PREDICTING OVER TARGET BASELINE (OTB)
ACQUISITION CONTRACTS

THESIS

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AFIT/GCA/ENC/10-01

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THESIS

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Approved:

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Abstract

Cost estimators use a variety of methods to develop estimates at completion (EACs) and new methods continue to be developed. Research has shown there is no best method for computing EACs for all acquisition contracts. However, some methods perform better under specific circumstances. In 2009, Captain Trahan investigated the use of a Gompertz growth model for developing EACs. She found that this method is more reliable for Over Target Baseline (OTB) contracts than the standard indexed based approaches. Captain Trahan's model is an excellent model to use for OTB contracts or contracts with a high likelihood of becoming an OTB contract. In this study, we attempt to develop a model that predicts whether an acquisition contract is likely to become an OTB. By identifying contracts that are likely to become OTB, we can apply the Gompertz growth model to develop better EACs. Furthermore, an OTB, by definition, recognizes a cost overrun. Therefore, the ability to predict OTBs would allow us to understand what may cause cost overruns. However, our models indicate that we are unable to predict an OTB. This indicates that the OTB process may be used randomly which leads us to question the benefits of OTBs.

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Kristine Thickstun

Table of Contents

List of Figures

List of Tables

PREDICTING OVER TARGET BASELINE (OTB)
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I: Introduction

Background

Approximately twenty percent of all acquisition contracts in the DoD experienced cost overruns over the past 20 years (based on analysis dataset). An Over Target Baseline (OTB) formally recognizes these cost overruns. By examining eighty percent of contracts between 1990 and 2005 for Major Defense Acquisition Programs (MDAPs), we identify over $26 billion in cost overruns (BY09$). The average cost overrun for each contract experiencing an OTB is $321 million (BY09$).

Since cost overruns are a major concern for the entire Department of Defense, it is important to understand why they occur. Two potential reasons for cost overruns are: 1) The existing cost estimates are not accurate to begin with which leads to the actual costs being far from the estimate and 2) Program costs are not effectively controlled to prevent overruns. Solutions to these problems include improving the original cost estimates, improving our control mechanisms for acquisition programs, and managing factors that lead to cost overruns. The DoD uses the Earned Value Management (EVM) system for monitoring and controlling acquisition programs. EVM requires the reporting of cost, schedule, and performance metrics for large acquisition systems. Two important EVM metrics determine how a program is doing and whether or not a program must make changes to get back on track. The Cost Performance Index (CPI) tells management officials whether or not a program is experiencing cost overruns to date and the Schedule Performance Index (SPI) tells management officials whether or not a program is currently behind schedule or not.

In order to ascertain whether a program will experience cost overruns at completion, it is necessary to know the Budget at Completion (BAC) and the Estimate at Completion (EAC). We can determine if a program will experience cost overruns by comparing the budgeted amount for a program (BAC) to the estimated cost at completion (EAC). Particularly, contracts experience a cost overrun at completion, also known as a variance at completion (VAC), when the EAC is larger than the BAC.

Determining the BAC is straightforward as it represents the planned amount of money allocated to a specific program and it is the amount included in the budget. However, developing the EAC is not as straightforward. The EAC is an estimate for what the program will actually cost once all of the work is completed. There is a vast amount of research in the area of developing accurate EACs. Some methods work better than others and several methods only work well under specific circumstances. Based on past research, it is not clear that there is one superior method of developing an accurate EAC for all acquisition contracts.

To improve the accuracy of EACs, cost estimators can focus on those programs where a specific estimating method performs better. By applying these superior estimating methods properly, cost estimators can develop EACs that are more accurate. In this thesis, we investigate the use of one of these methods in particular. In 2009, Captain Trahan investigated the use of growth models as a tool to develop better EACs in her AFIT thesis. She found that the growth model she applied to acquisition contracts performed superior to the standard indexed based approaches for developing EACs 71% of the time for Over Target Baseline (OTB) contracts (Trahan, 2009). Therefore, her method may provide a more accurate EAC for a specific type of acquisition contract: OTB contracts.

Finally, the DoD can address cost overruns by identifying the factors that lead to cost overruns and properly managing these factors. We can try to identify these factors by using statistical models that quantify the relationships between overruns and a variety of factors. While this thesis focuses on the topic of OTBs, it is important to recognize that an OTB is not only a special case of contracts, but an OTB also identifies a cost overrun. Based on the analysis of contracts in our dataset, there have been over $17 billion in cost overruns related to OTBs since 2000. The ability to identify factors related to OTBs provides insight into what may lead to cost overruns for the DoD.

Purpose of this Study

This study has two purposes: 1) Develop better EACs and 2) Predict whether an OTB would occur, which signifies a recognized cost overrun. To focus on our goal of developing better EACs, we would like to apply Captain Trahan's growth models to OTB contracts. However, cost estimators do not always know whether a contract will become an OTB contract. An over target baseline (OTB) occurs when the original baseline, in terms of costs, becomes unrealistic and for a variety of reasons the program ends up with a revised baseline for measurement purposes. Consequently, a program may be converted to an OTB and receive a new baseline later on in the program's life. To use Captain Trahan's models, we would like to know not only what contracts are currently OTB contracts, but also what contracts have a high likelihood of becoming an OTB contract. If we can accurately predict which contracts have a high likelihood of becoming OTB contracts, we can apply Captain Trahan's growth models to these programs to develop EACs that are more accurate.

This thesis attempts to build a model that predicts whether a contract is likely to become an OTB contract. The output of this model provides indicators as to what influences the likelihood of a contract being an OTB and hence experiencing a cost overrun. The output also allows us to develop better EACs for contracts that we identify as likely to be an OTB.

In military acquisitions, it is imperative to have EACs that are more accurate; otherwise, the DoD loses out on content. To elaborate, having too high of an EAC means that the DoD may be unable to fund other programs that the war fighter may need. Conversely, by having too low of an EAC, there will be issues developing and producing an essential program due to a lack of sufficient funds. Furthermore, if one program needs additional funding, decision makers may decide to borrow from another program, which in turn has the potential to stunt progress on both programs.

Using logistic regression models, we can try to find the best predictors that estimate how likely a contract is to become an OTB contract. These predictors may range from cost and schedule performance indicators to a variety of qualitative characteristics of the program. The implications of an effective model for predicting OTBs are substantial. Not only would this tell us if a contract is on the path to experiencing cost overruns, but it also allows us to develop better EACs.

Study Process

Our study begins by developing a better understanding of the requirements and importance of Earned Value Management (EVM) and its associated performance metrics. Then we look at research related to developing EACs and the issues associated with different estimating methods. That section also includes an in depth look at the OTB process. In the Data and Methodology section, we describe the sources of data for this study and the purpose of logistic regression models. Lastly, the results and the implications of these results are in Chapters IV and V.

II: Literature Review

Introduction

This chapter provides a better understanding of the concepts of Earned Value Management (EVM) and Over Target Baselines (OTBs). We first look at why analysts use EVM and discuss some of the important EVM performance measures and indices within EVM. The next step is to examine how Estimates at Completion (EACs) are calculated and look briefly at some of the past EAC research. Then we look specifically at calculating EACs using the Gompertz growth model as it pertains to Over Target Baseline (OTB) contracts. Since the Gompertz growth model provides us with a superior method of calculating EACs specifically for OTBs, we also study the OTB process and the typical characteristics of OTB contracts. Finally, we look at how other studies utilize logistic regression models and discuss the use of a logistic regression model for predicting OTBs, which allows cost estimators to predict cost overruns and calculate EACs that are more accurate.

Earned Value Management (EVM)

The Air Force Cost Analysis Handbook describes the primary purpose of Earned Value Management as:

> Earned Value Management (EVM) is a tool that provides Government and contractor system Program Managers (PMs) visibility into the technical, cost, and schedule performance of their projects, as well as the capability to mitigate the risks of a program not meeting its time, budget, and performance goals. (Air Force Cost Analysis Agency, 2007)

The Federal Acquisition Regulation (FAR) dictates that an earned value management system is required for all major federal acquisition programs (GSA FAR Secretariat, 2009). Specifically the Defense Federal Acquisition Regulation Supplement (DFARS) states that each cost or incentive acquisition contract in the DoD exceeding $20 million is required to adhere to the EVM standards and each contract exceeding $50 million is required to have a DCMA validated EVM system (Department of Defense, 2009). Furthermore, the DoD adopted the industry standards for EVM, the ANSI/EIA 748 standards, which includes 32 measures that acquisition programs must adhere to.

Within the EVM framework, each contract for an acquisition program has a performance measurement baseline (PMB) which is the time-phased budget for the contract. It includes the costs associated with all of the planned work packages for the specific contract. The Budget at Completion (BAC) for a contract is the total budgeted amount that encompasses all of the required work from start to finish. As the contract progresses and work is completed, the contractors, as well as the government, develop estimates at completion (EACs) which are revised projections of what the contract will cost at completion. Analysts compare the EACs to the PMB to measure contract performance and to determine the likelihood of completing a contract within the original budget. If the EAC is greater than the BAC (the PMB at completion), this is a positive Variance at Completion (VAC) and the program office expects to incur costs in excess of the amount budgeted for. Figure 1 shows the PMB, EAC, and BAC.

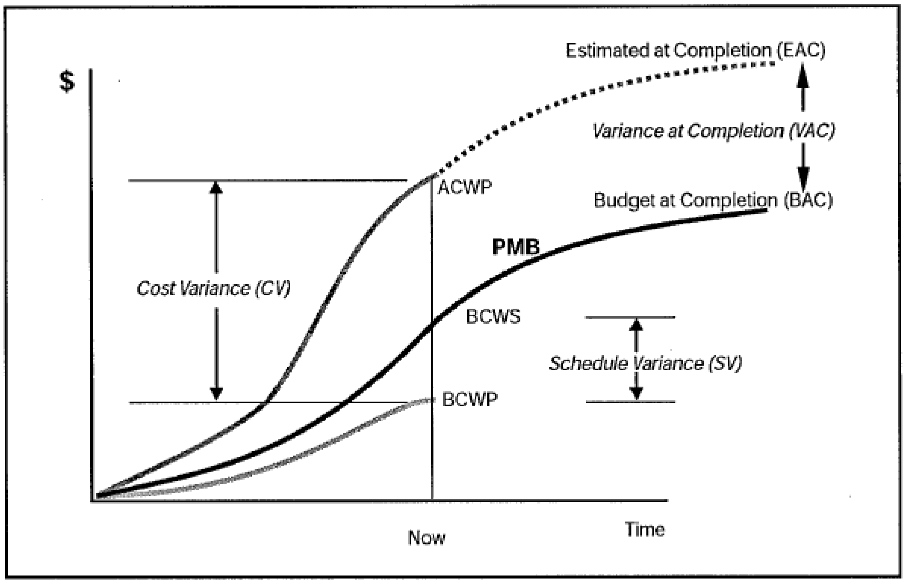


Figure 1: Performance Measurement Baseline (Christensen, 1999)

While the Variance at Completion tracks performance at the point of contract completion, there are performance indices that track performance throughout the project. The Cost Performance Index (CPI) tracks whether or not the amount of money spent on the contract is more that the amount budgeted for at a given point in time. The Schedule Performance Index (SPI) tracks whether or not the amount of work scheduled is complete at a given point in time. The Schedule Cost Index, which is the product of the SPI and CPI, reflects both schedule and cost performance. The Composite Index combines the SPI and CPI by specifying weights for the cost performance (CPI) and schedule performance (SPI). These four indices are in Table 1.

Table 1: EVM Performance Indices

$$CPI = \frac{\text{Budgeted Cost of Work Performed (BCWP)}}{\text{Actual Cost of Work Performed (ACWP)}}$$

$$SPI = \frac{\text{Budgeted Cost of Work Performed (BCWP)}}{\text{Budgeted Cost of Work Scheduled (BCWS)}}$$

$$SCI = CPI * SPI$$

$$\text{Composite Index} = (w1*CPI) + (w2*SPI)$$

Developing Estimates at Completion (EACs)

The PMB is easy to identify, it is simply the given budget for the contract less the management reserve. However, there is a variety of ways to calculate the EAC. Regardless of how the EAC is calculated, it is important to know that it is accurate in determining the likely cost at completion. Furthermore, the accuracy of the EAC is important for cost estimators when they are comparing the EAC with the PMB to determine if they are experiencing cost overruns or not. A variety of methods for computing EACs are available and numerous studies have analyzed how effective each method is at producing accurate EACs.

The most commonly used method of calculating an EAC is an indexed based approach. This approach is simplistic and produces an EAC rather quickly. Analysts calculate the EAC by taking the sum of two items: 1) The actual cost of work performed (ACWP) and 2) The remaining work, which is the Budget at Completion (BAC) minus the Budgeted Cost of Work Performed (BCWP), divided by a performance index. The first part of the formula, ACWP, represents the amount of money spent on the project to date. The second part represents the estimate for remaining work. By dividing the amount of work remaining, BAC minus BCWP, by a performance factor, we arrive at our estimate for how much the remaining work will cost. This assumes that future performance will be similar to past performance. The performance index used in this computation is usually the CPI, SPI, SCI, or a composite index (Christensen, 1994). While the indexed based method is the most commonly used way to calculate EACs, more complex methods are available that utilize forecasting techniques such as regression and time series analysis.

In 1995, Dr. Christensen reviewed 25 EAC studies. In this review, he summarized two types of studies: 1) studies that provided new techniques for developing EACs and 2) studies that compared a variety of techniques to determine which techniques provided better EACs. His review incorporates index-based methods, time series techniques, performance factors, and regression approaches. When Dr. Christensen looked at the comparison studies, he concluded, "The accuracy of regression-based models over index-based formulas has not been established…additional research exploring the potential of regression analysis as a forecasting tool is badly needed" (Christensen, 1995). This was due primarily to the fact that most studies had small sample sizes and some studies provided inconclusive results. Furthermore, he stated, "The accuracy of index based formulas depends on the type of system and the stage and phase of the contract" (Christensen, 1995). Dr. Christensen's review of EAC research in 1995 indicates that there is no best method for developing EACs for all contracts. These conclusions make a strong case for the use of specific forecasting methods that perform better under specific circumstances.

Following Dr. Christensen's review of EAC research, several studies investigated the use of regression models. In 2005, Captain Steven Tracy used multiple regression to develop EACs at five different points throughout the life of a contract. He developed five different regression models which utilize anywhere from three to six predictors each in forecasting the EAC. His results indicate that "the regression models generally dominate the performance with the early models, 25 and 35 percent complete, and begin to trade 'best' performance with the index based models at the 50 and 65 percent complete points" (Tracy, 2005). Therefore, Captain Tracy's thesis shows that regression models might be able to outperform index methods, but only at certain times, a conclusion similar to that of Dr. Christensen's in 1995.

Developing EACs Using a Growth Model

Similar to other recent efforts, in 2009 Captain Trahan attempted to find a superior method for developing EACs in her AFIT thesis. She examined the tendency for Air Force acquisition contracts to incur costs in an "S" shaped manner. That is, a contract tends to incur costs slowly at the beginning of its life, and then costs rapidly accrue until they taper off at the end. Based on this trend, she investigated the use of the Gompertz growth curves as models to predict the EAC for a contract as these curves exhibit an "S" shape. Figure 2 is an example of a growth curve that she applied.

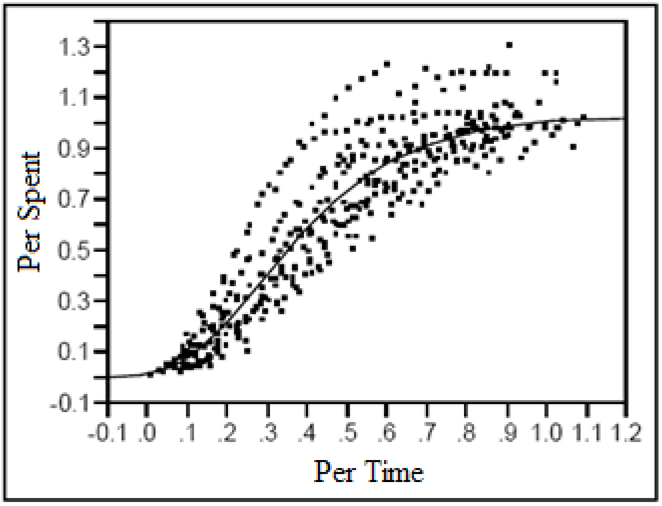


Figure 2: Development Growth Model (Trahan, 2009)

Using JMP®, Captain Trahan developed growth models of the functional form provided in Table 2. Based on the models she developed with specific values for α, β and γ, she could calculate the contract's growth in spending based on the percent time complete. Using this estimated amount of growth, she calculated the EAC for each contract with the second formula in Table 2.

Table 2: EAC Formula Using Growth Model (Trahan, 2009)

Gompertz Growth:	$GG(X) = \alpha(\exp(-\exp(\beta-\gamma*X)))$
EAC:	$EAC(X) = ACWP(X) + [\ (GG(1) - GG(X))*BAC]$

Once she developed three growth models for production contracts, development contracts, and mixed contracts (both development and production combined in one model), she compared the EAC estimates from the growth model to the actual costs at completion. She also compared the EAC estimates from using index-based approaches to the actual costs of completion. By using the Mean Absolute Percent Error (MAPE), which compares the estimates to the actual costs, she was able to compare the predictive capability of the Gompertz growth curve EACs to the index based EACs. The formula used for calculating the MAPE is in Table 3.

Table 3: MAPE Comparison (Trahan, 2009)

Absolute Percentage Error	APE = Abs [(EAC – TAC) / TAC]
Mean Absolute Percentage Error	MAPE = (Σ APE) / n
EAC = Estimate at Completion; TAC = Total at Completion; n = number of contracts	

Based on the MAPE comparisons for the Gompertz growth models and the index based models she concluded, "No best model exists [for all contracts] but our growth models present a better model than the popular index-based methods currently in use for estimating OTB contracts specifically" (Trahan, 2009). These results are similar to the findings of Dr. Christiansen and Captain Tracy in that this growth model may not be superior to the index based models in all cases, but this model does perform better in specific circumstances, primarily for OTB contracts. Furthermore, "this new methodology adds a unique perspective and consistently performs more accurately compared to the CPI, SCI, and Composite Index-based [methods] on an average of 71% of unique OTB contracts" (Trahan, 2009).

Since Captain Trahan's method of forecasting EACs is superior for OTB contracts, this thesis focuses on OTB contracts. We attempt to build models that identify contracts that are likely to become OTB. Once these models predict which contracts are likely to be OTB contracts, we can use the methods employed by Captain Trahan to develop better EACs. However, we must first understand what it means for a contract to be an OTB.

Cost Overruns and the OTB Process

Based on our analysis of contracts in the Defense Acquisition Executive Summary (DAES) database, twenty percent of the DoD's acquisition contracts are not completed within their allocated budgets (CBB). When a contract exceeds its allocated budget, it is termed a cost overrun. When a contract is behind schedule, it is a schedule overrun. While schedule overruns are common, the emphasis in the DoD tends to be on cost overruns.

Program managers can adjust the performance measurement baseline (PMB) in three major ways. Depending on the type of adjustment to the PMB, the contractor may recognize a cost overrun. The "three major categories [are]: authorized contract changes, internal re-planning, and inadequate remaining budget in the contract with a resulting requirement for an OTB" (Cukr, 2001). The first two categories are standard and require a minimal amount of work to remedy the situation in comparison to an OTB (Cukr, 2001). On the other hand, the process for implementing an Over Target Baseline (OTB) is very complex and an OTB implies that the acquisition program is in considerable trouble.

Authorized contract changes include additional requirements or deviations that each organization allows based on changes in the scope of the work. Authorized contract changes also include changes in the PMB related to work increments that did not originally have costs associated with them (un-priced work packages). The contractor adds these additional costs to the PMB as if they were included in the original baseline. These authorized changes do not indicate a cost overrun.

The second category, internal re-planning, occurs when the remaining work requires a new plan and certain work breakdown structure (WBS) elements may be experiencing cost overruns. In this case, the contractor can develop a new plan for the entire contract that is within the original budget. This prevents a cost overrun from occurring for the contract.

Finally, an Over Target Baseline occurs when the work scope does not change and the contractor cannot complete the remaining work within the original budget (Cukr, 2001). According to the DAU's handbook on OTBs:

> An OTB is a contract budget base that was formally reprogrammed to include additional performance management budget and which therefore exceeds the contract target cost… [And] ANSI/EIA-748-1998 defines it as 'a recovery plan, a new baseline for management when the original objectives cannot be met and new goals are needed for management purposes.' (Defense Acquisition University, 2003)

When an OTB is used, the program manager is recognizing a cost overrun.

In the process of implementing an OTB, a new PMB is developed and the cost and schedule variances are set to zero. This allows program managers to obtain a clean slate to work with. While this seems to make an OTB the preferred method for dealing with substantial cost overruns in defense acquisition programs, contractors do not always utilize an OTB. The OTB process is a lengthy 10-step process that can be very costly and take many months to complete. These additional costs are associated with the implementation of an OTB and are over and above the overrun costs that a contract has already incurred prior to the OTB. Furthermore, any time spent on the OTB process may delay progress made on the contract itself.

The Defense Acquisition University publishes the OTB/OTS handbook that describes in detail the ten steps in the OTB process. Figure 3 illustrates this process. The first step in the process is identifying the need for an OTB since it is not a required action. Then, the contractor reviews the remaining work and revises the schedules and cost estimates. After several reviews, the contractor and the government agree to the revised schedules and costs, which become the new PMB.

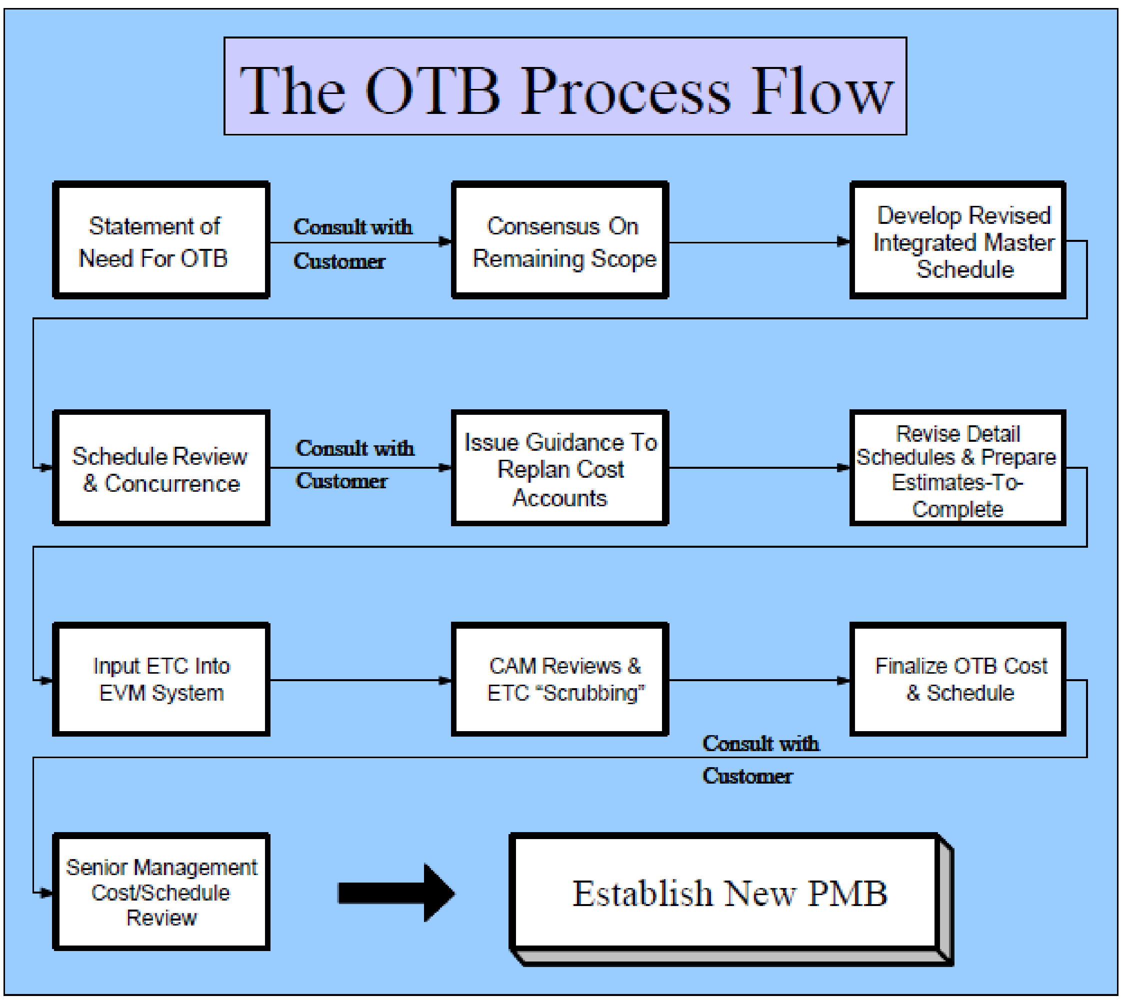


Figure 3: The OTB Process Flow (DAU, 2003)

While the contractor is ultimately responsible for the accuracy of the PMB, "The customer project manager [who is typically the program manager within the DoD] and business office will ultimately be held accountable for the significant changes an OTB/OTS can effect" (DAU, 2003). Therefore, the OTB process is typically a joint effort between the supplier (the contractor) and the customer (program office or DoD representative for the contract).

When a contract establishes a new baseline through the OTB process, it is a wake-up call to the program and the program manager. The decision to establish this new baseline implies that contract performance is out of hand and drastic changes are necessary to correct for deficiencies and to prevent the reoccurrence of past problems. The process of making a contract an OTB contract ensures that there is a true need for an OTB rather than establishing a new baseline just on the basis of improving EVM performance indices. Furthermore, an OTB establishes a realistic plan and a baseline for the remaining work, which the contractors must follow. Historically, some of the reasons provided for updating the PMB using an OTB include:

- Estimate at Completion (EAC) is less than actual costs for some elements
- Existence of zero budget work packages
- Cost and schedule variance explanations are no longer meaningful
- Inability to effectively use the performance data
- Unrealistic activity durations and relationship logic
- Depletion or rapid use of management reserve
- Lack of Confidence in contractor's EAC
  (Tiffany, 2004)

Due to the low probability of identifying all of the expected problems for a contract and the inability to capture realistic estimates early on, contractors do not typically use OTBs early in a contract's life. Additionally, OTBs are not practical late in a contract's life as the time and money invested in developing a new baseline exceeds the potential benefits from having a new baseline late in a contract's life. Typically, a contract is only rebaselined through an OTB once, therefore, it is important to get the new baseline right. While an OTB provides a contractor with the opportunity to establish new and realistic goals, the contractor and program office must consider it carefully to ensure that the benefits of a new baseline outweigh the costs incurred during the OTB process. The purpose of an OTB is not to make the numbers look better, but instead its purpose is to fix an ailing program and establish a realistic baseline for measurement purposes.

Identifying an OTB in Practice

When we develop our model to predict OTBs, it is helpful to understand where an OTB fits in and how to identify an OTB. When the government pays a contractor for work, they pay a contract price. Within the contract price, there are two components, the total allocated budget (TAB) and the profit or fees. If the TAB equals the contract budget base (CBB), the contract has not experienced an OTB. If the TAB exceeds the CBB, the difference between the two is an identified overrun and the contract has had an OTB. The CBB has two components: the negotiated contract cost (NCC) and authorized un-priced work packages (AUWs). When scope changes occur, the program office updates the NCC to include the additional work, which causes the CBB to increase. When a contractor identifies the costs associated with AUWs, the CBB also increases. Therefore, the CBB and TAB may change several times for a contract, but in this thesis, we are only concerned with changes that indicate that the TAB exceeds the CBB, which identifies OTBs and cost overruns. Figure 4 depicts these relationships.

Cost Overruns vs. Cost Growth

It is important to distinguish between "cost overruns" and "cost growth." A cost overrun, as shown in Figure 4, occurs when the TAB exceeds the CBB. Any changes in the contract budget base (CBB) such as scope changes affecting the negotiated contract cost (NCC) or the pricing of authorized un-priced work (AUW) do not create a difference between the CBB and the TAB and therefore do not indicate a cost overrun. A cost overrun occurs when the budgeted amount for a contract (including revised amounts) is less than the actual amount spent.

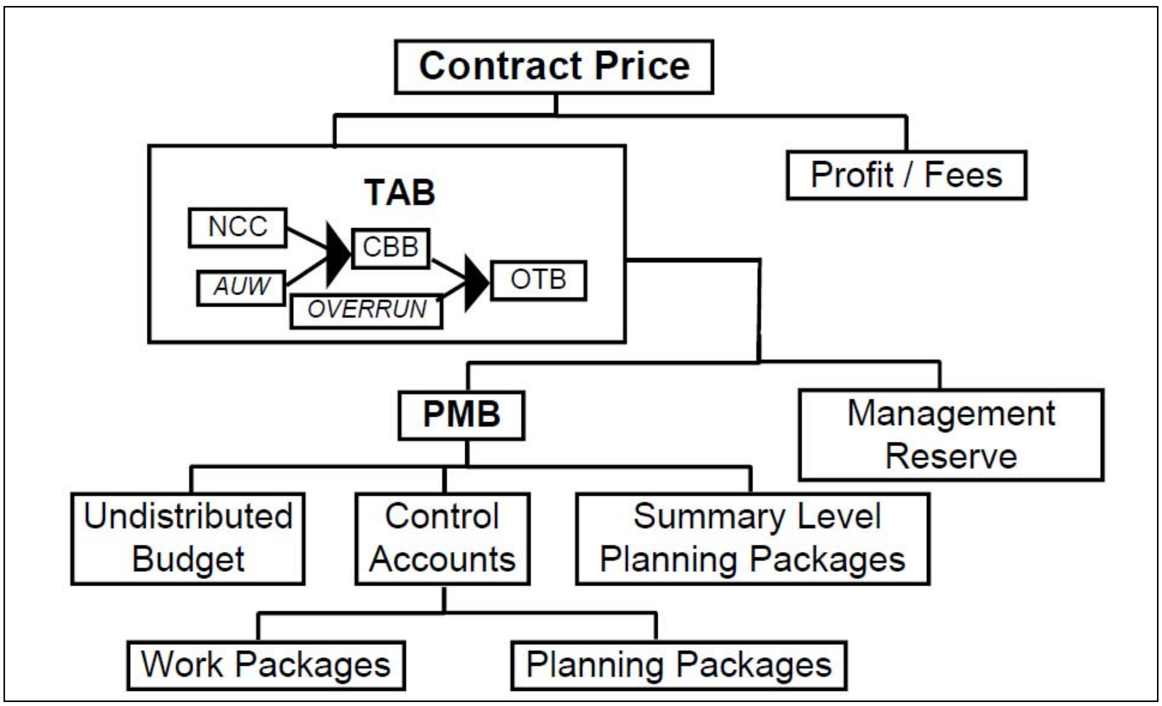


Figure 4: EVM Contractual Price Components (DAU, 2009)

On the other hand, cost growth refers to an increase in costs in comparison to the cost estimate at the beginning of the program. Therefore, cost growth includes the costs associated with scope changes, which may relate to the technical requirements, the number of production units, or any other change affecting the program over time. It is possible to have cost growth and no cost overrun, but the opposite is not possible as cost overruns are a subset of cost growth. Often, authors of cost literature compare current costs to either the initial budget or the initial cost estimate. These comparisons are referring specifically to cost growth and not cost overruns. For the purpose of this thesis, we quantify cost overruns based on the DAU definition in terms of the CBB and TAB.

Logistic Regression Two-Step Models

Analysts use logistic regression models, which predict dichotomous responses, to determine whether some event is likely to occur. While there are many uses for logistic regression models, the DoD acquisitions community has benefited from the use of these models when examining costs and schedules.

When researchers examine the costs of acquisition programs, they are often concerned only with those programs that are experiencing cost overruns or cost growth. They often ignore or give little attention to those programs that do not experience cost overruns or cost growth. Therefore, the variable of interest is dichotomous: cost growth or no cost growth.

In the past decade, a series of studies investigate the ability to predict cost growth. From 2004 to 2006, *The Journal of Cost Analysis and Management* highlights the use of two-step models to predict cost growth. White, et al (2004) first examined engineering cost growth for RDT&E dollars within the Engineering and Manufacturing Development (EMD) phase. They “illustrate the use of logistic regression in cost analysis to predict whether cost growth will occur. Given a program has a high likelihood of cost growth, [they] then use a log-transformed model to predict the amount of cost growth” (White, et al, 2004). In 2005, Lt Genest and Dr. White “built upon this work and concluded that the conjunction of logistic and multiple regression is also warranted when trying to model total RDT&E cost growth during EMD." A separate two-step study employing logistic regression and multiple regression "[concentrates] on cost growth in the procurement appropriation of the Engineering and Manufacturing Development phase of acquisition" (Rosetti and White, 2004). In another study, published by the *Cost Engineering* journal, Major Bielecki and Dr. White also build a model to predict cost growth. They use a similar process as the previous studies:

> First, the article looks at the utility of logistic regression on finding predictors of cost growth because of schedule changes [in RDT&E during the EMD phase and]…. secondly, given a program's likelihood of experiencing cost growth, the article seeks to predict the degree to which cost growth occurs. (Bielecki and White, 2005)

In 2006, Captain James Monaco and Dr. White used a similar two-step approach. However, instead of looking at the cost of a program, they looked at the schedule. They used "logistic and multiple regression… to predict if a program will experience schedule growth and, if applicable, to determine the expected percentage of schedule slip" (Monaco and White, 2006).

In each of the cost growth studies, the authors employ a logistic regression model to predict the likelihood of cost growth for a specific category of acquisition contracts. By doing so, the authors identify a set of contracts that are likely to experience cost growth. Next, each of the authors builds a multiple regression model and predicts the amount of cost growth for each of these contracts. This two-step method allows the authors to focus only on those contracts that experience cost growth, the variables that influence the likelihood of cost growth and how much growth will occur. Captain

Monaco and Dr. White employed a similar process to predict the amount of schedule slips.

This thesis is similar to the previous two-step studies, but this thesis focuses on step one of a two-step model. First, we build a logistic regression model that predicts the likelihood that a contract will be an OTB contract. Then, based on our model, we identify a set of contracts that we expect to be OTB. The second step comes from Captain Trahan's thesis. In the second step, we use the Gompertz growth model that Captain Trahan built to forecast EACs for OTB contracts. This two-step procedure is valuable in developing better EACs since the growth model that Captain Trahan developed is only superior to indexed based methods of developing EACs for OTB contracts. Therefore, the use of a two-step model allows us to focus on OTB contracts, opposed to looking at all contracts.

Summary

In this chapter, we discussed the concepts of EVM and a few of the EVM metrics, specifically as they apply to EACs. There are various models used to develop EACs. Captain Trahan's growth model is one such model, which pertains to OTB contracts. Therefore, we developed a better understanding of OTB contracts and the OTB process. Finally, we looked at several logistic regression models that are similar to the models that we build in this thesis. In the next chapter, we develop a better understanding of the data and the logistic regression models used to predict OTB contracts.

III: Data and Methodology

Introduction

In this chapter, we investigate the sources of data for our logistic regression models. We describe the predictor variables and response variables and explain how the data must be normalized before it can be used in a regression model. Then we explain why we chose to use a logistic regression model and how a logistic regression model works. Finally, we describe the methods used to interpret the predictor variables and assess the predictive capability of the model.

Data Sources

Since this thesis is concerned with predicting OTBs, we first look at data that indicates whether a contract is an OTB contract. Second, we look for data that may help predict whether a contract becomes an OTB contract.

The Defense Cost and Resource Center (DCARC) and the Defense Acquisition Management Information Retrieval (DAMIR) databases are the two main sources of earned value data for acquisition contracts. The DCARC database contains the actual Cost Performance Reports (CPRs) submitted by the program offices. Since these reports come directly from the program offices, this data is more reliable. However, the DCARC database only contains submissions back to 2007. This limits our ability to examine historical acquisition contracts. Furthermore, if we identify contracts that are OTB contracts, there is a high likelihood that the necessary data for predicting an OTB is not available in the DCARC database. Therefore, we are not able to use the DCARC database for this thesis. However, the DCARC database will be a good source of data for future analysis, as more data becomes available in the upcoming years.

One section of the DAMIR database includes the Defense Acquisition Executive Summary (DAES) data on Major Defense Acquisition Programs (MDAPs) and Major Automated Information System (MAIS) programs. This database includes earned value data taken from the CPRs submitted by the program offices. The data submissions in DAMIR date back to 1997 and include CPR reports as early as 1967. While there are many programs in the DAMIR database, only those contracts exceeding the $20 million dollar threshold requirement are required to submit CPR entries based on the EVM requirements in the DFARS. Therefore, our analysis is limited to these contracts. Furthermore, many of the inactive programs in the DAMIR database were undertaken prior to 1997 and do not have DAES reports available.

For the analysis to be meaningful, we limit the data to contracts in between 1990 and 2005. The acquisition environment prior to 1990 is quite different from the current environment. Furthermore, there is a limited amount of data available prior to 1990. Our initial collection of DAES reports includes 10,933 CPR entries from 797 contracts for 177 programs. This includes contracts reported in DAES (electronically) for the Army, Navy, Air Force, and DoD acquisition programs. For each contract entry, the following data is available:

- program name
- program number
- program status: active or inactive
- branch of service
- contractor
- type of contract
- contract number

- CPR report date
- Budgeted cost of work scheduled (BCWS)
- Budgeted cost of work performed (BCWP)
- Actual cost of work performed (ACWP)
- Management Reserve (MR)
- Total Allocated Budget (TAB)
- Contract Budget Base (CBB)
- Estimate at Completion (EAC)
- Program Manager's Estimate at Completion (PMEAC)
- Program Manager's Estimated Completion Date (PMECD)
- Schedule Variance (SV)
- Cost Variance (CV)
- Percent Schedule Variance (%SV)
- Percent Cost Variance (%CV)
- Schedule Performance Index (SPI)
- Cost Performance Index (CPI)
- Schedule Cost Index (SCI or SCPI)

In order to build a suitable model to predict OTBs, we decided to search for additional predictor variables to consider in each of our models. While the DAES reports provide useful earned value information, the DAMIR portal includes other data sources. Historically, many cost studies have utilized the Selected Acquisition Reports (SARs) as a source of program and contract information. One section of the SARs, available through the DAMIR portal, provides information pertaining to production information and threshold breaches. The production information addresses the quantity of units planned for, both for development and production, and the average procurement unit cost (APUC) over time. The threshold breach data identify when specific Acquisition Program Baseline (APB) breaches occur along with when significant Nunn-McCurdy Breaches occur. This additional data from the SARs includes the following:

- Development Quantity
- Production Quantity
- Total Quantity
- Average Procurement Unit Cost (APUC)
- APB Schedule Breaches
- APB Performance Breaches
- APD RDT&E Breaches
- APB Procurement Breaches
- APB MILCON Breaches
- APB O&M Breaches
- APB APUC Breaches
- APB Program Acquisition Unit Cost (PAUC) Breaches
- Current APUC Nunn-McCurdy Breaches (current baseline)
- Current PAUC Nunn-McCurdy Breaches (current baseline)
- Original APUC Nunn-McCurdy Breaches (original baseline)
- Original PAUC Nunn-McCurdy Breaches (original baseline)

Finally, additional characteristic data for each program is available in DAMIR. This information includes:

- Program type (MDAP, MAIS, special interest, etc)
- Acquisition Category (ACAT) (IC, ID, II, IAM, etc)
- Commodity Type (Aircraft, Satellite, Missile, etc)

Data Normalization

After collecting the data, we must ensure that the contract entries (CPR entries) are as consistent as possible for comparison and use in the modeling efforts. We must also normalize the data to accommodate for the effects of inflation on the costs reported in the DAES database.

One issue related to the contracts in the dataset is their duration. While some contracts may span several months, other contracts span several years. To accommodate for the different time lengths, we include percent complete as a variable that represents time. In EVM terminology, percent complete is the cumulative budgeted cost of work performed (BCWP) divided by the budget at completion (BAC) (DAU, 2009). The

DAES database does not report the BAC, but we can calculate the BAC based on other information in the database. The budget at completion is the same as the performance measurement baseline at completion as depicted in Figure 1 (Chapter Two). Furthermore, the total allocated budget (TAB) is comprised of two elements: the performance measurement baseline and the management reserve (see Figure 4, Chapter Two). The performance measurement baseline upon completion, also known as the BAC, can be calculated by subtracting the management reserve from the total allocated budget. Once the BAC is calculated, we can determine the percent complete for each contract entry and use this as our variable that accounts for the stage at which each contract is in.

Inflation

A second adjustment accounts for inflation. The cost data reported in the DAES database is in then year dollars (TY$). However, for comparison, we want all of our costs to be in the same base year (BY$) so that any differences in costs are related to the program and not the effects of inflation. The contracts in our dataset use the RDT&E, Procurement and Acquisition O&M appropriations. The Office of the Under Secretary of Defense (OUSD) (Comptroller) publishes the annual raw inflation indices to convert dollar figures from one base year to another. The OUSD comptroller also publishes the outlay rates for each appropriation. These indices are in Appendix A and B respectively. In order to convert our costs from then year to base year dollars, we apply a weighted inflation index. By using the raw index values and the appropriate outlay rates, we calculate a weighted index. Since the dataset includes contracts for the Army, Navy, Air

Force, and DoD it is appropriate to choose outlay rates that are applicable across the DoD. These weighted indices are in Appendix C. The base year for this table is 2009.

Combining DAES and SARs Datasets

Since the DAES and SARs reports are in separate sections of DAMIR, it is necessary to combine the two for use in our analysis. First, for each CPR entry, we match the program name (and program number) up with the program names listed in the characteristic reports in DAMIR. This allows us to add the program type, acquisition category, and commodity type for each program to each CPR entry.

Second, the CPR entries (in DAES) must align with the SARs entries. While CPR entries apply to specific contracts at specific dates, SARs entries apply to entire programs at specific dates. To accommodate for this, we apply the program level SARs information to each contract for that program. Based on the dates of the SARs and the dates of the CPR entries we align the CPR entries with SAR entries. Since the SARs reports are less frequent than the DAES reports, we assume that the last reported quantity (in SARs) is the current quantity until a new SARs report is available. Additionally, we track whether or not a breach has occurred in each category (APB or Nunn-McCurdy) on a cumulative basis.

Management Reserve (MR) Missing Values

The Management Reserve Data field in DAES frequently has missing values in the DAES reports. In order to include MR in our analysis, the values need to be available for the majority of our observations. When the MR value is empty, we assume that the last reported value for MR is the current value for the MR.

Data Assumptions and Limitations

In this thesis, our assumption is that the program offices accurately report the data in the DAMIR database. This is a reasonable assumption since the dataset is limited to programs that are required to adhere to the EVM requirements according to the DFARS.

Furthermore, the contracts range between 1990 and 2005 due to the lack of a sufficient amount of data prior to 1990. The 2005 limitation is to ensure that it is known whether a contract will become an OTB or not. Since an OTB may not occur until the contract is far enough along, we do not want to include contracts where an OTB may still occur in the future.

Furthermore, the analysis is restricted where certain data elements are unavailable. When the total allocated budget (TAB) or the contract budget base (CBB) amounts are unavailable, it is impossible to determine whether a contract is an OTB by definition. This prevents us from using these contracts in our analysis as identifying whether or not the contract is an OTB is required.

Since we need to normalize our data to account for inflation, we are required to identify each contract's appropriation to convert costs to base year 2009 dollars. While the DAES database does not report the contract's appropriation, the DAMIR database includes additional information from the Selected Acquisition Reports (SARs). Fortunately, the SARs identify the contract's appropriation. However, not all contracts in DAES are available in the SARs section of DAMIR. Therefore, we do not include contracts in our analysis where the appropriation is not available in the SARs. The appropriations in SARs are available for approximately 85% of the contracts.

Table 4 describes the final dataset that we use for analysis in terms of the number of programs, contracts, and CPR entries for each service. In comparison to the initial data set, 14% of the entries are lost due to a lack of appropriation provided in SARs, we remove 4% of the entries due to them not being RDT&E or Procurement contracts, and 1% of the entries are removed due to the inability to identify the OTB status. This leaves approximately 80% of the original data set for analysis. Therefore, the largest limitation is due to a lack of available appropriation categories for each contract. We remove an additional 1400 entries because they have already experienced an OTB, but this is not a limitation since the purpose of this analysis is to predict OTBs when they have yet to occur. Approximately half of the contracts in the final dataset are RDT&E contracts and half are Procurement contracts.

Table 4: Final Dataset Used in Analysis

	Programs	Contracts	CPR Entries
Air Force	28	143	1315
Army	37	137	2326
Navy	42	211	2901
DoD	7	40	812
Total	114	531	7354

The Response Variable: Over Target Baseline

The next step is to identify the variables to include in our regression models. Since the objective is to predict OTBs, this variable is our response variable. Specifically, the response is a "1" if the contract will become an OTB in the future and a "0" if it will not become an OTB. According to the Defense Acquisition University, an OTB is identified when the "sum of the budgets allocated to work, plus undistributed budget and management reserve, known as Total Allocated Budget (TAB), exceeds the Contract Budget Base (CBB)" (2003). Using this standard definition, we compare the TAB and CBB entries for each CPR submission to determine whether an OTB has occurred.

A second way to determine whether a contract is OTB is to consider the information the DAES database reports. One data field for each contract is the OTB date. If there is a date in this field, this indicates when the most recent OTB occurred. If there is no date present, an OTB has not occurred. Within each contract in the DAES database, individual instances of OTBs occur when the CPR entry has a bold border. These entries often indicate the adjustments to specific performance measures and the baseline. However, there is a limitation to using what the DAES database reports as OTB. This list only indicates those cases where the program offices identify an OTB within their CPR submissions. DAES does not identify an OTB if the program office does not submit an OTB into the database.

For the purpose of our analysis, we use the standard definition of an OTB as provided by the DAU to identify OTBs. Based on this definition, approximately one out of every five contracts has experienced an OTB.

Predictor Variables

The main predictor variables in this model include cost, schedule, and performance metrics. We also investigate the use of other potential predictors available, such as variables that identify contract or program characteristics. The goal is to identify those metrics or characteristics that best indicate an OTB. There has been very little research as to what indicates an OTB. The OTB handbook that the DAU publishes refers to a few reasons why contractors update a contract's baseline through an OTB. We list these reasons in Chapter Two, but are unable to identify the majority of these items based on the data available in the DAES and SARs databases. This limitation occurs because these databases do not provide enough detail about each contract. Based on this limitation and the fact that there is little research regarding what indicates an OTB, we consider a broad list of candidate variables to identify the best predictors of an OTB.

Logistic Regression Models

When analysts are interested in predicting a binary outcome, they typically use logistic regression models. Since the OTB variable is binary, this makes logistic regression the ideal tool to use. In this thesis, we build a logistic regression model that takes various predictors, both categorical and numerical, to try to predict whether an acquisition contract will become an OTB contract in the future. Before beginning the model building process, we describe the logistic regression function and the parameters that depict a particular logistic function.

When we plot binary data on a simple graph such as that in Figure 5, it becomes apparent that a linear regression technique does not provide a good fit. Instead, when trying to apply regression techniques to binary data, it is preferred to use a curve that better approximates the data. With a logistic function, analysts fit an S shaped curve to the binary data, which improves the fit for the model. Figure 6 depicts a typical logistic regression curve.

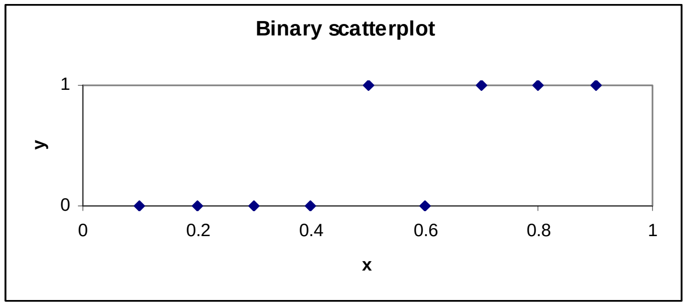


Figure 5: Plot of Binary Data

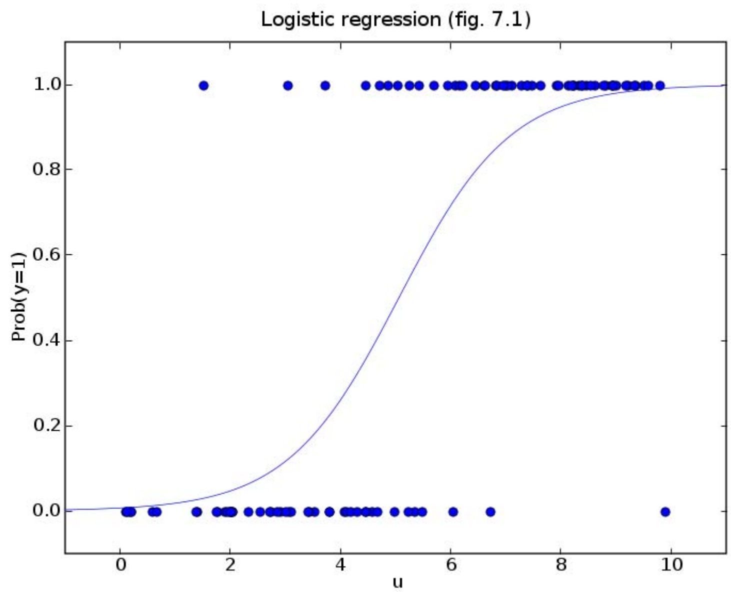


Figure 6: Logistic Regression Function (Dahl and Vandenberghe, 2009)

Table 5 provides the simplest functional form of the logistic function with one predictor. Here the outcome is denoted π(x) which represents the likelihood of an event. The terms B_0 and B_1 are parameters that describe our model. The outcome in a logistic regression model can range anywhere from 0% to 100% since the model estimates the likelihood of an event.

Table 5: Logistic Regression Equation, Single Variable Model

$$\pi(x) = \frac{e^{B_0 + B_1 x}}{1+e^{B_0 + B_1 x}}$$

It is important to understand what the outcome of a logistic regression model means. To provide a meaningful explanation, we consider the outcome in this thesis and explain how to interpret the response. This thesis focuses on predicting whether a contract will become an OTB contract in the future. If the outcome is an OTB, we assign a value of one to the contract and if the outcome is not an OTB, we assign a value of a zero. Suppose we fit a logistic regression model and want to know if a new outcome is likely to be an OTB. Furthermore, suppose the model has one predictor variable: type of contract. If the outcome of the logistic regression model is $\pi(x) = .75$ where x represents development contracts, this means a development contract has a 75% chance of becoming an OTB contract.[1]

While the previous example of a single variable logistic regression model is easy to understand, logistic regression functions are often extended to include multiple predictor variables. In the multivariate case, the logistic regression equation would be similar to the one in Table 6.

Table 6: Logistic Regression Equation, Multivariate Model

$$\pi(x) = \frac{e^{B_0 + B_1 x_1 + B_2 x_2 + \ldots + B_n x_n}}{1+e^{B_0 + B_1 x_1 + B_2 x_2 + \ldots + B_n x_n}}$$

The statistical software packages use a maximum likelihood function to estimate the parameters (B_0, B_1, ... B_n) of the logistic regression function. "The method of

[1] This is a hypothetical example and does not represent an actual relationship.

maximum likelihood yields values for the unknown parameters which maximize the probability of obtaining the observed set of data" (Hosmer and Lemeshow, 2000).

Interpreting the Predictors for the Logistic Regression Model

Once we develop a fitted logistic regression model, we want to interpret the parameters of the model. One option is to use the odds ratio to identify how the predictor variables relate to the outcome. With a dichotomous predictor variable (x), the odds ratio "approximates how much more likely (or unlikely) it is for the outcome to be present among those with x=1 than those with x=0" (Hosmer and Lemeshow, 2000). For example, an odds ratio of OR=2 indicates that the outcome is twice as likely to occur with a predictor variable of x=1. The odds ratio for a dichotomous variable is simply e^{B_1} where B_1 denotes the coefficient term for the dichotomous variable. For a continuous predictor variable, the odds ratio is calculated as $e^{(\Delta X * B_1)}$. In this case, B_1 denotes the coefficient term for the continuous variable and Δx denotes the given change in units for our variable. However, this method of determining the odds ratio only applies to one variable models.

When the logistic regression model includes multiple variables, it may be useful to determine the effect of each characteristic or variable individually. In order to calculate an odds ratio for the individual variable, the specific variable cannot interact with any of the other variables in the model. Otherwise, we would need to calculate a more complicated odds ratio that depends not only on the variable of interest, but also on value of the other variables that interact with the variable of interest.

Our model may end up with variables that interact to determine the likelihood of an OTB (our logistic regression response). Furthermore, if the model contains several predictor variables, the computation of the odds ratio becomes more complex and the value of the odds ratio becomes difficult to interpret. Therefore, we look at the use of p-values to determine how important individual variables are in predicting OTBs. When analyzing p-values, a value less than .05 indicates that there is a statistically significant relationship between that predictor and the response (assuming a 95% confidence level). Additionally, the lower the p-value for each predictor variable, the more influence it has on predicting OTBs.

Assessing the Predictive Ability of the Model

Once we identify the predictor variables in our model, we need to decide whether the model adequately predicts the outcome. When assessing regression models, analysts are concerned with the goodness of fit for the model, where the difference between the fitted values and actual values should be small. We use the "Pearson residual, [which] measures the difference between the observed and fitted values …The summary statistic based on these residuals is the Pearson chi-square statistic" (Hosmer and Lemeshow, 2000). Therefore, we look at the associated Pearson chi-square statistic to determine the model's goodness of fit.

Another measure of interest in assessing our model is the area under the Receiver Operating Characteristic (ROC) curve. "The area under the ROC curve, which ranges from zero to one, provides a measure of the model's ability to discriminate between those subjects who experience the outcome of interest versus those who do not" (Hosmer and Lemeshow, 2000). When predicting OTBs we are only interested in those cases where the outcome is an OTB. First, we are concerned with the "probability of detecting the true signal (sensitivity)" which would be defined as the probability of predicting an OTB when an OTB has occurred (Hosmer and Lemeshow, 2000). Secondly, we are concerned with the probability of detecting a "false signal (1-specificity)" which would be defined as the probability of predicting an OTB when an OTB when an OTB has not occurred (Hosmer and Lemeshow, 2000). The plot of the true signal versus the false signal for all possible cutoff points is the ROC curve. The cutoff point is the point at which we predict an outcome to be an OTB if it is greater than the cutoff point and not an OTB if it is less than the cutoff point. According to Hosmer and Lemeshow's description, Table 7 describes the model's ability to discriminate.

Table 7: Interpreting the Area Under the ROC Curve (Hosmer and Lemeshow, 2000)

If ROC = 0.5	This suggests no discrimination (i.e., we might as well flip a coin)
If $0.7 \leq$ ROC < 0.8	This is considered acceptable discrimination
If $0.8 \leq$ ROC < 0.9	This is considered excellent discrimination
If ROC ≥ 0.9	This is considered outstanding discrimination

An additional method for determining how good our model is at accurately predicting OTBs is to consider how far the models are off in accurately predicting OTBs. For example, suppose we use a cutoff point of 0.5 and identify all contracts with a probability of becoming an OTB greater than 0.5. We predict that these contracts will be OTB contracts and then examine which of these predictions are incorrect. The difference between the cutoff point and the individual contract's probability of becoming an OTB determines how far off the model is in accurately predicting OTBs. Suppose we use a cutoff of 0.5 and the contract's probability of becoming an OTB is 0.55, yet the contract does not become an OTB in the future. In this case, the model is not far off since the difference is only 0.05. Instead, suppose the contract's probability of becoming an OTB is 0.90 (a high chance of becoming an OTB) but it does become an OTB. In this case, the model is far from accurately predicting OTBs. We use this process in assessing our model in the validation phase of our analysis.

Summary

In this chapter, we described our data set and the variables to consider including in our logistic regression model. We also explained how a logistic regression model works. Finally, we explained how we assess the model and the variables included in the model. The next chapter applies these methods to build logistic regression models to predict the likelihood of a contract becoming an OTB contract.

IV: Results and Analysis

Introduction

This chapter describes the logistic regression models that predict the occurrence of an OTB. We construct multiple models to predict OTBs and analyze their predictive capability and validity to determine which model or models are superior. We are interested in four primary measures in assessing which models have the best predictive capability. First, we measure the overall significance of the model with the chi-square statistic and its associated p-value. Second, we assess the significance of each of the predictor variables with the associated p-values. Third, we wish to know how well the model discriminates between properly identifying an OTB and falsely identifying an OTB as measured by the area under the ROC curve. Finally, we examine how well the model accounts for or explains the result as measured by $R^2(U)$. Based on these four factors we choose our final models. Then we run a validation on our models to test whether or not these models do work and whether these models apply to other contracts.

Distinguishing Between Production and Development Contracts

Previous studies modeled development and production contracts separately due to their inherent differences. In our dataset, there is no explicit identification of "development" or "production" contracts. However, the RDT&E appropriation aligns well with the concept of a "development" contract and the Procurement appropriation aligns well with "production" contracts. We model these two categories separately in this thesis as RDT&E contracts and Procurement contracts. The initial attempt to model all types of contracts in one model provided no significant models to predict OTBs.

Therefore, this thesis models contracts in the same manner that previous cost studies used, which is by contract type.

Approach to Developing Models

Prior to building any models, we randomly select twenty percent of the data points to exclude. We reserve this data for use in the validation stage. We use the remaining eighty percent of the data to develop our models.

We employ JMP® to develop logistic regression models for RDT&E and Procurement Contracts using three different approaches to arrive at the best models. Each model uses the variables discussed in Chapter Three as candidate predictor variables. First, we used the stepwise function in JMP®, with the "mixed" direction, which is a combination of the "forward" and "backward" stepwise techniques. Using a p-value of 0.15 for the probability to leave and probability to enter, JMP® adds and removes predictor variables one by one based on their predictive capability until no other changes are possible. Using this method, we develop several models, which include five to ten predictor variables.

Secondly, we attempt a process by which all of the potential predictor variables are included and then we remove variables one by one based on their predictive ability. This is a "backward" stepwise procedure. In this case, predictors with high p-values have less predictive capability and they are excluded from the model one at a time. Using this process, we develop additional models are that contain five to ten predictor variables.

Since our database includes over 75 potential predictor variables, we make some modifications to our second attempt to seek out more models in a third approach. By excluding variables one by one, it is possible to eliminate a predictor variable at an earlier stage in the process even though it may be significant in a separate model. Therefore, we also chose to develop additional models by adding in variables that we consider good candidate variables. This method is rather exploratory as we continually repeat this process of adding and removing each of the candidate variables to search for better models. Certain variables such as the contract type (fixed price, cost plus incentive fee, etc) and the majority of the commodity types (ship, missile, aircraft, etc) never appear to be significant when added to the models. Based on findings such as these, the focus is on adding other variables that tend to be significant such as EVM performance metrics (CPI, SPI, EAC, etc) and production quantities.

In each of our models, there are approximately 2,000 observations[2]. When building each model, we would like our ratio of observations to predictor variables to be greater than or equal to ten (Neter, et al, 1996). Since there are a sufficient number of observations, it is possible to include many predictor variables based on this rule of thumb. However, the purpose of this thesis is to provide a model that can reasonably predict OTBs and explain why contracts become OTBs. A model with too many variables gets to be cumbersome and difficult to interpret. Therefore, we limit the number of predictor variables in each model to ten or less.

Logistic Regression Models for Development (RDT&E) Contracts

Using the contracts denoted by the RDT&E appropriation, we develop several models to predict whether a development contract will become an OTB contract in the future. Each of these models contains five to nine predictor variables. To determine

[2] This is for both RDT&E and Procurement models. This accounts for 80% of the data, which we chose randomly for the development of our models.

which model is the best for a given number of variables, a comparison of the R^2(U) statistic in JMP® is used. R^2(U) is defined as:

> The proportion of the total uncertainty that is attributed to the model fit…which is the difference between the negative log-likelihood value of the full model and the negative log-likelihood value of the reduced model divided by the negative log-likelihood value of the reduced model. (JMP®, 2009)

We interpret this statistic in the same manner as R^2 in a linear regression model. Typically, logistic regression models do not tend to have high values for R^2(U). Based on the R^2(U) values for each of the models developed with n predictor variables (where n is less than or equal to 10), the best model with n predictor variables is the model with the most explanatory power as indicated by the highest R^2(U) value.

Based on our evaluation of R^2(U) for each model with a specific number of variables, four different development models are developed (one model for each of six to nine variables). The R^2(U) statistic ranged from 0.18 to 0.24 and the area under the ROC curve ranged from 0.79 to 0.83. For our models to be significant we would like a p-value associated with the Pearson chi-square statistic of less than 0.05. In each model, the p-value is less than 0.0001, which indicates that each model is statistically significant. Similarly, each predictor variable is statistically significant when its p-value is less than 0.05. In each model, each variable has a p-value of 0.0051 or less indicating that each of the predictor variables is statistically significant. Furthermore, the ability to discriminate between properly identifying OTBs and not is considered to be either acceptable or excellent based on the guidelines for the area under the ROC curve provided in Chapter Three. However, the model's ability to explain the results is low based on the low R^2(U) values.

Since there is not much of a difference between the R^2(U) statistic and the area under the ROC curve for each of the models, we choose two models to consider which have fewer predictor variables. This provides the user with a simpler model with almost as much predictive power as the more complex models. Each of these models has slightly different predictors to consider, one with five variables and one with six variables. The regression results for development contracts are in Appendix D. Table 8 provides the summary output and parameters for each of these models.

Each of the predictors in these models has a significant effect on the likelihood of an OTB based on its associated p-value. To interpret these predictors, we must first recognize that the sign on the coefficient term that JMP® produces is the opposite of its sign in the typical logistic regression equation. By reversing the signs, we can interpret the predictor variables more easily. The results indicate that Air Force, Navy, and fighter aircraft contracts are more likely to experience an OTB. Contracts with a low SPI*CPI, also known as the SCI, are more likely to experience an OTB. A low SPI*CPI occurs when the contract is behind schedule, over budget, or both. In the five variable model, a contract that has not experienced an APB Performance breach yet is likely to experience an OTB. In the six variable model, contracts with a high EAC and contracts with a low value for % complete are more likely to experience OTBs. That is, a contract that is in the early stages in terms of percent complete is more likely to experience an OTB.

Table 8: Development Model Parameters

Development (RDT&E) Contracts Coefficients and P values	5 Variable Model	6 Variable Model
Intercept	-2.12134 (0.0001)	-3.10318 (<.0001)
Air Force	-1.74879 (<.0001)	-1.40268 (<.0001)
Navy	-1.68322 (<.0001)	-1.61499 (<.0001)
Fighter	-2.09911 (<.0001)	-1.39849 (<.0001)
SPI*CPI	4.98886 (<.0001)	5.63935 (<.0001)
EAC (BY09$)		-0.00013 (<.0001)
% Complete		0.98411 (<.0005)
APB Performance	0.44962 (0.0051)	
Summary Statistics		
R Square (U)	0.1953	0.1832
Area under ROC curve	0.80432	0.79467
Whole Model Test P Value (Prob>ChiSq)	<.0001	<.0001

Logistic Regression Models for Production (Procurement) Contracts

Using the contracts denoted by the Procurement appropriation, we develop several models to predict whether a production contract will become an OTB contract. Using the same method of comparing various models based on the R^2(U) statistic, we arrive at five different production models (one model for each of six to ten variables). The R^2(U) statistic ranged from 0.18 to 0.22 and the area under the ROC curve ranged from 0.78 to 0.83. Similar to our regression models for development contracts, all of our models are statistically significant with p-values less than .0001 and each of the variables in the model is statistically significant with the highest p-value for a predictor variable being 0.001. Again, our ability to discriminate between properly identifying OTBs and not is considered to range from acceptable to excellent based on the guidelines for the area under the ROC curve. However, the model's ability to explain the results is low based on the low $R^2(U)$ values.

Similar to our case for development contracts, there is not much of a difference between the $R^2(U)$ statistic and area under the ROC curve for each of the models. Therefore, we choose two models to consider which have fewer predictor variables. This provides the user with a simpler model without compromising much predictive power. Each of these models has slightly different predictors. One model contains five variables and the other contains seven variables. The regression results for development contracts are in Appendix E. Table 9 provides the summary output and parameters for each of these models.

To interpret the predictor variables in each of these models the signs of the coefficients are reversed. Contracts that have a high BCWS and a low BCWP are more likely to experience an OTB. This means that contracts with a large amount of work scheduled (BCWS) and a small amount of work performed (BCWP) are more likely to experience an OTB. Contracts that have experienced a large change in the production quantity since the initial report are more likely to experience an OTB. A contract that has experienced an APB schedule breach is also more likely to experience an OTB. For the five variable model, a contract with a large EAC is more likely to become an OTB. For the six variable model, a contract with a low value for % complete (early on) and has experienced an APB performance breach is more likely to experience an OTB.

Table 9: Production Model Parameters

Production (Procurement) Contracts Coefficients and P values	5 Variable Model	7 Variable Model
Intercept	2.99823 (<.0001)	2.45622 (<.0001)
BCWS (BY09$)	-.02918 (<.0001)	-.03368 (<.0001)
BCWP (BY09$)	0.03472 (<.0001)	0.03724 (<.0001)
MR (BY09$)		-0.01627 (<.0001)
EAC (BY09$)	-.00108 (<.0001)	
% Complete		1.92580 (<.0001)
% Change in Production Quantity	-0.00117 (<.0001)	-0.00140 (<.0001)
APB Schedule	-0.73515 (0.0010)	-0.84723 (0.0002)
APB Performance		-1.07029 (<.0001)
Summary Statistics		
R Square (U)	0.1840	0.2042
Area under ROC curve	0.78087	0.80413
Whole Model Test P Value (Prob>ChiSq)	<.0001	<.0001

Validation of Logistic Regression Models

Before coming to the conclusion that these models can be applied to predict OTBs, we must validate their predictive ability. Using the 20% of the data that we initially set aside, we test the performance of the final four models. Since the positive or negative signs of the coefficients for each predictor in JMP® are the opposite of what they would be in the standard logistic regression equation presented in Table 6 of Chapter Three, we must adjust our logistic regression equation. For computational purposes, we calculate the logistic regression response by using the formula in Table 10 along with the values that JMP® provides for the coefficients B_0, B_1... B_n.

Table 10: Computational Form of Logistic Regression Equation

$$\pi(x) = \frac{e^{-(B_0+B_1x_1+B_2x_2+\ldots+B_nx_n)}}{1+e^{-(B_0+B_1x_1+B_2x_2+\ldots+B_nx_n)}}$$

For each entry in the validation set, we compute the logistic response, which is the predicted likelihood that a contract will become an OTB contract. The model uses a cutoff of 0.5 to determine whether we predict an OTB with our model. If the logistic response is greater than 0.5, we identify the entry as a predicted OTB and code it as a one. If the logistic response is less than 0.5, we identify the entry as not being a predicted OTB and code it as a zero. The validation involves comparing these values with the actual values of whether a contract becomes an OTB. When the predicted value is a one and the actual value is a one, we correctly predict an OTB. When the predicted value is a one and the actual value is a zero, we incorrectly predict an OTB. Table 11 provides a summary of the validation results for the development (RDT&E) and production (Procurement) contracts.

We first interpret the results for the development contracts (RDT&E). When an OTB is predicted (Prediction = 1), the prediction is only correct approximately fifty percent of the time (Prediction=1, Actual=1). Furthermore, the model frequently fails to predict an OTB when an OTB occurs (Prediction=0, Actual=1). Based on these findings, we conclude that these models are not good predictors of RDT&E OTB contracts.

When analyzing the results for the production contracts (Procurement), we find that we rarely predict an OTB in comparison to the actual instances of an OTB. However, when an OTB is predicted (Prediction=1), the prediction tends to be correct since there are very few instances of incorrectly predicting an OTB (Prediction=1, Actual=0). While this may appear to be a good outcome, the objective is to identify OTBs. Since the models fail to identify the majority of OTBs when they occur, the conclusion is that these models are not good predictors of Procurement OTB contracts.

Table 11: Model Validation Results

RDT&E 5 Variables Outcome

Prediction	Actual	Frequency
0	0	592
1	1	27
0	1	112
1	0	30

RDT&E 6 Variables Outcome

Prediction	Actual	Frequency
0	0	580
1	1	24
0	1	113
1	0	29

Procurement 5 Variables Outcome

Prediction	Actual	Frequency
0	0	587
1	1	6
0	1	51
1	0	0

Procurement 7 Variables Outcome

Prediction	Actual	Frequency
0	0	572
1	1	8
0	1	49
1	0	2

Recall in Chapter Three, that to determine how close the model is to accurately predicting OTBs, we can consider how far off our predicted values are from the cut-off point, which is 0.5. When examining the inaccurate predictions (either prediction=1 and actual=0 or prediction=0 and actual=1), the logistic responses for these inaccurate predictions are far from the cutoff point of 0.5. Therefore, the cutoff point that we choose does not affect our predictive capability. Since this process of predicting OTBs did not produce sufficient models for predicting OTBs, we seek other methods to refine our models.

Additional Attempts at Predicting OTBs

One method to try to improve the model's predictive ability is to limit the data set to a more applicable period. In Figure 6, the box plot for the value of percent complete one period prior to an OTB indicates that OTBs tend to occur midway through a contract's life. Since OTBs do not tend to occur early or late in a contract's life, we attempted to build models that exclude data beyond a certain value of percent complete, specifically looking at the values of 60% and 70% complete. By excluding data points beyond these periods, the models still lacked sufficient predictive capability. We also considered models that only included data points in the ranges of 10-60% complete and 20-70% complete. Again, neither of these models produced significant results.

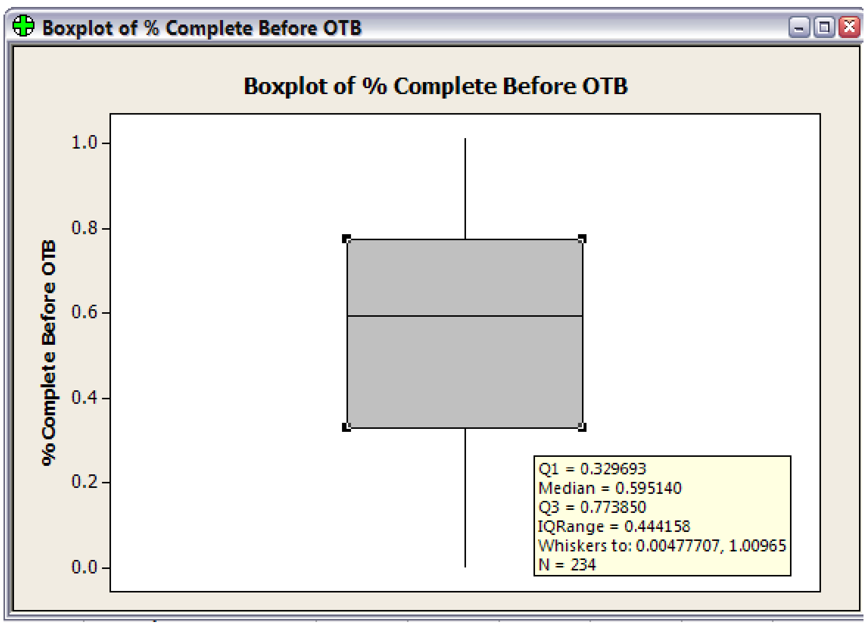


Figure 6: Box Plot of % Complete Prior to OTB

A second method is to search for trends in OTB contracts. By identifying a common trend, we can see if this trend exists in non-OTB contracts. Since the OTB process is not a mandatory process, it is possible to flag non-OTB contracts as contracts that were candidates for an OTB. Then we can develop new models that incorporate the identification of OTBs along with OTB candidate contracts. Unfortunately, we were unable to identify any common trends among the OTB contracts. This suggests that the process of identifying contracts to become OTB may be random since the OTB process is an optional step.

Finally, there is an alternative method for identifying OTBs. All of the previous models use the standard definition of an OTB provided by DAU, which defines an OTB based on the TAB exceeding the CBB. However, the DAES database also has a data field that identifies an OTB when the program office reports an OTB in the DAES database. When we rerun our models based on this alternative way of identifying an OTB, we obtain similar results to what we have already found: correct OTB predictions approximately half of the time and the failure to predict the majority of OTBs. This alternative also fails to provide better predictive capabilities.

Conclusion

After the initial model building attempts that considered all of the available predictors, interactions between predictors, and changes in predictors along with the additional attempts to develop predictive models, we conclude that the models are unable to predict OTBs based on the data available to us. In the next chapter, we discuss the implications of these findings.

V: Discussion and Conclusion

In this chapter, we recall the purpose of this thesis and the results from the analysis. We discuss the implication of our results and what policy implications our results provide. Finally, we suggest some potential areas for future research related to earned value management.

Thesis Purpose

In 2009, Captain Trahan developed a growth model, which improves EACs for contracts that are Over Target Baselines (OTBs). To apply this model to improve EACs, the contract must be an OTB or it must become an OTB in the future. This thesis attempts to predict OTB contracts with the intent of applying Captain Trahan's model to develop better EACs. By improving EACs, cost estimators provide the DoD with the capability to provide more content to the war fighter. A high EAC limits the ability to acquire additional capabilities with the additional (unnecessary) funds allotted to a program. A low EAC creates problems for the program with a low estimate since it will require additional funds to deploy that capability to the field. Furthermore, when one program has too low of an EAC, the services (Army, Navy, Air Force, etc.) tend to borrow money from other programs and this causes problems for all of the programs involved. In addition to improving EACs, the ability to predict OTBs allows decision makers to identify cost overruns since an OTB formally recognizes cost overruns.

Summary of Results

We built separate logistic regression models to predict OTB contracts for production and development contracts and chose four models to use based on an evaluation of the predictive capabilities for each of the models. These models contain five to seven predictor variables capturing EVM metrics, production information, and threshold breach information. While we were able to develop significant models for the model building set, all of the models failed in the validation stage. The validation results indicate that the ability to predict OTBs is no better than a coin flip. Furthermore, the models fail to predict the majority of OTBs when they occur. Since our objective is to identify OTBs, the failure to predict an OTB is substantial. Additional attempts at refining the model based on the definition of an OTB and the period considered also proved unsuccessful. Based on these results, we are unable to predict an OTB.

However, in one of the attempts, we examine a variety of predictor variables from the regression models. In this analysis, there were no common trends in these variables for OTB contracts. This is an important observation as it suggests that OTBs may occur randomly, which would explain the inability to predict OTBs.

Policy Implications

Since OTBs are not required and contractors conduct OTBs at their discretion, contractors may not utilize the OTB process when it may be beneficial to them. Furthermore, the limited number of OTB contracts limits the amount of cost overruns that the DoD can quantify. Without the use of OTBs, decision makers can identify cost growth, but the ability to quantify cost overruns becomes much more difficult.

Perhaps contractors could be required to distinguish between increased costs due to requirement changes and increased costs due to cost overruns or contract performance issues. This topic needs to be addressed carefully as contractors are less likely to report contract performance issues and are more likely to report increased costs due to requirement changes. One option is to require contractors to estimate the costs of the specific requirement changes opposed to presenting a revised single estimate for the entire program when a requirement change occurs. Another way to prevent contractors from hiding cost overruns in a new baseline would be to require contract changes be implemented in a follow on increment or to use a spiral acquisition strategy.

The ability to identify cost overruns separately from cost growth allows decision makers to measure a contractor's performance. If the DoD can require contractors to report cost overruns or create an environment that prevents contractors from hiding overruns, such as with a spiral acquisition strategy, the DoD could better evaluate and manage contractor performance. With increased visibility into the costs incurred by the DoD, cost estimators could identify the reasons for increased costs and recommend actions to control costs.

Future Research

The OTB process appears to be random within the DoD. So decision makers must ask the question, why do contractors use it? The DAU guide on OTBs explains the purpose of an OTB, but it does not quantify the benefits realized for OTB contracts. One possible research topic would be to quantify the benefits of a contract going through the OTB process versus not going through the OTB process. This would determine if the process is worthwhile or not.

Additionally, in the process of collecting data, we discovered that the DCARC database has more detailed CPR data available along with the original CPR submissions. Researchers should use the DCARC database for studies that require EVM data on recent contracts since the data is more reliable. However, since the database only includes entries back to 2007, researchers should wait until more data becomes available to conduct extensive studies.

Appendix A: The Office of the Under Secretary of Defense (OUSD) (Comptroller) Raw Inflation Indices

National Defense Budget Estimates for FY 2010

Table 5-4: DoD Deflators – TOA by Appropriation Title

Deflators = Current/Constant

FISCAL YEAR	MILPERs	O&M	O&M excl DHP	PROCURE-MENT	RDT&E	MIL CON	FMLY HSNG
1970	13.01	16.63	16.63	19.31	19.86	20.60	19.19
1971	13.92	17.57	17.57	20.43	20.88	22.14	20.61
1972	15.83	18.57	18.57	21.70	21.98	23.64	21.60
1973	17.58	19.87	19.87	23.51	23.41	26.21	22.55
1974	18.74	22.12	22.12	25.76	25.70	29.51	24.08
1975	20.12	24.02	24.02	28.82	28.32	32.45	27.12
1976	21.28	26.40	26.40	31.99	31.33	35.22	29.23
1977	22.42	28.51	28.51	33.16	33.14	36.09	31.75
1978	23.94	30.94	30.94	36.33	36.02	39.05	33.96
1979	25.41	32.76	32.76	40.42	40.27	42.95	38.80
1980	27.43	38.39	38.39	44.67	44.16	45.88	44.59
1981	31.42	42.76	42.76	48.79	48.07	49.32	48.80
1982	36.01	44.97	44.97	52.22	50.80	51.54	52.38
1983	37.70	46.30	46.30	54.92	52.77	52.67	53.97
1984	39.45	47.13	47.13	56.85	54.80	54.54	55.42
1985	43.62	48.52	48.52	58.57	56.53	56.48	57.16
1986	45.26	48.86	48.86	60.32	58.00	57.93	58.56
1987	46.46	50.66	50.66	62.36	59.86	60.15	60.40
1988	48.30	52.38	52.38	64.79	62.32	63.02	62.52
1989	49.88	54.84	54.84	67.25	64.90	65.54	64.98
1990	50.69	56.67	56.67	69.64	67.35	67.66	67.32
1991	53.46	62.31	62.31	71.64	69.68	69.82	70.32
1992	54.73	61.93	61.93	73.33	71.68	71.52	72.02
1993	57.19	60.22	62.90	74.82	72.53	72.57	73.59
1994	58.59	61.80	64.57	76.21	73.99	74.81	75.25
1995	60.05	63.50	66.17	77.53	75.53	75.99	76.45
1996	61.38	65.08	67.75	78.69	77.01	77.39	78.01
1997	63.26	66.57	69.30	79.57	78.19	78.16	79.12
1998	66.06	68.87	71.63	80.38	79.20	78.88	79.88
1999	68.12	70.71	73.32	81.45	80.05	80.12	80.82
2000	71.38	72.06	74.90	82.66	81.60	81.43	81.93
2001	73.85	75.10	78.10	83.82	82.98	82.55	83.49
2002	78.08	77.50	80.34	85.07	84.23	84.31	84.47
2003	81.14	80.45	82.19	86.79	85.81	86.36	85.71
2004	83.62	83.17	84.88	89.02	88.09	88.81	87.89
2005	86.47	87.93	89.53	91.48	90.70	91.40	90.84
2006	89.32	91.30	92.85	93.78	93.18	93.56	93.48
2007	91.67	93.85	95.06	95.77	95.40	95.49	95.54
2008	94.37	97.14	98.07	97.30	97.22	97.12	97.73
2009	97.46	98.11	98.56	98.59	98.69	98.58	98.76
2010	100.00	100.00	100.00	100.00	100.00	100.00	100.00
2011	103.16	102.93	102.41	101.67	101.67	101.74	101.61
2012	106.47	105.63	104.54	103.47	103.52	103.62	103.42
2013	109.93	108.52	106.72	105.34	105.46	105.52	105.32
2014	113.50	111.34	108.82	107.24	107.44	107.49	107.26
2015	117.20	114.40	111.02	109.17	109.46	109.47	109.24

(Office of the Under Secretary of Defense (Comptroller), 2009)

Appendix B: The Office of the Under Secretary of Defense OUSD (Comptroller) Outlay Rates

Table 5-11: Outlay Rates for Incremental Changes in BA Purchases

Outlay Profiles:	1st Year	2nd Year	3rd Year	4th Year	5th Year	6th Year	7th Year
Procurement (Defense Wide)	0.23	0.41	0.25	0.07	0.02	0.01	0.01
RDT&E (Defense Wide)	0.44	0.43	0.07	0.04	0.01	0.01	
O&M (Defense Wide)	0.51	0.40	0.05	0.02	0.01	0.01	

(Office of the Under Secretary of Defense (Comptroller), 2009)

Appendix C: Weighted Inflation Indices

Weighted Indices (base year of table: 2009)			
	Procurement	RDT&E	O&M
1970	21.20	20.95	17.57
1971	22.67	22.10	18.60
1972	24.55	23.49	19.82
1973	26.95	25.43	21.56
1974	29.78	27.94	23.74
1975	32.57	30.75	25.90
1976	35.02	33.35	28.25
1977	37.97	35.86	30.58
1978	41.89	39.44	32.98
1979	46.06	43.54	36.38
1980	50.00	47.35	41.44
1981	53.37	50.61	44.83
1982	56.04	52.96	46.64
1983	58.15	54.95	47.78
1984	60.01	56.85	48.86
1985	61.91	58.54	49.89
1986	64.03	60.32	50.98
1987	66.38	62.53	52.83
1988	68.79	65.06	54.91
1989	71.06	67.56	57.24
1990	73.06	69.89	60.41
1991	74.76	71.96	63.26
1992	76.26	73.43	62.49
1993	77.65	74.63	62.41
1994	78.92	76.12	64.07
1995	80.04	77.61	65.75
1996	81.01	78.92	67.38
1997	81.96	80.04	69.26
1998	83.05	81.05	71.39
1999	84.26	82.29	73.15
2000	85.56	83.78	75.32
2001	87.03	85.19	78.17
2002	88.84	86.74	80.90
2003	91.02	88.75	83.91
2004	93.35	91.21	87.52
2005	95.56	93.72	91.65
2006	97.48	96.02	94.69
2007	99.09	98.01	97.50
2008	100.53	99.66	99.83
2009	102.04	101.12	101.35
2010	N/A	102.68	103.78

Appendix D: Logistic Regression Models: Development Contracts

Nominal Logistic Fit for Will it become an OTB? (yes=1, no=0)

Whole Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	221.5882	5	443.1763	<.0001*
Full	912.7929			
Reduced	1134.3810			

RSquare (U)	0.1953
Observations (or Sum Wgts)	2257

Converged by Gradient

Lack Of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack Of Fit	2081	888.05881	1776.118
Saturated	2086	24.73404	**Prob>ChiSq**
Fitted	5	912.79285	1.0000

Parameter Estimates

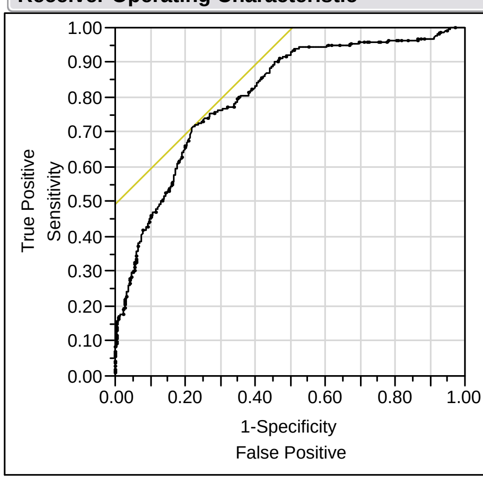
Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-2.1213432	0.5481341	14.98	0.0001*
Air Force	-1.7487887	0.1512736	133.64	<.0001*
Navy	-1.6832163	0.1468049	131.46	<.0001*
Fighter=1	-2.0991097	0.1732385	146.82	<.0001*
SPI*CPI	4.98886162	0.6015667	68.78	<.0001*
APB Perf (since program began)	0.44961724	0.1604091	7.86	0.0051*

For log odds of 0/1

Effect Likelihood Ratio Tests

Source	Nparm	DF	L-R ChiSquare	Prob>ChiSq
Air Force	1	1	139.223595	<.0001*
Navy	1	1	136.948261	<.0001*
Fighter=1	1	1	153.323909	<.0001*
SPI*CPI	1	1	74.0553979	<.0001*
APB Perf (since program began)	1	1	8.22450541	0.0041*

Receiver Operating Characteristic



Using Will it become an OTB? (yes=1, no=0)='1' to be the positive level
Area Under Curve = 0.80432

Nominal Logistic Fit for Will it become an OTB? (yes=1, no=0)

Whole Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	246.0426	6	492.0853	<.0001*
Full	1096.6904			
Reduced	1342.7330			

RSquare (U) 0.1832

Observations (or Sum Wgts) 2809

Converged by Gradient

Lack Of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack Of Fit	2646	1081.4411	2162.882
Saturated	2652	15.2492	**Prob>ChiSq**
Fitted	6	1096.6904	1.0000

Parameter Estimates

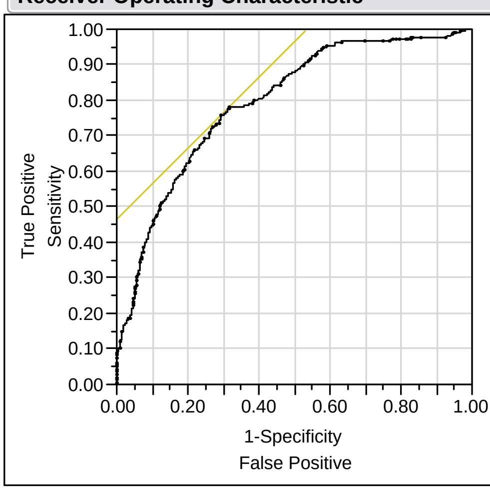
Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-3.1031811	0.4946008	39.36	<.0001*
Air Force	-1.4026827	0.139231	101.50	<.0001*
Navy	-1.6149947	0.1326298	148.27	<.0001*
Fighter=1	-1.3984851	0.1767598	62.60	<.0001*
SPI*CPI	5.63935418	0.5434839	107.67	<.0001*
EAC (BY09$)	-0.0001286	0.0000208	38.27	<.0001*
% Complete	0.98410535	0.1966273	25.05	<.0001*

For log odds of 0/1

Effect Likelihood Ratio Tests

Source	Nparm	DF	L-R ChiSquare	Prob>ChiSq
Air Force	1	1	99.577974	<.0001*
Navy	1	1	152.01374	<.0001*
Fighter=1	1	1	59.5560043	<.0001*
SPI*CPI	1	1	115.885391	<.0001*
EAC (BY09$)	1	1	44.7105976	<.0001*
% Complete	1	1	25.307887	<.0001*

Receiver Operating Characteristic



Using Will it become an OTB? (yes=1, no=0)='1' to be the positive level

Area Under Curve = 0.79467

Appendix E: Logistic Regression Models: Production Contracts

Nominal Logistic Fit for Will it become an OTB? (yes=1, no=0)

Whole Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	107.62019	5	215.2404	<.0001*
Full	477.20578			
Reduced	584.82597			

RSquare (U)	0.1840
Observations (or Sum Wgts)	2153

Converged by Gradient

Lack Of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack Of Fit	2068	477.20578	954.4116
Saturated	2073	0.00000	**Prob>ChiSq**
Fitted	5	477.20578	1.0000

Parameter Estimates

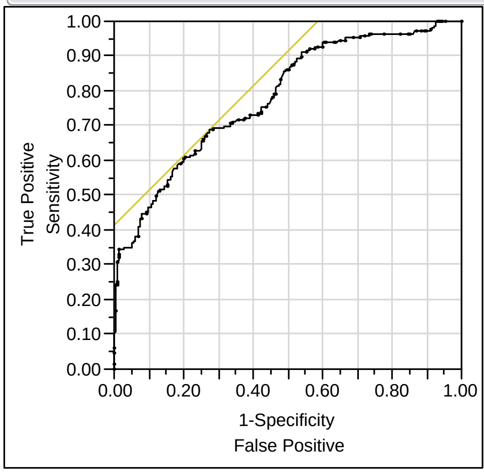
Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	2.99823206	0.2113997	201.15	<.0001*
BCWS (BY09$)	-0.0291836	0.0037638	60.12	<.0001*
BCWP (BY09$)	0.03472149	0.0039848	75.92	<.0001*
EAC (BY09$)	-0.0010841	0.0001488	53.06	<.0001*
%Change in Prod Qty	-0.0011729	0.0001372	73.12	<.0001*
APB Sched (since program began)	-0.7351471	0.2228897	10.88	0.0010*

For log odds of 0/1

Effect Likelihood Ratio Tests

Source	Nparm	DF	L-R ChiSquare	Prob>ChiSq
BCWS (BY09$)	1	1	64.2231264	<.0001*
BCWP (BY09$)	1	1	84.6860049	<.0001*
EAC (BY09$)	1	1	48.8409568	<.0001*
%Change in Prod Qty	1	1	71.5295638	<.0001*
APB Sched (since program began)	1	1	11.9958743	0.0005*

Receiver Operating Characteristic



Using Will it become an OTB? (yes=1, no=0)='1' to be the positive level
Area Under Curve = 0.78087

Nominal Logistic Fit for Will it become an OTB? (yes=1, no=0)

Whole Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	119.64819	7	239.2964	<.0001*
Full	466.27867			
Reduced	585.92686			

RSquare (U)	0.2042
Observations (or Sum Wgts)	2136

Converged by Gradient

Lack Of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack Of Fit	2053	466.27867	932.5573
Saturated	2060	0.00000	**Prob>ChiSq**
Fitted	7	466.27867	1.0000

Parameter Estimates

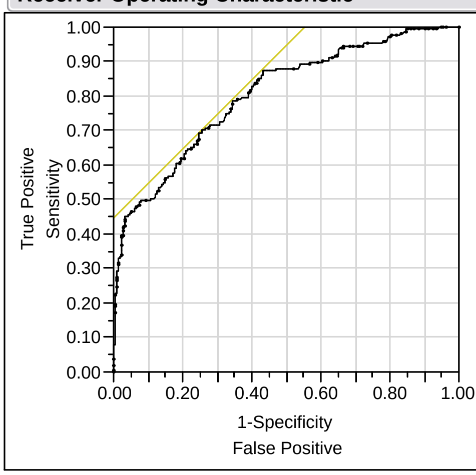
Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	2.45621515	0.2135546	132.29	<.0001*
BCWS (BY09$)	-0.0336802	0.0038816	75.29	<.0001*
BCWP (BY09$)	0.03724202	0.0041528	80.42	<.0001*
MR (BY09$)	-0.0162715	0.0026889	36.62	<.0001*
% Complete	1.92580313	0.3488721	30.47	<.0001*
%Change in Prod Qty	-0.0013979	0.0001473	90.04	<.0001*
APB Sched (since program began)	-0.8472259	0.2239202	14.32	0.0002*
APB Perf (since program began)	-1.0702907	0.2110283	25.72	<.0001*

For log odds of 0/1

Effect Likelihood Ratio Tests

Source	Nparm	DF	L-R ChiSquare	Prob>ChiSq
BCWS (BY09$)	1	1	80.1344568	<.0001*
BCWP (BY09$)	1	1	90.5358401	<.0001*
MR (BY09$)	1	1	15.7144622	<.0001*
% Complete	1	1	33.6027505	<.0001*
%Change in Prod Qty	1	1	89.0189208	<.0001*
APB Sched (since program began)	1	1	15.7997568	<.0001*
APB Perf (since program began)	1	1	23.7841223	<.0001*

Receiver Operating Characteristic



Using Will it become an OTB? (yes=1, no=0)='1' to be the positive level
Area Under Curve = 0.80413

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Vita

Captain Kristine Thickstun attended Miami University (OH) where she graduated Magna Cum Laude in 2005 with a Bachelor of Science degree in Mathematics and a minor in Economics. In May of 2005, she received a commission as a 2nd Lt in the Air Force out of the AFROTC program.

Upon commissioning, she reported to headquarters Air Education and Training Command (AETC), Randolph AFB, Texas. She worked at the Studies and Analysis Squadron within AETC A5/8/9 as a scientist. During her three-year assignment she supported the command on technical training studies, flying training studies, pilot selection studies, cost studies, and a variety of AETC initiatives.

While serving at Randolph AFB, Captain Thickstun was a student in the MBA program at St. Mary's University in San Antonio, Texas. In 2008, she graduated as a distinguished graduate with an emphasis in financial planning. For her academic achievements at St. Mary's University, she was chosen as the 2008 St. Mary's University recipient of the Texas Business Hall of Fame Scholarship, an award given to 16 graduate students in Texas.

In August of 2008, she entered the Cost Analysis program at the Air Force Institute of Technology. Upon graduation, she will be assigned to Los Angeles AFB, CA.

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14. ABSTRACT
Cost estimators use a variety of methods to develop estimates at completion (EACs) and new methods continue to be developed. Research has shown there is no best method for computing EACs for all acquisition contracts. However, some methods perform better under specific circumstances. In 2009, Captain Trahan investigated the use of a Gompertz growth model for developing EACs. She found that this method is more reliable for Over Target Baseline (OTB) contracts than the standard indexed based approaches. Captain Trahan's model is an excellent model to use for OTB contracts or contracts with a high likelihood of becoming an OTB contract. In this study, we attempt to develop a model that predicts whether an acquisition contract is likely to become an OTB. By identifying contracts that are likely to become OTB, we can apply the Gompertz growth model to develop better EACs. Furthermore, an OTB, by definition, recognizes a cost overrun. Therefore, the ability to predict OTBs also allows us to understand what may cause cost overruns. However, our models indicate that we are unable to predict an OTB. This indicates that the OTB process may be used randomly which leads us to question the benefits of OTBs.

15. SUBJECT TERMS
Over Target Baseline (OTB), Earned Value Management (EVM), Estimate at Completion (EAC), cost overruns, logistic regression

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