FP Comps	Greater than 44 pin	Chips	Passives	FP Leads	Hand Placed
FP Comps	1.000					
Greater than 44 pin	0.181	1.000				
Chips	0.013	0.442	1.000			
Passives	0.111	0.455	0.890	1.000		
FP Leads	0.822	0.125	0.066	0.287	1.000	
Components Hand Placed	-0.012	0.058	-0.338	-0.416	-0.142	1.000

Figure 5.2 Pearson Product-Moment Correlation Matrix

It is important to note that *Fine Pitch Components* is highly correlated with *Fine Pitch Leads* ($\rho = 0.822$). This implies that if we are looking at using *Fine Pitch Leads* as a driver, it may be reasonable to consider *Fine Pitch Components* instead. Components are much easier to track than leads. This data is for a limited sample size, and decisions such as whether to track fine pitch components versus leads should be continually reviewed with due regard to new and emerging technologies. If fine pitch devices evolve to where they have a wide range of lead counts, and there are many of these devices on a board, then this correlation may decrease.

For the rest of this analysis, I have chosen to use *Fine Pitch Components* as an independent variable, and have eliminated *Fine Pitch Leads*. *Fine Pitch Components* must be tracked for the CRP tool. *Fine Pitch Leads* is not currently tracked. Since only one can be used in the regression analyses, I chose the more readily available quantity.

Fine Pitch Components is not highly correlated with *Greater than 44 pin*, *Chips*, or *Passives* ($\rho = 0.181$, 0.013, and 0.111 respectively). Therefore, it is okay to use *Fine Pitch Components* with any of these.

The independent variable *Greater than 44 pin* is correlated to some extent w: : *Chips* and *Passives* (ρ = 0.442 and 0.455). When it is used in a regression with these, some of the effect of *Greater than 44 pin* on the variability of the dependent variable is accounted for by either *Chips* or *Passives*. Even still, in some of the regressions, *Greater than 44 pin* proved to be significant in conjunction with either *Passives* or *Chips*.

Components Hand Placed in SMT is not very highly correlated with *Fine Pitch Components, Greater than 44 pin, Passives,* or *Chips*, although, it does have a correlation coefficient ρ = -0.416 with *Passives*. Consequently, *Components Hand Placed* can be used in regression analyses with these variables.

Number of Process Steps is somewhat correlated with the component classifications; the correlation coefficient is near to 0.5 in all cases. This poses some problems with including it in regression analyses. Therefore, in the regression analysis section, there is a section dedicated to *Number of Process Steps* as both an independent and a dependent variable.

Correlation Analysis For Independent and Dependent Variables

Appendix G presents a correlation matrix with independent variables and also dependent variables. In that matrix, I have only included one independent variable from every set that is highly correlated. For example, I did not include both *Total Leads* and *Non-Fine Pitch Leads*, but rather included *Passives* which is highly correlated with these and four other independent variables (see Figure 5.1 above).

This matrix serves to support the regression analysis by providing preliminary insight into which independent variables are associated with which dependent variables. The results of the correlation analysis are consistent with the results of the regression analysis. The

following sections on regression analysis explain in more detail which independent variables are significantly related to the dependent variables.

Regression Analysis Results

Regressions were performed for each of the four dependent variables. For each dependent variable, a series of models was attempted until one was found that resulted in a high R^2(adjusted), statistically significant t-ratios for the independent variables, and a residual vs. predicted plot that showed no significant trends.[12] Appendix H presents the full regression results. Overall, considering the limited number of data points, and the estimations made while gathering the data, the regressions proved to be very encouraging. The R^2(adjusted) values range from 43.5% to 74.4%. The R^2 values range from 52.0% to 77.6%, implying that between 52.0% and 77.6% of the variability in the dependent variables was explained by the chosen independent variables. Each dependent variable had at least two independent variables with statistically significant t-ratios. The residual vs. predicted plots for each regression were essentially random with no noticeable trend.

For each regression analysis, a summary of the regression results is presented, along with an interpretation of the results with respect to the realities of the physical process.

---

[12] R^2, sometimes called the coefficient of determination, measures the fraction of variability in the dependent variable accounted for by its least squares regression on the independent variables. R^2(adjusted) is used for multiple regressions where there are several independent variables.
See Velleman, Learning Data Analysis with Data Desk (New York: W.H. Freeman & Co., 1989) for further explanation.

Results of Regression for *Defects per Board*

Dependent Variable:	Square Root of Defects per Board	
R^2 (adjusted) = 65.0%		
Degrees of Freedom = 17		
Independent Variables	**Coefficient**	**t-ratio**
Fine Pitch Components	0.3278	4.45
Passives	0.0015	3.83
Components Hand Placed in SMT	0.0870	2.62

Figure 5.3 Summary of *Defects per Board* Regression

Initial regressions against *Defects per Board*, while yielding excellent numerical results, provided residual vs. predicted plots with a distinct pattern. There was significantly more spread of points toward the higher predicted values than there was for the lower. This suggested a transformation of the dependent variable. Using the square root of *Defects per Board* as a dependent variable resulted in a much better model.

The regression with the transformation yields an R^2(adjusted) value of 65.0%. *Fine Pitch Components, Passives*, and *Components Hand Placed* all contribute significantly to the variation in *Defects per Board.* In this analysis, with seventeen degrees of freedom, all three variables yield t-ratios that translate to a greater than 99% confidence that they are significant.[13]

Interpretation of Results for *Defects per Board*

The results support my initial hypothesis that it is essential to include fine pitch components as a separate cost driver in the surface mount area. Fine pitch components are known to be more difficult to place than components with more widely spaced leads. They can easily be misaligned on the solder pads during placement. For boards with large distances between

[13] See Robert V. Hogg and Johannes Ledolter, Engineering Statistics (New York: Macmillan Publishing Co., 1987) for Student's t-Distribution table.

fine pitch components (approx. greater than 5 inches), misalignment can occur due to irregularities in printed circuit boards. Also, during the re-flow operation, fine pitch components can lift up and "float" on the board causing them to lose alignment.

In the regression analysis, *Passives* had a more significant effect on defects than *Chips*. Generally, passive devices are smaller than chips with many fewer leads. Their low mass, and few points of contact with the board, allow them to vibrate and move easily during processing. One defect that can result from this is "tombstoning." In this instance, one side of the component does not attach to the board, and the component flips up on one edge. Chips, which do not exhibit this defect, are heavier, with more short and thick leads. Once set in place, they tend to remain there. Considering this distinction, one would expect passive devices to exhibit more opens than chips, and thus for *Passives* to be somewhat more significant than *Chips*, as in this analysis.[14]

Some might argue that while the above distinctions between *Passives* and *Chips* are true, they are not significant enough to affect this analysis. But, there is situation specific evidence that supports the results. For example, at DEC's Albuquerque plant, recently pad and part geometry for passives have not consistently matched - the pads are not located precisely where they should be. Therefore, the components do not become securely affixed to the pads during the initial placement process, and more defects are recorded for *Passives* than for *Chips*.

Components Hand Placed in SMT proved to be a significant variable with respect to *Defects per Board*. This is reasonable since the quantity represents a deviation from a

---

[14] "Open" refers to a defect where a lead is not soldered properly to the circuit board and thus creates an *open* circuit. Similarly, "shorts" refers to defects where solder is touching two or more leads resulting in a *short* circuit. Both terms are used to describe types of defects that frequently occur when components are attached to circuit boards using surface mount technology.

standard process, which introduces variability and, therefore, more opportunities for defects. For example, there are more handling steps involved when a board is taken off-line to have components hand attached. Also, during hand placement, technicians can affect (bump) other components while they are working on the board. It is easy to imagine a sleeve being dragged across a board, and subsequent misalignment of a few components.

It is somewhat surprising that *Greater than 44 pin* did not appear as a significant variable in this regression. Recently, these devices have been exhibiting co-planarity problems, and many opens have occurred. It is possible that the particular boards I chose for the analysis did not have components with this problem.

Results of Regression for *Test Time*

Dependent Variable: Test Time		
R^2 (adjusted) = 66.3%		
Degrees of Freedom = 18		
Independent Variables	**Coefficient**	**t-ratio**
Passives	0.0329	4.44
Greater than 44 pin	0.5629	2.12

Figure 5.4 Summary of *Test Time* Regression

As I mentioned in Section 4, the values for *Test Time* were derived from the plant's Capacity Resource Planning (CRP) tool. They represent the "best guess" of engineers and technicians, taking into account yield data and standards.

This regression yielded an R^2(adjusted) value of 66.3% with both *Passives* and *Greater than 44 pin* having a significant impact. The t-ratio for *Passives* implies a greater than 99.9% confidence level that it is significant. The *Greater than 44 pin* variable's t-ratio suggests that it is significant with 92.5% confidence level.

Fine Pitch Components and *Components Hand Placed* were not significant. *Number of Process Steps* was significant when it was regressed using a simple linear regression against *Test Time*, but when other values were included, it was not significant. This is because *Process Steps* correlates reasonably well ($\rho \approx 0.5$) with both *Passives* and *Greater than 44 pin*.

Interpretation of Results for *Test Time*

The most notable omission in this analysis is *Fine Pitch Components*. When one considers the test process, where it takes more time to test fine pitch components than non-fine pitch, it is surprising that *Fine Pitch Components* did not prove to be significant. This is not as startling though, after one explores the source of the data.

The *Test Time* dependent variable was derived from the CRP tool. This tool is used primarily for forecasting, so the test times in it are projections of where the test engineers and technicians want, and expect, their process to be in the future. The model represents a goal, not necessarily today's reality. Additionally, the actual test time data the engineers use to build the model probably under-represents the effort spent on testing fine pitch components. This is because, if a defect is visually evident, for example a series of leads are shorted, the board may not even be tested, but rather just tagged and sent back to surface mount. The time spent on this board is never recorded. Considering both of these sources of underestimation, it is reasonable to expect that the effect of *Fine Pitch Components* on *Test Time* would be underestimated in this analysis.

Passives proved to have a significant impact on *Test Time*. On automatic test equipment (ATE), there is approximately a 500 to 1 difference between the length of time it takes to test an analog versus a digital component. The boards usually pass through four test steps,

and ATE is one of these steps. So, on one out of four of the steps, there is a significant difference between *Passives* and *Chips*. On the other three steps, there is almost the opposite effect, where digital components take longer to test. But, the difference at the ATE station is probably more significant than the other three combined, so it is feasible that *Passives* have a more significant impact than *Chips* on *Test Time*.

Greater than 44 pin also proved to be significant with respect to *Test Time*. This could be because the higher pin count devices require more sophisticated diagnostics, and thus take longer to test. Generally, the more complex the component, the longer it will take to test, so the number of *Greater than 44 pin* devices on a board should affect *Test Time*.

Results of Regression for *Diagnose & Repair Time*

Dependent Variable:	Diagnose & Repair Time	
R^2 (adjusted) = 63.0%		
Degrees of Freedom = 18		
Independent Variables	**Coefficient**	**t-ratio**
Chips	0.2747	4.00
Number of Process Steps	3.2591	2.07

Figure 5.5 Summary of Diagnose & Repair Time Regression

As with *Test Time*, the *Diagnose and Repair Time* values were derived from the CRP tool.

The residual vs. predicted plot for this regression suggested that maybe a transformation of the dependent variable would be useful. After trying the reciprocal, log, and a few other transformations, it was not possible to produce a regression analysis better than that of the original. The regression against the straight *Diagnose & Repair Time* yielded an R^2(adjusted) value of 63.0% with *Chips* and *Process Steps* both proving to be significant variables. *Chips* had a t-ratio suggesting a greater than 99.5% confidence in its

significance, and *Process Steps* resulted in a t-ratio suggesting greater than 95% confidence.

Fine Pitch Components was insignificant both in conjunction with other variables, and alone. *Heat Sinks* and *Components Hand Placed* were also insignificant.

Interpretation of Results for *Diagnose & Repair Time*

Here, as in *Test Time*, *Fine Pitch Components* did not prove to be significant in the regression analysis. This is a major inconsistency between the statistical results and reality. According to test engineers and technicians, *Fine Pitch Components* take much longer to diagnose and repair than non-fine pitch components. Again, this discrepancy in the statistics is probably due to two factors. The first is that the *Diagnose and Repair Time* data is from the CRP tool, which is a future projection. The second is that there is probably significant under-reporting of actual defects found for fine pitch devices. It is much easier to fix twenty leads than it is to enter a defect report into the data collection system twenty times. Since defect data is used as one of the bases of the *Diagnose and Repair Time* estimates, this under-reporting would affect data collected from the CRP tool.

It is not clear why *Process Steps* proved to be so significant in this analysis. Because the *Process Steps* variable is subject to interpretation (i.e. everyone does not agree on what constitutes a process step and how to measure one), and the *Diagnose & Repair Time* data itself was derived from a model, it is probably not very worthwhile to spend too much time pursuing this.

Chips proved to be more significant here than *Passives* which makes sense because of circuit complexity. Defects related to *Chips* take longer to diagnose and repair than defects related to *Passives*.

One issue that was not captured in this analysis, but may be worth pursuing is the distinction between "J-Lead" and "Gull Wing" parts. As Figure 5.6 depicts, these are two geometries of leads. J-lead parts tend to take longer to diagnose and repair than Gull Wings. They have more delicate joints than the Gull Wings, and thus have a higher tendency to result in opens. Also, since the part footprint is smaller, the components tend to be placed close together making them difficult to visually inspect. Gull Wings have a larger surface area in contact with the board, and so result in fewer opens. In the future, it might be useful to separate the *Greater than 44 pin* category into *J-Leads* and *Gull Wing* distinctions.

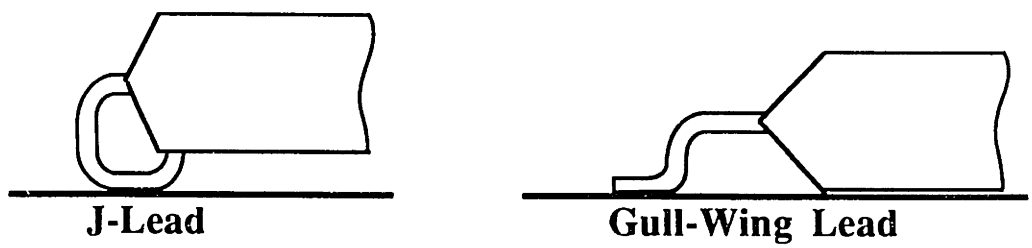

Figure 5.6 J-Lead vs. Gull Wing Lead Geometries

Results of Regression for *Set-Up Time*

Dependent Variable: Set-Up Time		
R^2 (adjusted) = 74.4%		
Degrees of Freedom = 14		
Independent Variables	**Coefficient**	**t-ratio**
Chips	1.1099	6.96
Components Hand Placed in SMT	7.7928	1.39

Figure 5.7 Summary of *Set-Up Time* Regression

The *Set-Up Time* data was estimated from data collected manually in the surface mount area by the machine operators. For four of the products, no data was available. The regression against *Set-Up Time* analysis yielded an R^2(adjusted) value of 74.4% with *Chips* and *Components Hand Placed* both proving to be significant. *Chips* had the higher t-ratio representing a greater than 99.5% confidence level that it is significant. *Hand Placed* was significant with approximately 95% confidence.

Interpretation of Results for *Set-Up Time*

The largest factor that drives set-up time is the number of distinct part numbers for components on a board (e.g. if a board had 100 components, but all were the same part number, the set-up time would be <u>much</u> lower than if all were different part numbers). *Chips* proved to be significantly related to *Set-Up Time*, which is reasonable since, for these boards, *Chips* is very highly correlated with *Number of Part Numbers*. There is no significant reason that *Chips* proved to be more significant than *Passives* - either can serve as a surrogate for *Number of Part Numbers*.

Components Hand Placed should not directly have an impact on set-up time. In this analysis, the variable proved to be significant. This is probably due to the estimates of *Set-Up Time*.

As I mentioned earlier, as Albuquerque and other plants move to off-line set-ups, the impact of set-up time on cost will be reduced. Also, some plants may be able to dedicate machines to product families, or have a system where parts for all products can be kept on machines. In these cases, set-up time will become even less critical to cost analysis.

Number of Process Steps: Independent or Dependent Variable?

The number of process steps which a product must pass through was initially considered an independent variable - it potentially could affect the cost and the quality. But, it also can be viewed as a dependent variable - the result of design and production decisions. I treated both to see what would happen. As an independent variable, it is somewhat inappropriate because it is correlated with many of the other independent variables (e.g. with *Chips, Passives, Greater than 44 pin*, etc.), and therefore is troublesome in the regressions. As a dependent variable it does not perform very well either. Following are the regression results for *Number of Process Steps* as a dependent variable.

Results of Regression for *Number of Process Steps*

Dependent Variable:	Number of Process Steps	
R^2 (adjusted) = 43.5%		
Degrees of Freedom = 17		
Independent Variables	**Coefficient**	**t-ratio**
Chips	0.0131	1.60
Greater than 44 pin	0.2400	1.97
Fine Pitch Components	1.3851	2.15

Figure 5.8 Summary of *Number of Process Steps* Regression

In a regression analysis against *Process Steps*, the highest R^2(adjusted) value obtained was 43.5% with *Fine Pitch Components, Chips,* and *Greater than 44 pin* proving to be significant independent variables. While this shows that almost half the variability in

Process Steps can be explained by these variables, it is much lower than the other regressions performed.

Process Steps may not be a good candidate driver, given the current systems in the plant, so it is not a concern that the R^2(adjusted) value was low. As mentioned earlier, the plant has not specifically decided what constitutes a process step, or how to measure one. When operators visually inspect boards as they unload them from machines, should that be considered a separate step? There does not seem to be general consensus yet. Until there is a more standardized approach to defining process steps, it is impossible to track them as drivers. Therefore, while I kept the variable in the analysis to see how it performed, I was not concerned when it did not produce a very strong effect in the regressions. As its correlation with other variables suggests, it will be accounted for in other drivers, such as in *Chips*, *Passives*, *Greater than 44 pin*, and *Fine Pitch Components*.

Summary of Regression Results and Recommendations

Following is a chart summarizing which independent variables proved to be significant for the five dependent variables tested.

Defects per Board	Test Time	Diagnose & Repair Time	Set-Up Time	Process Steps
FP Comps Passives Hand Placed	Passives Greater than 44 pin	Chips Process Steps	Chips Hand Placed	FP Comps Chips Greater than 44 pin

Figure 5.9 Significant Independent Variables For Each Dependent Variable

The regression results support my initial hypothesis that *Fine Pitch Components* should be considered separately as a driver. I do not believe that, at this time, it is necessary to use fine pitch <u>leads</u> as a driver, but rather suggest fine pitch <u>components</u>.

The regression analysis also confirms the acceptability of using *Passives*, *Chips*, and *Greater than 44 pin* as drivers. These drivers, along with *Fine Pitch Components*, break the original cost per placement driver into four sub-categories that reflect a more accurate interpretation of board complexity. They are a finer cut of the previous metric.

Additionally, I recommend that *Number of Components Hand Placed,* which represents components hand placed on a board in the surface mount area, be considered as an additional driver. This quantity is not highly correlated with any of the other four, so it is not accounted for by any of the other drivers. It was determined to be significant in regression analyses against *Defects per Board* and *Set-Up Time*. The significance to *Set-Up Time* is probably not a direct effect, but is merely a result of more complex boards (with higher set-up times) having components which are hand placed in SMT.

The recommendation to include *Components Hand Placed* as a driver is supported by more than the statistical analyses. After observing the process, and speaking with supervisors and operators in the surface mount area, I conclude that boards which require deviating from the normal automated process, are more likely to incur cost to the area. They require much higher direct labor content, are in the area longer, and are exposed to more opportunities for defects.

Section 6 • Applications and Cautions

The research performed in support of this project had multiple customers, including:

- Activity-Based Costing team at Albuquerque plant (ABO);
- Assembly Engineering organization at ABO;
- Other personnel at ABO (e.g. Industrial Engineers);
- DEC designers;
- Other DEC personnel;
- MIT (especially LFM) professors, students, and alumni;
- Researchers unrelated to MIT or DEC.

Some were interested in the final results, others in the research process, and still others in subsets of the results (e.g. the set-up time analysis). In the previous chapters, I addressed generically the problem of determining cost and quality drivers in the surface mount process of a module assembly facility. I did not specifically discuss how this method can be applied by many of these groups. This chapter will highlight some of the applications of this research, and will present some cautions.

Applications of This Research

Choosing Cost And Quality Drivers for Activity Based Costing Systems

Finance organizations in many plants, including DEC's Albuquerque plant, are currently embarking on the implementation of large scale activity-based cost accounting systems. Kaplan and Cooper have written extensively on the virtues of these systems, especially for determining product costs. They stress the importance of choosing appropriate cost drivers, yet they do not present a formal methodology to do so.[15] In their case studies, they rely entirely on interviews as their means for choosing drivers. While interviews are important, a statistical technique that verifies the appropriateness of driver selection is also

[15] Robin Cooper and Robert Kaplan, The Design of Cost Management Systems Text, Cases, and Readings (New Jersey: Prentice Hall, 1991).

beneficial. This research presents a statistical methodology to use in conjunction with interviews while selecting drivers.

Once the drivers are determined, they can be incorporated into an ABC system, and used to calculate the cost to produce specific products. Information from the ABC system can be used to report actual spending, and forecast future spending. Albuquerque incorporated four new drivers from this research into their ABC system to clarify their product costing system. They have also adopted the new drivers to improve their process costing capabilities.

Focusing Process Improvement Efforts Using Quality Drivers

The methodology presented in this thesis highlights the factors affecting the quality of a production process. Organizations can use regression analysis to determine where to focus their process improvement efforts. The analysis can point them in the right direction, even when they have a limited understanding of the intricacies of their processes. Defects, or some other measure of quality, can be used as a dependent variable, and potential quality drivers can be included as independent variables. Those variables that prove to be most significant are the ones on which they should concentrate their improvement efforts. Since product mixes and assembly processes evolve rapidly, plants should perform this analysis regularly rather than adopting a static model. They can use the results to target their continuous improvement efforts.

The process of preparing for the regression analysis may be just as useful as the results. To perform this type of analysis for process improvement efforts, the quality data must be accurate, timely, and relevant. A significant value of this type of work is focusing those involved on data integrity and appropriateness.

Using Drivers as a Link Between Design and Manufacturing

When designers and manufacturing personnel discuss products and how they are performing (or will perform) in the factory, they need an objective language. Manufacturing engineers can explain that one design is more difficult to build than another, yet it is easy for designers to dismiss this. If manufacturing engineers have conclusive evidence that one design yields one level of quality, while another evokes a higher level, than the discussion becomes clearer. What is not clear, is who "owns" the driver. Should the design group change their design, or should manufacturing change their process? The answers to this type of question cannot be derived directly from this methodology. The regression results show what has an influence, but the difficult strategic decisions about how to deal with the issues still must be resolved by those involved.

Cautions for Use of This Methodology

Driver Selection Cannot Replace Designer/Manufacturer Communication

In the preceding section, I explained that cost drivers can be used to enhance discussion between design and manufacturing. It is important to note though, that ABC systems, cost and quality models, design guidelines, and other tools cannot substitute for continuous cooperation between design and manufacturing personnel. These types of tools are not substitutes for concurrent engineering efforts, but rather facilitators for better communication.

Driver Selection Does Not Address New Technology Decisions

Regression analysis is based on historical data. The results can be interpreted with respect to the timeframe of the analysis (i.e. "These variables were important during the period when this data was collected.") If the system remains in a steady state, then the results can be extrapolated to a future time period. As soon as the process changes dramatically, the

results are no longer valid. Therefore, regression analysis cannot be used to predict the success or failure of major new technological introductions.

This Methodology Alone Does Not Provide Full Scale Cost Models

Product cost models incorporate many aspects of the resources consumed in producing a product. Lee Ng presents an example of technical cost modeling for printed circuit boards which includes a detailed breakdown of the significant process steps involved in producing a board.[16] The methodology I present in this thesis can be used in conjunction with other techniques to build cost models, but alone does not result in a cost model. The techniques presented here should be used to determine the important factors to be considered in a more inclusive cost model.

Statistics Are Not A Black Box

It is impossible to use regression analysis without a thorough understanding of the assumptions underlying the regression model. An example of this is highlighted in this analysis by the use of *Defects per Board* as a dependent variable. In the original analysis, *Defects per Board* was an inappropriate dependent variable when used without employing a transformation. In other words, the independent variables were not linearly related to *Defects per Board.* Once a transformation was performed, it was reasonable to use the least squares approximation model. While performing a regression analysis, one must test the validity of variables, and perform diagnostics on the results.

Since many engineers are not familiar with regression analysis, a reasonable paradigm might suggest a team of engineers working in concert with a statistician. The engineers' role would be to determine which variables should be investigated as potential drivers and

---

[16] Lee Ng. "Printed Circuit Board Materials: An Evaluation of Manufacturing Technologies and Market Requirements." MIT Doctoral Dissertation, 1990.

then to gather the appropriate, accurate, data. The statistician would run the analyses and present the results to the team for their interpretation. This is similar to how this project developed. In this case, I determined the lists of variables with the help of many engineers, searched for the data and ran the analyses, and then went back to the engineers to discuss the interpretation of the results. As a group, we were able to determine where the statistics were valid, and where the results were inaccurate.

Section 7 • Recommendations and Conclusions

In the previous chapter I outlined some recommendations for applications of this research. In the last section of Section 5, I presented specific recommendations regarding driver selection for DEC's Albuquerque plant. This section will discuss a few general recommendations and conclusions.

Address the Disturbances Associated With New Product Introductions

The statistical analysis in this paper does not address the fluctuations associated with new product introductions. However, it might be useful to provide designers with two models - one addressing steady-state cost and quality drivers and one incorporating new product start-up issues. That way, the variation in new product start-up complexity could be captured in addition to general assembly complexity. Some products are easier to introduce than others, and drivers should be able to capture this. It may even be possible to include a new product start-up driver as a product costing driver. As product lifecycles continue to shrink, this will become even more appropriate.

Use Quantitative Analysis as a Catalyst

In many organizations, the type of analysis presented in this thesis might be considered too academic or non-mainstream. In reality, an effort such as this can be used as a catalyst to address data collection issues. A project like this one forces people to decide what is appropriate data to collect, and then to verify whether it is accurate. It encourages cross-functional cooperation because the problem spans functional boundaries. This kind of cooperation is critical to allow personnel to understand implications of their work beyond the scope of their specific job function.

Integrate the Resources of Academia and Industry

This research presents an excellent example of a project that was developed jointly between academic researchers and industry personnel. Neither group alone would have formulated this project without the input from the other. The personnel at the factory explained a problem facing them, and the researchers proposed a methodology for a solution. Both groups learned a great deal about the specifics of the application and about the realities of conducting this type of research. I encourage the continued interaction between industry and academia, especially on well defined projects. For industry, the projects provide an outside perspective and tools of which they might not have been aware. For academia, the research provides a reality check on theory.

In Conclusion

As time-to-market becomes more and more critical, and product life cycles continue to shorten, companies that generate new products will have to strive to understand what affects their processes. They might not always be able to thoroughly understand the physics of a process, but they must recognize what factors significantly affect the output. This thesis presents a methodology to determine these factors. It also highlights the importance of relevant, accurate data collection strategies. Additionally, it presents an example of successful collaboration between academia and industry to address a specific organizational need.

Bibliography

Berlant, Debbie, and Reese Browning, et. al. "Tomorrow's Accounting Today: An Activity Accounting System for PC Board Assembly." Unpublished paper based on work performed at Hewlett Packard, Roseville Networks Division, June 1988.

Chao, Jackson Sheng-Kuang. "Analysis of Variance Impact on Manufacturing Flowtime." Massachusetts Institute of Technology, Leaders for Manufacturing Masters Thesis, 1991.

Cooper, Robin, and Robert S. Kaplan. The Design of Cost Management Systems - Text, Cases, and Readings. New Jersey: Prentice Hall, 1991.

----------. "Measure Costs Right: Make the Right Decisions." *Harvard Business Review*, September-October 1988, pp. 96-103.

----------. "Profit Priorities from Activity-Based Costing." *Harvard Business Review*, May-June 1991, pp. 130-135.

Digital Equipment Corporation, Annual Report 1991.

Digital Equipment Corporation, "Cost Driver Product Cost Model," unpublished document, 1990. (An internal document outlining a cost model used by Augusta, ME plant to determine product costs. Model does not address how to determine drivers.)

Digital Equipment Corporation, "Thoughts on Cost Drivers in Modules Processes," unpublished document, 1991. (An internal document beginning to pull together information on potential cost drivers.)

Fine, Charlie. "Cost Modeling to Support Product Development." Presentation at the MIT Sloan School of Management, October 1990.

Fine, Charlie, and Karl T. Uhlrich. "Process-Driven Product Design: A Printed Wiring Board Cost and Resource Consumption Model for Digital Equipment Corporation." MIT Sloan School of Management, August 1990.

Foster, George and Mahendra Gupta. "Manufacturing Overhead Cost Driver Analysis." Graduate School of Business, Stanford University, Research Paper #1036, March 1989.

Foster, George and Mahendra Gupta. "Implementation of An Activity Accounting System in The Electronics Industry." Unpublished paper based on ABC implementation at Digital Equipment Corporation, Albuquerque plant, January 1989.

Hogg, Robert V., and Johannes Ledolter. Engineering Statistics. New York: Macmillan Publishing Company, 1987.

Koopmans, Lambert H. Introduction to Contemporary Statistical Methods. Second Edition. Boston: Duxbury Press, 1987.

Kuehn, Charlie. "Functionality Blueprint, Activity Based Costing System for ABO & ASO," unpublished document of Digital Equipment Corporation, 1991. (An internal document outlining the pilot ABC system's functionality.)

Ng, Lee Hong. "Printed Circuit Board Materials: An Evaluation of Manufacturing Technologies and Market Requirements." Massachusetts Institute of Technology, Doctoral Dissertation, 1990.

Prasad, Ray P. Surface Mount Technology: Principles and Practice. New York: VanNostrand Reinhold, 1989.

Ulrich, Karl T. Charles H. Fine. "Cost Estimation Tools to Support Product Design." ASME Manufacturing International Conference, Chicago, IL, March 1990.

Velleman, Paul F., Learning Data Analysis with Data Desk. New York: W.H. Freeman And Company, 1989.

Weisberg, Sanford. Applied Linear Regression. Second Edition. New York: John Wiley & Sons, 1985.

Appendix A • Definitions of Component Classes

Passives:	SMT Passive Components. Components such as resistors, capacitors, and inductors. Generally small parts. Tape carrier sizes 8 mm. and 12 mm. Run at highest chipshooter speed. (At DEC, usually 10, 11, and 13 class parts.)
Chips:	SMT Chips. Pin counts range from 8 to 28 for the majority of them, although starting to see some 32 to 40 pin packages. SOIC/SOL, SOJ, and PLCC package styles. Carrier sizes are 16 mm., 24 mm., and 32 mm. (At DEC, 13 class SOJ packages, 19, 21, and 23 class parts.)†
Greater than 44 pin:	SMT 44+ Components. Non-Fine Pitch, 44 to 84 pin packages. PLCC and gull wing quad flat packages (QFPs). Generally come in trays or tubes. (At DEC, mostly 21 class parts.)
Fine Pitch Components:	SMT Fine Pitch Components. Lead centers on 0.025 inch spacing (25 mil.). Will include 20 mil. when it arrives. Trays only. Pin counts 132 - 224 at present. Gull wing quad flat packages (QFPs).

† SSOP's (Small Single Outline Packages) are an anomaly in this classification scheme. For the CRP tool, they are treated as Chips, because they are tape fed, and placed like Chips. For the ABC system, they will be treated like Fine Pitch Components, because the re-work associated with them is fine pitch.

Appendix B • Independent Variables: Long List

Variables are grouped under four headings:

I. Overall Component Related
II. Specific Component Related
III. Board Design Related
IV. Process Related

Variables with asterisks are those that were used in the final analysis. Variables without asterisks are future possibilities for analysis, finer cuts of chosen variables, or just alternative variables to consider.

I. Overall Component Related

* Number of SMT Leads at 25 mil. pitch (i.e. Fine Pitch Leads)
* Number of SMT Leads at Greater than 25 mil. pitch (i.e. Non-Fine Pitch Leads)
* Total Number of SMT Leads
* Number of SMT Passive Components†
* Number of SMT Chips†
* Number of SMT Greater than 44 pin Non-Fine Pitch Components†
* Number of SMT Fine Pitch Components†
* Number of SMT Non-Fine Pitch Components
* Total Number of SMT Components
* Number of Components Hand Placed in SMT
* Number of SMT Part #'s

Number of Components Hand Tacked in SMT
Number of Unique ABO Components
Number of SMT Leads on SSOP's
Number of SMT Leads on LDCC's
Number of SMT Leads on PQFP's
Number of SMT Leads at Greater than 50 mil. Pitch
Number of Components placed with MV, MK, or CP-3
Number of Components placed with MPA, or IP-II
Number of Components placed by robots
Number of Fine Pitch Components placed with chipshooters
Average Number of Solder Connections/Sq. Inch
Max. Number of Solder Connections/Sq. Inch
Number of Parts/Board Area
Ranking of Board Density
Number of non-standard SMT components
{similar to hand placements in SMT}
Number of components which require gluing

---

† See Exhibit C. for component class definitions.

II. Specific Component Related

* Are there heat sinks on the board? (Yes/No)

Ratio of number of DEC formed fine pitch parts to total fine pitch parts.
- {captures PQFP vs. LDCC issue}
Orientation Metric: % components not aligned at 0 degrees.
Also: % of components at 180 degrees
% of components at 90 degrees
% of components at -90 degrees
Location of Heat Sinks
Greater than one inch heat sinks? (yes/no)
Greater than two tier heat sinks? (yes/no)
Two tier or above heat sinks? (yes/no)
Pre- or post- re-flow attach of heat sinks?
SMT Connectors? (yes/no)
PGA vs. QFP?
Other special troublesome components...

III. Board Design Related

* Greatest Distance between outer pads on Fine Pitch Parts

Number of modules per panel (1,2,8,14)
Is board thickness within limits? ($0.062 < t < 0.1$ inches) (yes/no)
Actives on side 2? (yes/no)
0.125 in. dead zone (including no fiducials) around perimeter of board? (yes/no)
Deviation between artwork and tooling holes

IV. Process Related

* Number of Process Steps {Can also be a dependent variable.}

Re-flow characterization (uniform thermal mass metric? ranking?)
Ranking of potential for mis-handling? More primitive characteristics?
Average number of boards/batch
Total annual volume
Need for greater than one chip shooter? (yes/no)
Number of non-standard processes
Number of thermal processes seen by board
Mechanical stresses on board during test, MI, etc.
Deviations from ordinary process

Appendix C • Effects of Variables on Defect Rate

This appendix presents an explanation of why some components are more likely to exhibit soldering defects than others. The appendix does not break the components into specific types (e.g. LDCC vs. PQFP), but rather groups them according to the variables used in this research.

The variables are listed in the order in which they exhibit defects (e.g. *Fine Pitch Components* shows the most defects). In the interpretations of the regression analyses in Section 5 these are discussed further.

Independent Variable	Possible Relationship to Defects
Fine Pitch Components	Heavy devices. Some components exhibit problems with incoming lead quality. Also, tend to drift off pads during re-flow process step.
Passives	Light components. Tend to move around on boards. Sometimes exhibit "tombstoning" where one side of component flips up off board. Some boards, recently, have had design flaws where pads are not located exactly where they should be, so have trouble attaching component securely. Also, sometimes have difficult cross-sections.
Chips	Big, heavy devices, with short, thick leads. Tend to stay put.
Heat Sinks? (yes/no)	Should not have big effect on defect rate. Does affect the complexity of the thermal profile, and limits the choice of placement machines.

Appendix D • Dependent Variables: Long List

Variables are grouped under eight headings:

I. Set-Up Time
II. Equipment Run Time
III. Test Time
IV. Diagnose & Re-work Time
V. Defect Data
VI. Labor
VII. Process Time
VIII. Capital and Other Spending Required

Variables with asterisks are those that were used in the final analysis. Variables without asterisks are ones not used in this analysis.

I. Set-Up Time

* Screen Printer Set-Up Time
* Placement Equipment Set-Up Time
* Re-Flow Set-Up Time

II. Equipment Run Time

Screen Printer Equipment Time (although probably fixed across boards)
Placement Run Time
Re-Flow Run Time
Materials Handling Equipment Time

III. Test Time

* Zehntel and other Machine Test Time (including avg. re-test time)

Hand Inspection (including avg. re-test time)

IV. Diagnose & Re-Work Time

* Diagnose & Re-work Time (includes all stations with diagnose and re-work)

V. Defect Data

* Number of Defects Found per Board
  (This could be broken into functional vs. process, or other classifications.)

VI. Labor

Direct Labor Hours Required (beyond set-up and equipment run time)
Supervisory Labor Hours Required
Engineering Labor Hours Required
Materials Handling Labor Hours

VII. Process Time

Time Elapsed Since Board Entered Area (Throughput Time or Flow Time)

VIII. Capital and Other Spending Required

Stencil Cost
Screen Printer Tooling Cost
Feeders (for components unique to this product for Albuquerque plant)
Profile Boards
Re-Flow Stand-offs
Other Capital Required

INDEPENDENT VARIABLES

Number of Part Numbers -
There is not an automated way to gather this. I simply counted the part numbers listed on the surface mount bills of materials.

Total Number of Process Steps -
With the input of the assembly engineers who support the surface mount area, I constructed a process complexity matrix. Each product was listed down the left side, and process steps were listed along the headings of the columns. If a product passed through a process step, it had a "1" placed in its column under that process step. If it passed through that step twice (i.e. for double sided boards) it had a "2." For each row, the columns were summed and the total was the number of process steps.

Product	Bake	Bake PLCCs	Affix Label	Paste	...	Total Process Steps
A	1		1	1	...	11
B	1	1	2	2	...	18
C	1	1	2	2	...	13
...	...	...	...	...	...	...

Figure E.1 Abridged Process Complexity Matrix

Number of Fine Pitch Leads -
This was determined manually for each board containing fine pitch devices. If possible, it should be made available from the design database tools.

Number of Total Leads -
This information is not currently available through design databases. It is entered, manually, by quality engineers into the plant quality database system, and can be retrieved from the system.

Number of Non-Fine Pitch Leads -
Obtained by subtracting *Number of Fine Pitch Leads* from *Number of Total Leads*.

Numbers of Fine Pitch Components, Passives, Chips,and >44 Components† -
These numbers were determined manually for the capacity resource planning tool by a summer co-op student. The student counted the types of components on product bills of materials. Albuquerque is currently working on a system to automate gathering this data.

Total Number of Components -
Counted manually from bills of materials.

Number of Non-Fine Pitch Components -
Total Number of Components minus *Number of Fine Pitch Components*.

Heat Sinks? (1=yes/0=no)
Gathered by interviewing assembly engineers.

† See Appendix A for component class definitions.

Number of Components Placed by Hand in Surface Mount Area (SMT) -
Obtained from supervisors in SMT area.

Greatest Distance Between Fine Pitch Parts -
Measured manually with digital comparator.

DEPENDENT VARIABLES

Defects Per Board -
Estimated from data available through the plant's quality database system. Discussed in more detail in Section 4.

Test Time Per Board -
Taken from plant's capacity resource planning model (CRP), and represents best estimate of many engineers and technicians. Includes a factor to take into account yields and re-testing.

Diagnose plus Repair Time Per Board -
Also from CRP tool. See *Test Time* above.

Set-Up Time Per Board -
Gathered for this project through a worksheet provided to all operators in the surface mount area. Operators recorded the time they spent setting up machines for each product changeover for approximately two months. See Appendix F for form, and Section 4 for more detailed discussion.

Appendix F • SMT Set-Up and Run Time Form

•• GENERAL INFO ••

Date: _____ # of People on Machine: _____

Name: _____

Product you are setting up: _____ (Ex: 20605-01 3MIN Base)

Side 1 or Side 2? : _____ (Ex: Side 1)

Product you just ran: _____ (Ex: 20830-01 LPS20 Turbo)

Check One:

__ MPM #1	__ MV	__ Robot 1	__ Electrovert
__ MPM #2	__ MK1	__ Robot 2	__ BTU
__ MPM #3	__ MK2	__ MPA	__ Vitronics I
__ Pass Through	__ CP-3	__ IP-2	__ Vitronics II
			__ Vapor Phase

•• TO COMPLETE DURING SET-UP ••

ACTUAL TOTAL TIME SPENT SETTING UP FOR PRODUCT? _____ (Ex. 2 hrs.)
(How long was spent actually setting-up for this product, not including breaks, meetings, etc.? If the product was set-up over more than one shift, add the times from the different shifts and record the total time.)

Was off-line set-up help used? (Yes/No) _____
Was this a typical (normal) set-up for this product? (Yes/No) _____

If Not, Why Not? _____

COMMENTS ON SET-UP?? (notes about shift changes, etc.)

•• TO COMPLETE DURING A PRODUCT RUN ON ANY MACHINE ••

Batch Size? _____ (How many boards did you run??)

ACTUAL RUN TIME FOR THIS PRODUCT? _____
(How much time was spent running this product not including breaks, down-time, etc.? If the product was run over more than one shift, add the times from the different shifts and record the total time.)

COMMENTS ON RUN-TIME?? (notes about shift changes, etc.)

Appendix G • Correlation Matrix

	Passive	FP Comps	>44 pin	Hand Placed	Heat Sinks?	Process Steps	Defects /Board	Test Time	Diag. & Repair	Set-Up Time
Passives	1.000									
FPComps	0.111	1.000								
> 44 pin	0.455	0.181	1.000							
Hand Placed	-0.416	-0.012	0.058	1.000						
Heat Sinks?	0.349	0.212	0.284	-0.130	1.000					
Process Steps	0.480	0.440	0.575	-0.074	-0.125	1.000				
Defects/ Board	0.358	0.654	0.222	0.181	0.194	0.463	1.000			
Test Time	0.788	-0.021	0.604	-0.417	0.243	0.461	0.078	1.000		
Diag. & Rep. Time	0.634	0.082	0.407	-0.347	0.188	0.610	0.090	0.605	1.000	
Set-Up Time	0.773	0.202	0.601	-0.038	0.532	0.531	0.641	0.530	0.633	1.000
Square Rt. of Def./Bd.	0.468	0.651	0.284	0.141	0.154	0.567	0.967	0.179	0.172	0.671

Figure G.1 Pearson Product-Moment Correlation Matrix

Dependent Variable:	Square Root of Defects per Board			
22 Total Cases of which 1 is missing				
R^2 = 70.2%	**R^2 (adjusted)** = 65.0%			
s = 0.2663 with 21 - 4 = 17 **Degrees of Freedom**				
Source	**Sum of Sq.**	**df**	**Mean Sq.**	**F-ratio**
Regression	2.8430	3	0.9476	13.4
Residual	1.2057	17	0.0709	

Indep. Variables	**Coefficient**	**S.E. of Coeff.**	**t-ratio**
Constant	0.1395	0.1312	1.06
Fine Pitch Comps	0.3278	0.0737	4.45
Passives	0.0015	0.0004	3.83
Hand Placed	0.0870	0.0332	2.62

Dependent Variable:	Test Time			
22 Total Cases of which 1 is missing				
R^2 = 69.6%	**R^2 (adjusted)** = 66.3%			
s = 5.057 with 21 - 3 = 18 **Degrees of Freedom**				
Source	**Sum of Sq.**	**df**	**Mean Sq.**	**F-ratio**
Regression	1,055.91	2	528	20.6
Residual	460.29	18	25.572	

Indep. Variables	**Coefficient**	**S.E. of Coeff.**	**t-ratio**
Constant	7.0441	1.929	3.65
Passives	0.0329	0.0074	4.44
Greater than 44 pin	0.5629	0.2649	2.12

Dependent Variable:	Diagnose & Repair Time			
22 Total Cases of which 1 is missing				
R^2 = 66.7%	**R^2 (adjusted)** = 63.0%			
s = 18.97 with 21 - 3 = 18 **Degrees of Freedom**				
Source	**Sum of Sq.**	**df**	**Mean Sq.**	**F-ratio**
Regression	12989.6	2	6495	18.1
Residual	6474.8	18	359.71	

Indep. Variables	**Coefficient**	**S.E. of Coeff.**	**t-ratio**
Constant	-27.7245	19.52	-1.42
Chips	0.2747	0.069	4.00
Process Steps	3.2591	1.572	2.07

Dependent Variable:	Set-Up Time			
22 Total Cases of which 5 are missing				
R^2 = 77.6%	**R^2 (adjusted)** = 74.4%			
s = 44.14 with 17 - 3 = 14 **Degrees of Freedom**				
Source	**Sum of Sq.**	**df**	**Mean Sq.**	**F-ratio**
Regression	94615.0	2	47308	24.3
Residual	27280.9	14	1948.63	

Indep. Variables	**Coefficient**	**S.E. of Coeff.**	**t-ratio**
Constant	124.107	18.63	6.66
Hand Placed	7.7928	5.591	1.39
Chips	1.1099	0.1594	6.96

Dependent Variable:	Number of Process Steps			
22 Total Cases of which 1 is missing				
R^2 = 52.0%	**R^2 (adjusted)** = 43.5%			
s = 2.299 with 21 - 4 = 17 **Degrees of Freedom**				
Source	**Sum of Sq.**	**df**	**Mean Sq.**	**F-ratio**
Regression	97.352	3	32.45	6.14
Residual	89.834	17	5.284	

Indep. Variables	**Coefficient**	**S.E. of Coeff.**	**t-ratio**
Constant	10.2413	0.8610	11.9
Chips	0.0131	0.0082	1.60
Greater than 44 pin	0.2400	0.1219	1.97
Fine Pitch Comps	1.3851	0.6442	2.15