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Developing Standard Production Cost Factors for Major Defense Acquisition Program (MDAP) Platforms

Jordan S. Edwards

DEVELOPING STANDARD PRODUCTION COST FACTORS FOR MAJOR DEFENSE ACQUISITION PROGRAM (MDAP) PLATFORMS

THESIS

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Abstract

Cost estimators commonly use the analogy and factor method when developing Major Defense Acquisition Program (MDAP) estimates. Previous studies discussing and developing factors for the production lifecycle phase have been limited in scope and statistical analysis efforts. This research significantly expands the currently available toolkit for Department of Defense cost analysts by updating the current database of historical data and exploring potential relationships through statistical testing. Specifically, 3,462 unique factors were created across nine level II Work Breakdown Structure (WBS) elements broken down into four categories; commodity type, contract type, contractor type, and service. The production cost factors were created using data points from 145 MDAPs spanning from 1953 to 2018. Calculated factors were statistically tested for significant differences in their respective WBS element (by category) using non-parametric methods. The updated database and findings will aid analysts in quickly identifying categories that may impact their cost estimate. The practical and statistical analysis performed provide cost estimators with guidance and an improved toolkit for production cost factors.

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I would like to express my sincere appreciation to my thesis research advisor, Dr. Daniel Ritschel, for his guidance and support throughout the course of this thesis effort. The structure provided and milestones throughout were critical in the learning process. Dr. Ritschel always made himself available to share his insight and experience. He allowed me to work individually while steering me in the right direction when necessary. I would also like to thank the experts of my committee. Their input ensured my research remained on a relevant and logical path. Lastly, I'd like to acknowledge Mr. Shawn Valentine, my sponsor from the Air Force Lifecycle Management Center. His proficiency in the cost analysis field and various software platforms (and his ability to educate me on them) was paramount during the data collection process.

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DEVELOPING STANDARD PRODUCTION COST FACTORS FOR MAJOR DEFENSE ACQUISITION PROGRAM (MDAP) PLATFORMS

I. Introduction

Background

The Department of Defense (DoD) accomplishes cost estimates to inform decision makers of the resource costs necessary to acquire a system, carry out a process, or perform a service. Examples of programs requiring cost estimates include aircraft, missiles, avionics, software, and information systems. DoD cost estimators utilize four primary cost estimating techniques: analogy and factor, parametric, build-up (engineering), and expert opinion (Subject Matter Expert (SME)) (Air Force Cost Analysis Handbook (AFCAH), 2007). These methods can be used singularly, in combination, or as a crosscheck for an estimate completed using an alternate method. The method(s) chosen to develop an estimate will affect many aspects of the estimate including its accuracy, time to accomplish, and level of detail. To facilitate a consistent framework for developing cost estimates in major acquisition programs, DoD Instruction 5000.02 mandates usage of the Work Breakdown Structure (WBS) construct in MIL-STD-881-D. Of particular interest to this research are the “common” WBS elements (e.g. data, training) delineated at Level II in MIL-STD-881-D.

No program, no matter how advanced, represents an entirely new system or technology. The analogy/factor method uses known costs of similar existing elements to estimate the cost of a new element. Factors can be used very early in a program, before all system requirements are fully developed. Data collection for the factor method is not extensive and programs with strong similarities will exhibit similar costs, which factors can easily and quickly capture (AFCAH, 2007). Factors are also a quick method to sanity check other cost estimating techniques. The disadvantages to using the analogy/factor method are the program being estimated must be similar in scope and effort and the data required to create accurate factors may be difficult to obtain.

The Air Force Life Cycle Management Center (AFLCMC) currently publishes standard factor tables periodically for Major Defense Acquisition Program (MDAP) production that captures prime contractor data. Although useful, additional data exists that can assist in refining and developing new production factors. Including new commodity types and contract types will create a more versatile and useful table. Furthermore, production factor analysis at the subcontractor level has not been accomplished. Creation of these new factors will provide cost estimators with a more robust toolkit to produce more accurate cost estimates.

Problem Statement

The AFLCMC production factor table uses standard factors to crosscheck cost estimates with similar historical programs. Factor research by Blair (1988) and Wren (1998) undergirds the current AFLCMC cost factor tables. However, these studies focused solely on avionics. Following these studies, there were sporadic updates to aircraft factors as well as studies which were not well publicized. In 2019, Markman et al. (2019) accomplished the most recent and relevant factor study focusing on Engineering, Manufacturing, and Development (EMD) factors. Their study discovered over 400 new factors while updating old ones. Markman et al. (2019), however, did not conduct any factor development outside the EMD phase. Thus, the current production factor tables remain outdated and lack recent analytic efforts. This study represents a comprehensive update to prior factor studies, but focuses primarily on MDAP cost factors in the production stage. It increases the utility and accuracy of the production factor tables by including data not utilized in previously published research or AFLCMC factor tables.

Research Objectives/Questions

Several questions must be considered in order to discover relevant and update existing factors for production programs, publish them for use, and rely on them for cost estimate crosschecks. Conclusions drawn from these questions will also vector future research.

1. What are the standard production factors for MDAP programs with respect to the level II WBS elements?
2. What is the statistical difference in standard factors between differing commodity types with respect to the level II WBS elements?
3. What statistical differences exist between contract types utilized for MDAP procurement?
4. What differences are found in the standard factors when comparing prime and subcontractor data?
5. What statistical differences exist in factors between DoD service departments?

Methodology

Data is collected from the Cost Assessment Data Enterprise (CADE) system and added to the AFLCMC/FZC cost library database. Cost Data Summary Reports (CDSR), more commonly known as 1921s, are the primary documents from which program data is gathered. Data is collected by commodity type, contract type, contractor type, and service. Several statistical techniques will be used to analyze the data for each of these categories and the relationship between them. Descriptive statistics will begin the process of developing standard factors. The mean, median, and standard deviation for each element offers a point of origin from which to identify trends. Interquartile ranges amongst the individual elements allow for analysis of variance at multiple levels. The descriptive statistics build the foundation for more detailed analysis and statistical testing.

Once the production factors are determined, the data is tested for normality with the Shapiro-Wilk test. In the event of non-normality results, non-parametric testing is employed to determine relationships between the different categories. Non-parametric statistical tests used include the Kruskal-Wallis test and the Steel-Dwass test which perform multiple comparison tests to identify statistically different medians between two or more independent groups. Additionally, the results of the non-parametric test results will uncover the new data's applicability to future cost estimating practices.

Scope and Limitations

The CADE database is the official Office of the Secretary of Defense data source used to gather the data required to establish and analyze standard factors of production. DD Form 1921s are used to store cost data within CADE and represent the satisfaction of Contractor Cost Data Reporting (CCDR) requirements as defined by the Defense Cost Resource Center (DCRC) for all Acquisition Category I and IA programs (Department of Defense, 2007). Data used in this study relies on the recorded cost data and its accuracy contained on the 1921s within CADE and the AFLCMC/FZC cost library.

1921s use established Work Breakdown Structure (WBS) elements that have remained consistent throughout the years and are defined in MIL-STD-881D. This makes it possible to study 1921s and the production factors associated with each WBS element across the range of years available within CADE and the AFLCMC/FZC cost library database. WBS elements analyzed within this study are at WBS level II and include Systems Engineering/Program Management (SE/PM), System Test and Evaluation (ST&E), Training, Data, Peculiar Support Equipment (PSE), Common Support Equipment (CSE), Site Activation, Other, and Spares (Department of Defense, 2018). Analyzing additional commodity types, contract types, subcontractor, and services data will add usefulness to the current production factor tables.

There are several limitations to this study. In order to capture all program costs, final 1921s (reporting all cost data for a program) are used for data collection. Where a final 1921 is not available, an interim 1921 will be considered if the data contained on that 1921 is greater than or equal to the final contract price. Programs within CADE that have lack of data, errors in reporting, or inconsistent reporting by the contractor will be considered for exclusion and explained where applicable. While these issues are more common in older programs, there are recent examples. Data exclusions will be determined on a case by case basis and are done with the intent of developing the most accurate and relevant production factors.

Thesis Overview

The use of standard factors in cost estimating is widely accepted and previous factor research has enabled DoD cost estimators to produce more accurate estimates. The primary objective of this research is to improve upon the cost estimator toolkit by the creation of new cost factors of production. Data exists to improve upon the existing factors and explore new ones to strengthen the credibility of this cost estimating technique. This research will use the available data within CADE to develop cost factors for a wide range of common WBS elements in the production phase of the MDAP life cycle.

This research expands upon a previous factor development study conducted under the Acquisition Research Program (Project # F19-017) that developed and analyzed factors in the same WBS elements, but exclusively for the EMD life cycle phase. Combining these two studies will result in a robust cost factor toolkit for cost analysts to provide more accurate cost estimates across the entire acquisition program life cycle. This will ensure DoD cost estimators are as effective as possible at providing decision support for the allocation of scarce resources.

The process of calculating production factors is outlined in the remainder of the analysis, beginning with a literature review of applicable studies in Chapter II. A thorough explanation of the data gathering and methodology follows in Chapter III. The methodology describes the application of descriptive statistics and statistical tests followed by the results and analysis. The significance of each factor and future research opportunities are discussed in the results and analysis chapter (Chapter IV). Finally, Chapter V answers each research question and applies the results to an operational use for DoD cost estimators.

II. Literature Review

Chapter Overview

Cost estimating involves using incomplete, inaccurate, and changing data for an outmoded and ineffective space system to derive the precise cost of purchasing an unknown quantity of an undefined new space system to satisfy an overly exaggerated and unvalidated requirement at some time in the future, under uncertain conditions, with a minimum of funds.

-NASA advisory council, 2008

Cost estimating combines the objectivity of science with the subjectivity of art to best guess at a program's total cost given the available data. Cost estimators have the responsibility of obtaining the maximum value possible for each taxpayer dollar. Thus, it is imperative that cost analysts understand the nature of their program(s) and use their available resources effectively to paint a defensible cost picture. Four primary cost estimating methods exist for cost analysts to utilize. Standard factors (analogy/factor) is one of the four common techniques described in the Air Force Cost Analysis Handbook (AFCAH) and used in program offices today (AFCAH, 2007). This research aims to enhance the cost estimator's toolkit, specifically with respect to standard factors in the production phase, for Major Defense Acquisition Programs (MDAP).

In order to comprehend standard factor's role in the cost estimating world, a basic understanding of the four primary cost estimating methods and the Work Breakdown Structure (WBS) construct is essential. The utility of standard factors in cost estimating as well as an examination of previous standard factor research is also necessary to illustrate the context of this study. This chapter will explain the four primary methods of cost estimating, provide a background of the WBS and its elements, describe the utility of standard factor's role in cost estimating, and review the relevant literature and past research of cost factors as an estimating tool.

Cost Estimating Methodologies

The Government Accountability Office (GAO) is an independent non-partisan agency that works directly for Congress. Their primary purpose is to examine how public funds are spent and provide Government agencies with information to save money and operate more efficiently (GAO, n.d.). The GAO created its' Cost Estimating and Assessment Guide in order to establish consistency in cost estimating methodologies across federal agencies. It is based on best practices—both industry and Government—designed to prevent cost overruns, missed deadlines, and performance shortfalls (Government Accountability Office, 2009). The Department of Defense (DoD) uses this guide alongside service developed guidance such as the AFCAH to develop cost estimates that are consistent, accurate, and ensure the efficient use of taxpayer dollars. While government publications outline acceptable cost estimating methods, they cannot capture every unique scenario inherent to cost estimating. This chapter will discuss the primary methods, their strengths and weaknesses, and when they are generally acceptable to use.

The AFCAH details four cost estimating techniques; analogy and factor, parametric, build-up (engineering), and expert opinion (Subject Matter Expert (SME)) (AFCAH, 2007). A technique is chosen based on parameters and constraints for the program being estimated, each having strengths and weaknesses. Combining techniques can prove useful as it increases the confidence and defensibility of an estimate. Individual methods can often times leave out details that may have been captured or explained by incorporating a second cost estimating technique. At the very least, utilizing a second method can serve as a crosscheck of reasonability for a cost estimate. A brief explanation of each of the four cost estimating techniques follows.

Analogy and Factor

MDAPs rarely represent a totally new system. The analogy and factor estimating method uses this concept and relates known costs of an existing program to an unknown cost of a new (and similar) program (AFCAH, 2007). An adjustment, known as a factor, is calculated and accounts for program differences in complexity, materials, performance, design, quantity, etc. When the factor is applied to the historical program costs, the new program cost estimate results. Cost estimators need to identify important cost drivers, determine how old elements relate to new ones, and decide how each driver impacts the total program cost. Analogies must pass a "reasonable person" test. This means that the sources of the analogy and any adjustment factors must be logical, credible, and acceptable to a reasonable person (GAO, 2009). Therefore, the analogies also rely heavily on expert opinion. This subjectivity should be limited to the greatest extent possible. The analogy and factor method can be performed at the lowest possible level of cost elements of a program to build-up to a complete cost estimate.

The analogy and factor method is typically used early in a program's lifecycle, when cost data may not be available, but the technical and program definitions are enough to make objective cost factor adjustments (GAO, 2009). One of the major advantages of this method is its usefulness before program requirements are known. Additionally, creating a strong analogy will make the estimate more defensible and credible. Analogies can be developed quickly, inexpensively, and the relationship to historical data can be easily understood. However, detailed program and technical information for both the new and analogous program must exist in order to develop an accurate cost estimate. Another weakness is analogies usually rely on a single data point; the analogous historical program. Subjectivity can be difficult to avoid when relying on expert opinion to create adjustment factors. The last disadvantage to the analogy and factor method is detailed cost, technical, and program data can be difficult to obtain to create a defensible analogy (GAO, 2009). Because of its low cost, comprehensiveness, and quick use, the analogy and factor method is often used as a crosscheck—no matter the primary method chosen for an estimate.

Parametric

The parametric cost estimating method identifies cost drivers through statistical relationships between historical costs and a program's physical and performance characteristics (GAO, 2009). It is also known as the top-down approach. Physical characteristics may include size, weight, and software lines of code while performance characteristics consider program traits such as site deployment, maintenance plans, technical measures, crew size, or test and evaluation schedules. These characteristics are just some examples of which program features may share a statistically significant relationship with cost (i.e. a cost driver). Parametric Cost Estimating Relationships (CERs) can be developed for a specific cost estimate or sourced from an existing parametric study. Unlike the analogy and factor method, parametric CERs utilize data from many historical programs and the relationship is explained by statistical inferences rather than expert opinion or past experience alone. Although CERs can be established early on in a program, they should be continually revised to maintain the accuracy of the cost estimate. The parametric method relies on the assumption that the characteristics affecting the cost of past programs will have the same relationship with cost on future programs (GAO, 2009). Parametric techniques are useful as a primary estimating method or for crosscheck estimates.

The parametric method is normally used when little is known about a program other than factors that have explained cost on previous MDAPs. Parametric relationships are extremely versatile because they can be derived at any program level and can be quickly modified to facilitate program design changes. This also allows for sensitivity analysis by adjusting input parameters or program characteristics. The statistical relationships identified are objective and create a valid, credible, and defensible method for a cost estimate (AFCAH, 2007). Additionally, the statistical significance of the CER can be used to calculate an accurate program cost confidence interval. The parametric method does have some disadvantages. In order for a parametric model to be useful, the underlying database must be consistent, reliable, and contain current technology and programs (GAO, 2009). CERs may not allow a cost breakdown to the lowest detailed cost levels. Analysts may not have insight into how the parametric model was developed or is used to manipulate the inputs to create the cost estimate; this is known as "black box syndrome" (AFCAH, 2007). Using CERs in this context increases the estimate's risk. Therefore, knowledge of the parametric model and the CERs it establishes (which are often complex) is a necessity to maintain the estimate's confidence (GAO, 2009).

Build-up (Engineering)

The build-up method estimates each program element, starting at the lowest level, and sums them up into a total program cost. For this reason, it is also known as engineering, grass roots, or bottom-up estimating (AFCAH, 2007). Build-up estimates are based on detailed engineering information about the program end item and have overhead and fees added. They require actual labor hour projections and materiel costs at the lowest WBS element levels. Cost improvement curves, labor rates, and burden factors are all considered. A detailed statement of work (SOW), program schedule, and other program specific data is necessary to complete a build-up cost estimate. Work flow stages should be identified, measured, and tracked with outcomes for each element aggregated resulting in the point estimate. Cost estimators work closely with engineers to get reasonable, complete, and consistent program data to build the cost estimate (GAO, 2009). Validation of engineering estimates is a necessity. The build-up method relies on the assumption that historical program costs are good predictors of its future costs. In other words, program development costs predict its production costs. The amount of time and detail required make this method more of a primary cost estimating technique than a crosscheck.

The build-up method is usually used in late development and the production program life cycle phases. This is where development and production cost actuals have accrued and the program configuration is stable (AFCAH, 2007). Since the concrete cost data used in this method captures system technology and configuration, the need for engineering support or SMEs is minimized. The build-up method also allows cost estimators, engineers, and auditors to determine exactly what was included and what program features may have been left out. It is tailored to each program and does not rely on other programs data. While this method can produce a detailed and accurate program estimate, it involves a great deal of time, effort, and resources. Sensitivity analysis is hard to conduct and different estimates must be built for each alternative when performing an analysis of alternatives (GAO, 2009). Errors at the lower levels of estimating can grow into significant errors at the program level and there is a possibility of excluding program elements entirely or double counting.

Expert Opinion (SME)

Cost estimators often rely on SMEs to define programmatic and technical features and apply analogies/factors, parametric models, or produce build-up estimates with the information. However, when other costing tools are inadequate or when data is non-existent, SMEs may be used to directly establish costs. As the name of the technique would suggest, expert opinion is inherently subjective. Expert opinions should be investigated for reasonableness and the potential for data to corroborate the opinion and document the source (GAO, 2009). Cost estimators must be able to elicit the SMEs knowledge and convey the information correctly into the estimate. Cost analysts must also be able to relate the given information to the SMEs area of expertise and not derive cost information from which they are not qualified to develop. Validating credentials is essential. In order to minimize the subjectivity and increase the defensibility of expert opinion, multiple SMEs can be consulted and/or the Delphi technique can be used. This technique gathers answers from SMEs anonymously to avoid a single person influencing the outcome of what would otherwise be a group environment (AFCAH, 2007).

Expert opinion has unique advantages and is best used when combined with other cost estimating techniques. It can be used when no data is available. Interviewing SMEs offers a valuable perspective and may identify program aspects that have not been considered. Implementing an expert's opinion into a program estimate often takes little time or effort and can be applied during any acquisition phase (GAO, 2009). It is easily blended with other cost estimation techniques and adds credibility. Some disadvantages of expert opinion include its lack of objectivity, accuracy, or the risk that a SME will dominate a group discussion and only one cost opinion will result. Expert opinion is best used as a starting point, crosscheck estimate, or when combined with another method and is generally not acceptable as a primary means to develop a stand-alone cost estimate (GAO, 2009).

Other Methods and Method Selection

The AFCAH and GAO Cost Estimating and Assessment Guide reference cost estimating methods beyond the aforementioned four primary techniques. While used less frequently than the four discussed, they are often used in combination and are useful for specific programs. They include catalog, manloading, industrial engineering standards, earned value at completion, cost extrapolation from actual costs, and learning curves. The cost estimating method chosen depends largely on program features, cost, life cycle phase, available data, level of detail required by the estimate, the time available to complete the estimate, and other potential factors. The AFCAH provides an illustration (Figure 1) to show how the primary cost estimating methods vary based on a program's life cycle phase and the level of detail required (AFCAH, 2007). The extrapolation from actuals method is referenced in the illustration and simply means actual data from earlier program stages is used to predict future costs. This would also include the use of learning curves.

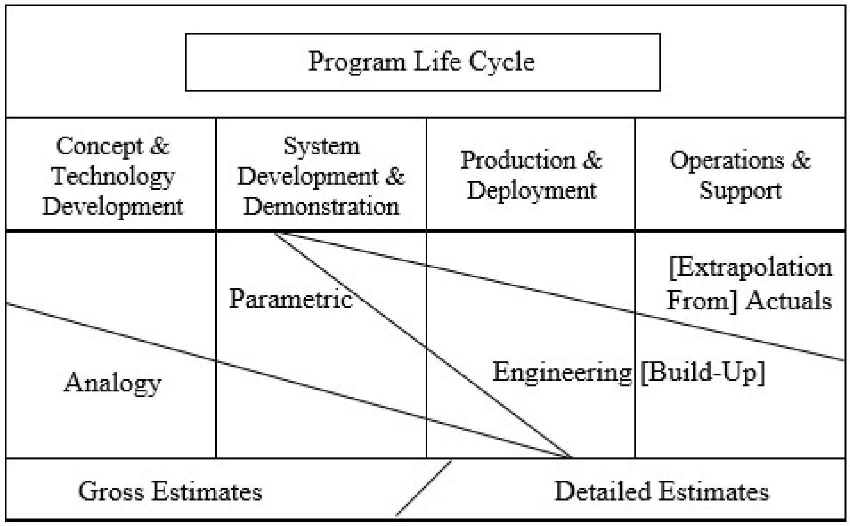


Figure 1. Selection of Methods (AFCAH, 2007)

Work Breakdown Structure (WBS)

The purpose of a WBS is to provide a consistent and visible framework for both the contract and the defense materiel items within a program. The WBS defines the product to be developed and relates the elements of work to be accomplished to the end product. MIL-STD-881D was developed to create uniformity in definition and a consistency of approach when developing a WBS (DoD, 2018). Having a uniform WBS creation method improves communication within the acquisition process and provides direction to the industry performing contract work. It allows for a consistent application of the WBS for all program requirements such as performance, cost, schedule, risk, budget, and contractual. DoD Instruction 5000.02 mandates the use of a WBS (DoD, 2018). Although guidance has evolved, incorporating lessons learned, the WBS concept remains unchanged over the years (DoD, 2005). This allows the creation of cost factors using data from 1953 to present.

The WBS has two fundamental and interrelated structures; the program WBS and the contract WBS. The program WBS is developed to specify program objectives, defining the program with hierarchical, product-oriented elements. These elements are logical summary levels that allow the government to assess technical accomplishments and measure cost and performance. It includes the contract WBS (DoD, 2018). The contract WBS is the government-approved WBS used for reporting and includes all contractor-responsible product deliverables. It also addresses the contractor's discretionary extension to lower levels while adhering to the contract Statement of Work (SOW) and Government direction (DoD, 2005). These two WBS structures facilitate the documentation of work performed as resources are allocated and expended and allow for the reporting of performance, cost, schedule, and technical data (DoD, 2005). This type of reporting allows the program to be continually monitored by the program manager and contractor to identify, coordinate, and implement adjustments to achieve desired program requirements (DoD, 2018).

The WBS can contain any level of detail, but the top three hierarchical levels are the minimum recommended for reporting purposes. The WBS can contain fourth and fifth levels of detail when necessary for the management of more complex programs (or those of high risk/cost/interest) (DoD, 2018). This research considers only the top two WBS levels. The first level is the defense materiel end item, such as an aircraft system, electronic/generic systems, missile/ordnance systems, sea systems, space systems, etc. Level two elements are the major elements subordinate to the end-item identified by level one. They are prime mission products and contain all hardware and software elements (DoD, 2018). Level two also aggregates system level services and includes “common elements” that are applicable to all major systems and subsystems. These common elements are integration, assembly test and checkout, systems engineering/program management (SE/PM), system test and evaluation (ST&E), training, data, peculiar support equipment (PSE), common support equipment (CSE), operational/site activation, industrial facilities, and initial spares and repair parts (DoD, 2018). Level three elements are subordinate to level two major elements and include hardware, software, and services. Some examples of level three elements are avionics or vehicle subsystems. Levels four, five, and below follow the same break-down process and are subordinate to level three. These lower levels are used to further define hardware, software, and services. Figure 2 shows the identification of WBS systems, major subsystems, and functional requirements. It visualizes the hierarchy established by the WBS levels.

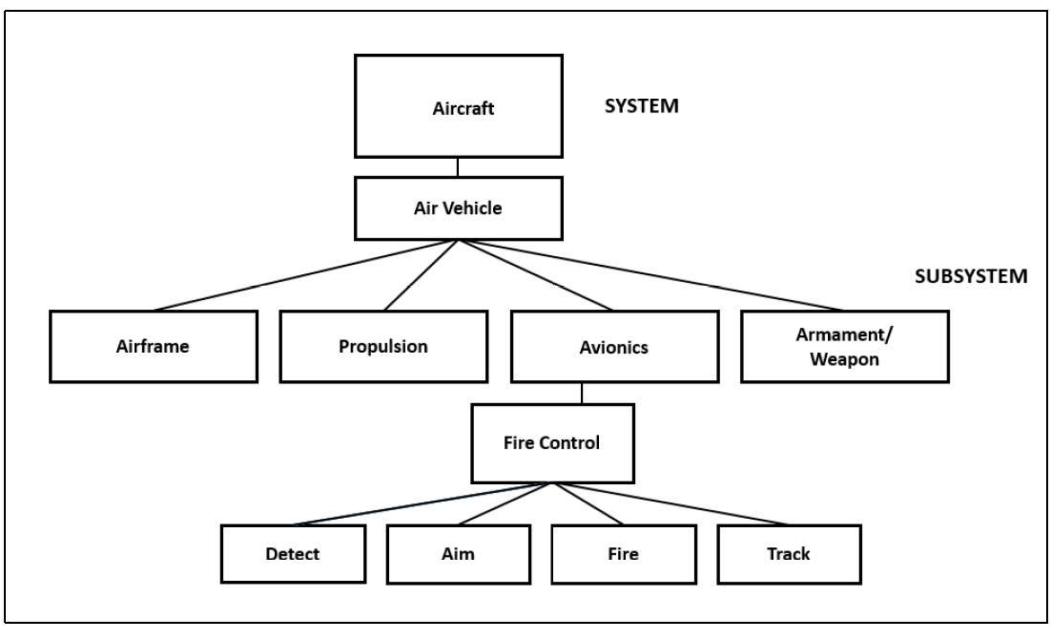


Figure 2. Identification of Major Subsystems and Functional Requirements (MIL-STD-881D, 2018)

Figure 3 depicts a generic WBS with varying levels of detail (down to four) for each system and subsystem.

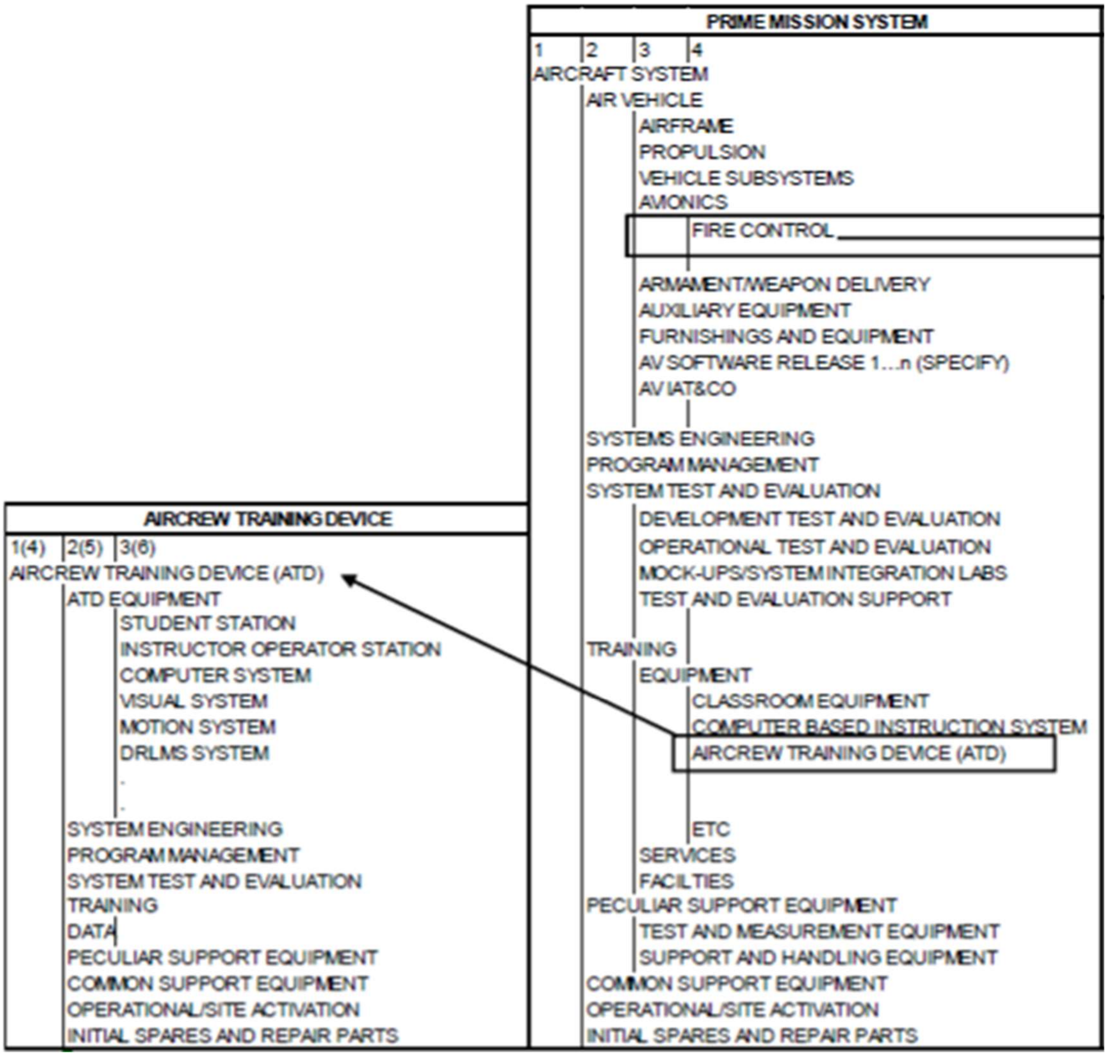


Figure 3. Work Breakdown Structure Matrix (contract WBS) (MIL-STD-881D, 2018)

The WBS offers many benefits over a program's lifecycle. It decomposes defense materiel items into their component parts clarifying the relationship of tasks to the end item. This allows for effective planning and management of the program (DoD, 2018). The uniform structure outlined in MIL-STD-881D provides a consistency and uniformity for contractors and government to communicate effectively both internally and with each other. It ensures contractors identify the item and task requirements and their relationship to the end product. The WBS also allows for the tracking and reporting of technical efforts, risks, resource allocation, expenditures, and cost/schedule/technical performance (DoD, 2005). It provides a common means to accomplish Earned Value Management reporting, the Integrated Master Plan (IMP), and the Integrated Master Schedule (IMS) (DoD, 2018). Producing a WBS that defines logical relationships within a WBS can be challenging and time consuming. Another challenge when developing a WBS is balancing the program definition aspects with the data-generating aspects. The need for data should not hinder the contractor's ability to deliver the program. While challenging to develop an effective WBS, the ability to accurately track cost, schedule, and performance factors is critical to have insight on the health of a program. Program managers must have this means to express confidence in their MDAPs to Government leaders and the American public. The WBS provides this utility along with the ability for personnel to relate previous MDAPs to current ones to predict costs, schedules, and other program factors.

Factors in Cost Estimating

Cost underestimation is a common occurrence in public projects. In their 2002 study, Flyvbjerg, Holm, and Buhl found that transportation infrastructure development projects are underestimated 9 out of 10 times. For rail projects in particular, actual costs were (on average) 45% higher than estimated. When pooling all project types (rail, tunnels, bridges, and roads) the average actual costs were 28% higher than estimated. Furthermore, they concluded that cost underestimation had not decreased over the previous 70 years. Cost misrepresentation was discussed as a possible reason for the lack of "learning" during this time. This is where costs are underestimated on purpose to receive initial funding before "discovering" new expenses that add to the project cost. This leads to the misallocation of resources and ultimately produces losers among those financing and using infrastructure (i.e. tax payers or investors) (Flyvbjerg, Holm, Buhl, 2002). Their study used a sample size of 258 projects totaling $90 billion throughout North America, Europe, and 10 other developing countries. It is the first known large sample study of its kind exploring cost underestimation in non-defense public works that was able to draw statistically valid conclusions due to the large sample. The study even controls for different geographic regions, historical periods, and project types.

While the study does not cover MDAPs specifically, this same problem is evident in Government contract awards. When developed using prior cost data, standard factors represent a potential solution to the issue of underestimation or misrepresentation. Had the data been available during these projects, factors could have been established as a crosscheck method to cost estimating and shown that historical cost estimates were underestimated 90% of the time. The factor may have uncovered any misrepresentation, errors, or systematic issues with estimating infrastructure project costs. While establishing factors can be a great benefit to combatting cost underestimation or misrepresentation, the data may not always exist to create reliable factors or assure decision makers of a not to exceed project cost. As shown by the Flyvbjerg et al. study, the utility of the analogy and factor method is not exclusive to the DoD and MDAPs. Given the historical data exists to create credible analogies, it can be used by either private or public entities.

Infrastructure projects are not the only types of projects that would benefit from improved estimation methods and tools. Other studies have linked poor cost performance to varying projects such as nuclear plants, environmental restoration projects, oil and gas platforms, and other construction projects (Baloi & Price, 2003). Baloi and Price (2003) state that more often than not contractors and practitioners rely on assumptions, rules of thumb, experience and intuition which cannot be fully defined or described rather than tools built of statistical decision models (2012). Cost estimation is the most important preliminary process in any construction project (Elfaki, Alatawi, & Abushandi, 2014). It is crucial to ensure the successful completion of a construction project and that success depends on the expertise of the human professional. Elfaki, Alatawi, and Abushandi (2014) focus on how artificial intelligence can take the human subjectivity element out of costing to improve accuracy. Their study recommends computerized management systems using cost estimating factors over what they call "constrained" human expertise. The common occurrence of inaccurate cost estimating shifts a focus to improving tools to add precision to financial decision support. Standard factors are one such tool.

The cost estimating practice is used in different capacities for different projects around the globe, but the common theme is its function in decision support (Greves & Joumier, 2003). Shortcomings of the misuse of historical cost data and estimation information are highlighted by consistent cost overruns no matter the project type or geographic location. There is a need within the cost community to define more objective and consistent criteria for more effective use of historical data (Rique & Serpell, 2012). This will allow cost estimators to arrive at more accurate and credible cost estimates. Estimating costs with accuracy allows decision makers to effectively organize project tasks and plan considerable economic and strategic program factors. This is vital in the software estimating world where cost and schedule control the success of projects and ultimately the organization and how long they are in business (Ali Abbas et al., 2012). In some cases, cost estimates are necessary when sufficient data doesn’t exist nor does time allow for a detailed cost estimate. These are normally done to meet decision maker needs who desire a ballpark reference, but results in estimates with no methodology or mathematical cost relationships that places more emphasis on the point estimate and not the data that was used to derive it (Akintoye & Fitzgerald, 2000). The analogy and factor technique is one way cost estimators can utilize historical data to generate reasonable and defensible estimates.

Standard factors make more effective and extensive analysis possible at a variety of levels to construct credible cost estimates, regardless of the constraints of program infancy or having limited information from which to draw cost data (Mislick & Nussbaum, 2015). Program offices can consider analyzing how standard factors are impacted by commodity types, contractor designation (prime or sub), and contract type. These basic program characteristics are the origin for data normalization, and can offer a more in-depth examination within the structure of the WBS. WBS elements act as qualitative context factors and support the effective understanding and use of historical data, which enhances the legitimacy of cost estimates that use the standard factor approach (Riquelme & Serpell, 2012). The Cost Assessment Data Enterprise (CADE) central database encompasses all commodity types, contractor designations, and contract types. This database enables analysis and data manipulation to create relevant and useful factors for each level two element of the WBS. With the WBS data in-hand, DoD cost analysts have the necessary MDAP cost data at their fingertips to create factors useful to their specific programs. These factors allow analysts to target specific analytical levels and conduct more accurate and defensible cost estimates for the DoD.

Previous Research on Factors in Cost Estimating

Adequate cost factor research does not yet exist to maximize the utility the available data can provide cost estimators. Limited scope factor studies within the Air Force began in the 1980's and were trailed by periodic studies with equally limited results. The first major USAF aircraft factor study was conducted in 1988, by Ms. Joan Blair and established cost element factors for MDAPs in the Engineering and Manufacturing Development (EMD) phase of the acquisition life cycle (Wren, 1998). Blair's study consisted of 24 programs and encompassed data solely for aircraft avionics support systems. The study proved useful for its specific purpose and maintained relevance for a 10-year period at the Aeronautical Systems Center (ASC), Wright Patterson Air Force Base (WPAFB) (Wren, 1998). However, it ultimately became outdated and unusable in newer Air Force programs.

In 1998, Mr. Don Wren used Blair's study as a starting point for his own factor study, adding an additional 20 aircraft avionic programs to the dataset, but was again for the sole use of ASC at WPAFB (Wren, 1998). The Blair and Wren studies represent a significant contribution towards a comprehensive standard factor reference for DoD cost analysts, but they were not applicable to any other programs outside of those based at WPAFB. Wren recognized that his study was unable to update the factors from the Blair's study due to non-availability of data and substantial program adjustments over the course of a decade (Wren, 1998). This made evident the need for a more exhaustive study and periodic updates to maintain the credibility and usefulness of the developed factors. In 2015, Mr. Jim Otte conducted a factor study to update and expand the outdated factors utilized by many Air Force Life Cycle Management (AFLCMC) cost analysts. His work was another step toward increasing the utility of standard factors for DoD analysts and even included previously omitted WBS elements for analysis and factor development (Otte, 2015). Despite the significant contribution of Otte's findings, many shortfalls remained, including the lack of additional commodity types besides aircraft, modification programs, subcontractor data, and contract type. In 2019, Mathew Markman conducted a large-scale research effort to establish cost factors relating to the EMD phase of the acquisition life cycle. The intent was to update AFLCMC factor tables, address the shortfalls of previous factor research, and create new factors for analyst use (Markman, Ritschel, White, & Valentine, 2019). 102 MDAP programs were analyzed, representing one of the largest DoD factor research efforts to date. The study took full advantage of the data within the CADE database, creating 443 unique factor values across numerous commodities, development types, contract types, and services for each WBS element (Markman, Ritschel, White, & Valentine, 2019).

The utility of factors extends beyond just acquisition programs, reaching across various Government agencies and functions to support more competent budgeting and execution of public money (Mislick & Nussbaum, 2015). With such prevalent DoD utilization of the factor method, a variety of different research exists within the DoD. The Naval Center for Cost Analysis (NCCA) conducts continuous research on cost estimation and publishes periodic discoveries to guide and strengthen cost analysis within the Navy

(NCCA, 2018). In addition to this research, the NCCA performs economic and business case analyses for the Department of the Navy, creating benchmarks from which factors can be derived for cost estimate use (NCCA, 2018). While all military branches adhere to DoD guidance, service-specific directives highlight differences in the application of certain requirements; such is the case with cost estimation. The Air Force’s use and research of the factor method extends beyond the acquisition field and is detailed in lower-tiered guidance like functional area Air Force Instructions (AFIs). This allows organizations within the Air Force to better predict costs in logistics, personnel, programming, and flying hour operations (Department of the Air Force, 2018). Additionally, the Air Force publishes dozens of factor tables for personnel to use for their specific functions; these tables are updated regularly and serve as a benchmark for cost estimation within the Air Force. Another example of cost factors’ role in the DoD is the publishing of Area Cost Factors (ACF). ACFs assist in the preparation and review of military construction, Army and Army Family Housing projects, and a variety of other facility related projects (PAX, 2018). These factors are the basis from which analysts accomplish broad levels of analysis and estimation and allow for estimators to add their own individual details to modify the factors and arrive at an accurate and defensible estimate (PAX, 2018).

Chapter Summary

This chapter discussed the cost estimator’s role in the DoD and the responsibility they have to ensure public funds are executed in the most efficient and effective manner. Accurately predicting costs of multi-million-dollar technically complex programs while considering evolving requirements and constrained budgets is challenging. Cost estimators employ four primary methods of cost estimating to accomplish such a task; each offering different benefits and drawbacks depending on program constraints, needs, timeline, and available data. Standard factors is one of the four common techniques described in the AFCAH and requires a basic understanding of the WBS. This chapter discussed the WBS structure and utility in detail. This research aims to enhance the cost estimator's toolkit, specifically with respect to standard factors in the production phase, for MDAPs. Thus, the utility of standard factors in cost estimating as well as an examination of previous standard factor research was conducted to explain the context of this study. The following chapter will explain the statistical methodology used to analyze the data for this research effort.

III. Methodology

Chapter Overview

This chapter discusses the data and methodology used to analyze it. The data source, collection process, and inclusion/exclusion criteria will be outlined. Necessary steps for normalization and factor calculations will be shown prior to the comparison analysis and statistical tests of the data. These topics will be discussed to facilitate greater understanding of the data and initial findings. This chapter also summarizes the key points of the methodological components of the study.

Data

The data consists of DD Form 1921s, Cost Data Summary Reports (CDRS) (referred to simply as 1921s). These documents contain the cost data necessary to establish standard production factors for Major Defense Acquisition Programs (MDAPs). Appendix A contains a redacted sample DD Form 1921. The 1921s in this study were gathered from the Defense Automated Cost Information Management System (DACIMS), within the Cost Assessment Data Enterprise (CADE) system and added to the existing Air Force Life Cycle Management Center (AFLCMC)/FZC cost library database. This research focuses only on the production life-cycle phase, which has not yet been statistically analyzed to create standard factors. Chapter II identified a gap in production factor research, as well as a lack of data in the current AFLCMC/FZC MDAP database.

Currently, CADE contains cost data for 202 MDAPs. 119 of these programs contain the production data necessary to perform factor analysis; each having a varying amount of 1921s for different production lots, program modifications, or different contracts. Aircraft and missiles were the top priority for this research in order to focus on Air Force relevance. Due to time constraints, only 1921s in .xlsx (excel) format were collected. CADE also has data in .xml (web based) format. These 1921s were not gathered since each cell of data would have to be manually transferred into excel. Space programs, in particular, had a lack of available data within CADE due to .xml formatting and mostly interim or initial 1921s. However, additional data (both .xlsx and .xml format) is still available within CADE that could be incorporated into a future research effort. Table 1 shows a list of CADE program exclusions.

Table 1. CADE Exclusions

Category	Number Removed	Remaining Programs
Available Programs in CADE		202
Programs without Production Data	83	119
Electronic Automated Software	23	96
Ordnance	5	91
Surface Vehicle	14	77
System of Systems	2	75
Final CADE Programs for Analysis		**75**

Only final 1921s were used for data collection; programs containing only initial or interim 1921s were excluded. This is because final 1921s contain the complete and accurate cost history of a program/subprogram. In total, 145 MDAPs were captured in the dataset; 75 from CADE added to the existing 70 in the AFLCMC database. Appendix B contains a list of the MDAP mission design series and the associated number of 1921s that contributed to the final dataset—a total of 1,033 DD Form 1921s (each representing a data point) ranging from 1953 to 2018. The total Prime Mission Equipment (PME) value of the data is $662.7M with an average PME value of $642.5K. Table 2 provides an overview of the final dataset characteristics for this research.

Table 2. Dataset Characteristics

Category	Total	% of Data
1921s	1,033	100%
Commodity Type		
Aircraft	650	62.9%
Missile	357	34.6%
UAV	22	2.1%
Space	2	0.2%
Ship	2	0.2%
Contract Type		
FFP	313	30.3%
FPI	104	10.1%
FPAF	22	2.1%
CPIF	33	3.2%
MC	53	5.1%
None Listed	508	49.2%
Contractor Type		
Prime	969	93.8%
Subcontractor	64	6.2%
Service		
Air Force	344	33.3%
Army	172	16.7%
Navy (Includes Marine Corps)	517	50.0%

Data Collection

Data gathering required a manual process. Cost data from individual 1921s were pulled from CADE and entered into AFLCMC's existing central database file (referred to as their cost library). Designators were established for the data to allow for analysis. These include WBS element, branch of service, commodity type, whether a prime or subcontractor, and contract type. The cost data was normalized into base year (BY) 2019 to allow for the analysis of programs that occurred in different years. In order to normalize the data, the "report as of" date on the 1921 was logged in the database and cross referenced with the contract period of performance (PoP) to establish an escalation year (the midpoint of the PoP). This allowed calculations for each program's cost figures. Where a 1921 had no PoP annotated, a deduction of two years from the "report as of" date was recorded as the escalation year. The deduction of two years was based upon an AFLCMC study of 294 programs that revealed an average time of five years for an MDAP to progress from Milestone B to Initial Operating Capability. The midpoint value of that time span was then rounded down to two years. Escalation to BY 2019 was accomplished using the Producer Price Index (PPI) in accordance with AFLCMC best practices.

Factor Calculation

The standard production cost factors calculated in this research are a ratio of the level II WBS elements to a base cost. The base cost is the program's PME value. PME is used because it does not include contractor fees or other miscellaneous expenses (general and administrative (G&A), undistributed budget, management reserve, facilities capital cost of money (FCCM)). An example of this ratio is shown in Table 3. It depicts the cost of System Engineering/Program Management (SE/PM) being divided by the program's PME value and the resulting factor.

Table 3. Example Cost Factor Calculation

Prime Mission Equipment (PME) Value	\$500K
System Engineering/Program Management (SEPM)	\$150K
Cost Factor = 150 ÷ 500 = .3 or 30%	

Cost factors can be calculated for the level II WBS elements, contractor fees, miscellaneous expenses, and other unique categories. Additionally, each level II WBS element can be analyzed in groups (e.g. similar programs) to create aggregate values that represent an average which can result in more accurate estimates given the circumstances warrant such use. These groupings allow for analysis at commodity levels (e.g. fixed wing aircraft) or a specified contractor or their role (prime or sub). Many other combinations of categories exist to create the most useful factor given a specific scenario. Table 4 illustrates how a grouping of like programs is used to calculate an average cost factor. Using the data in this way reduces issues that may result from an estimate based on a single data point.

Table 4. Example Composite Cost Factor Calculation

	PME	SEPM	Percentage
Program 1	300K	80K	0.27
Program 2	400K	45K	0.11
Program 3	275K	60K	0.22
Program 4	180K	35K	0.19
TOTAL	**1,155K**	**220K**	**0.19**
Cost Factor = 220 ÷ 1,155 = .19 or 19%			

Comparison Analysis

Once the factors were established for each program, the mean, median, and standard deviation values for the various program groupings were calculated. In addition, interquartile ranges were calculated to examine variability among factors. This allowed for descriptive analysis prior to statistical testing and analysis. This also provided a basis from which the programs were grouped and analyzed to compare differences in total cost. While many comparisons can be performed using this dataset, this study performs four major types: service, commodity type, contractor designation, and contract type. Table 5 lists the categories and respective sub-categories compared in this research.

Table 5. Categories for Comparison Analysis

Categories			
Service	**Commodity Type**	**Contractor Designation**	**Contract Type**
Air Force	Aircraft	Prime	CPIF (Cost Plus Incentive Fee)
Army	Missile	Sub	FFP (Firm Fixed Price)
Navy (includes Marine Corps)	Ship		FPI (Fixed Price Incentive)
	Space		FPAF (Fixed Price Award Fee)
	UAV		MC (Multiple Contract types)

For each categorical comparison, the hypothesis test in Equation 1 will be used:

Equation 1

$$H_o: \Delta_x = \Delta_y$$

$$H_a: \Delta_x \neq \Delta_y$$

Where *x* and *y* represent different sub-categories of a given category type for each comparison. For example, when comparing commodity type, *x* and *y* could be defined as Aircraft and Missile (or two other commodity types) for each individual test. If there is a failure to reject the null, we can conclude that the medians of the sub-categories are not different. If the null is rejected, then a difference between the medians exists.

Statistical Tests

Several statistical tests were used to perform hypothesis testing, including the Shapiro-Wilk test and the Kruskal-Wallis test. The Steel-Dwass test was performed as a multiple comparison test. The Shapiro-Wilk test was used to determine non-normality, leading to the rejection of the null hypothesis that the data within each WBS element's dataset was normally distributed. Due to these findings, non-parametric testing was employed to indicate how the sub-categories related to each other. The Kruskal-Wallis test compared medians to determine if statistically significant differences existed between the sub-category data. Finally, the Steel-Dwass multiple comparison test identified which medians were statistically different for each instance of sub-category comparison.

Chapter Summary

This chapter outlined the methodology to establishing standard factors for MDAPs within the production life cycle phase. The overview of the data, its source, and collection process offers insight into how the database compiled for this research is an effective means to develop factors. It also shows how the database can be maintained and used for future studies should the data continue to be available within CADE for research. The comparison categories and sub-categories were emphasized to highlight areas of interest this research covers. The chapter also detailed the steps necessary to create individual and composite (groupings) cost factors. Finally, the comparative analysis process presented the statistical tests used to identify trends and analyze the data. The following chapter will provide the results and analysis.

IV. Analysis and Results

Chapter Overview

Chapter IV presents the results from Chapter III's outlined methodology divided into five sections. The first section is an overview of the dataset. The second section calculates the descriptive statistics by Work Breakdowns Structure (WBS) level II elements and establishes values for mean, median, interquartile range (IQR), and standard deviation. Section three presents a detailed set of statistical test results and findings for each WBS category. The fourth section examines the results from four subsets of the dataset: commodity type, contract type, contractor designation, and branch of service. Finally, a scenario is explored for purpose specific analysis showing how more detailed data can result in a more accurate production cost factor.

Dataset Characteristics

Data utilized in this research for statistical analysis was gathered from the Defense Automated Cost Information Management System (DACIMS), within the Cost Assessment Data Enterprise (CADE) system as well as the Air Force Life Cycle Management Center (AFLCMC)/FZC cost library. CADE contains cost data for 202 MDAPs. 119 of those programs contain the production data necessary to perform factor analysis; each having a varying amount of Cost Data Summary Reports (CDSRs) or 1921s for different production lots, program modifications, or different contracts. Aircraft and Missiles were the top priority for this research in order to focus on Air Force relevance. Table 6 shows a list of CADE program exclusions.

Table 6. CADE Exclusions

Category	Number Removed	Remaining Programs
Available Programs in CADE		202
Programs without Production Data	83	119
Electronic Automated Software	23	96
Ordnance	5	91
Surface Vehicle	14	77
System of Systems	2	75
Final CADE Programs for Analysis		**75**

Only final 1921s were used as data points as they contain the complete cost history of a program/subprogram; thus, initial and interim 1921s were excluded. 145 MDAPs were captured in the dataset; 75 from CADE added to the existing 70 in the AFLCMC database. Appendix B contains a list of the MDAP mission design series and the associated number of 1921s that contributed to the final dataset—in total, 1,033 DD Form 1921s (each representing a data point). Table 7 displays the dataset characteristics.

Table 7. Dataset Characteristics

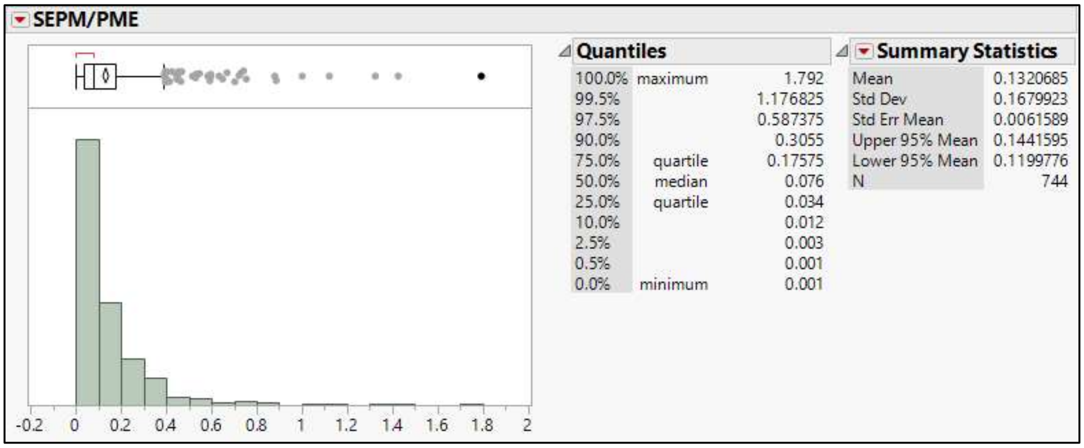
Category	Total	% of Data
1921s	1,033	100%
Commodity Type		
Aircraft	650	62.9%
Missile	357	34.6%
UAV	22	2.1%
Space	2	0.2%
Ship	2	0.2%
Contract Type		
FFP	313	30.3%
FPI	104	10.1%
FPAF	22	2.1%
CPIF	33	3.2%
MC	53	5.1%
None Listed	508	49.2%
Contractor Type		
Prime	969	93.8%
Subcontractor	64	6.2%
Service		
Air Force	344	33.3%
Army	172	16.7%
Navy (Includes Marine Corps)	517	50.0%

Descriptive Statistics

The cost factors in this research are the ratio (percentage) of the individual level II Work Breakdown Structure (WBS) element's cost to the Prime Mission Equipment (base) cost. The PME is considered the base cost as it excludes the contractor's fee or miscellaneous expenses; including general and administrative (G&A), undistributed budget, management reserve, and facilities capital cost of money (FCCM). As shown in Chapter III, an example cost factor is the dollar value of System Engineering/Program Management (SE/PM) divided by a program's PME dollar value. Upon calculating individual level II WBS element factors, specific ones can be analyzed in groupings. This can prove useful when formulating estimates as groupings allow for analysis at numerous levels, such as fixed wing aircraft, engines, a specified contractor, or whether or not they are a prime or sub, and many more. Averaged cost factors may be accurate as they mitigate the skewness that can result from single data point predictions.

SEPM

The Systems Engineering and Program Management (SEPM) WBS element had the most available data of any level II WBS element. 749 of the 1,033 (72.5%) data points contained SEPM values greater than zero. SEPM values ranged from 0.1% to 1,066.8% of Prime Mission Equipment (PME) value. The extreme values may represent potential reporting flaws or other issues. In order to establish exclusion criteria, the distribution of all SEPM values was analyzed using JMP software. This resulted in values above 197.1% of PME being removed from the dataset for the SEPM analysis. The excluded values represented only 0.7% of the SEPM dataset and were more than three standard deviations from the mean. These five data points were all under the missile commodity and part of sub programs with a total PME of less than $30.1K. Figure 4 shows the SEPM distribution after exclusions and provides the descriptive statistics. The calculated coefficient of variation (CV) is 127.2%. We can compare this CV to other WBS element CVs to understand how the variance differs between the elements.



Quantiles

100.0%	maximum	1.792
99.5%		1.176825
97.5%		0.587375
90.0%		0.3055
75.0%	quartile	0.17575
50.0%	median	0.076
25.0%	quartile	0.034
10.0%		0.012
2.5%		0.003
0.5%		0.001
0.0%	minimum	0.001

Summary Statistics

Mean	0.1320685
Std Dev	0.1679923
Std Err Mean	0.0061589
Upper 95% Mean	0.1441595
Lower 95% Mean	0.1199776
N	744

Figure 4. SEPM Descriptive Statistics

Distributions and descriptive statistics for individual level II WBS elements are broken out by commodity type, contract type, contractor designation, and service and will be discussed in the next section of this chapter. Table 8 shows the SEPM distribution and descriptive statistics by category. Other WBS elements will have the same summary table. The detailed analysis displayed in Table 8 for the remaining WBS elements in Chapter IV (ST&E, Training, Data, PSE, CSE, Site Activation, Other, and Spares) is found in Appendix C.

Table 8. SEPM Summary Table

SEPM Descriptive Statistics									
	Mean	Std Dev	CV	N	Max	75%	Median	25%	Min
Commodity Type									
Aircraft	0.0916	0.1135	1.2391	427	0.742	0.115	0.054	0.024	0.001
Missile	0.1833	0.2094	1.1424	291	1.792	0.245	0.132	0.05	0.001
UAV	0.1678	0.07685	0.4580	22	0.345	0.2245	0.1465	0.115	0.012
Space	0.601	0.5657	0.9413	2	1.001	1.001	0.601	0.201	0.201
Ship	0.441	0.4426	1.0036	2	0.754	0.754	0.441	0.128	0.128
Contract Type									
FFP	0.0891	0.1135	1.2738	237	0.729	0.1145	0.05	0.0205	0.001
FPI	0.1011	0.0949	0.9387	75	0.399	0.138	0.069	0.027	0.005
FPAF	0.046	0.0486	1.0565	21	0.23	0.059	0.027	0.022	0.009
CPIF	0.2401	0.245	1.0204	29	1.001	0.336	0.155	0.0595	0.005
MC	0.0648	0.0601	0.9275	48	0.265	0.09425	0.0515	0.0158	0.002
No Value	0.1752	0.2015	1.1501	334	1.792	0.2403	0.1205	0.05	0.001
Contractor Type									
Prime	0.1297	0.1691	1.3038	686	1.792	0.174	0.0735	0.032	0.001
Subcontractor	0.1604	0.1522	0.9489	58	0.669	0.2358	0.1065	0.047	0.024
Service									
Air Force	0.1084	0.1297	1.1965	262	1.001	0.143	0.0635	0.0248	0.001
Army	0.189	0.2188	1.1577	155	1.792	0.263	0.143	0.048	0.012
Navy (Inc Marines)	0.1241	0.1618	1.3038	327	1.425	0.154	0.07	0.031	0.001

ST&E

System Test & Evaluation (ST&E) contained 275 data points; 26.6% of the 1921s. The values ranged from 0.1% to 221.8% of PME, again indicating potential reporting issues in the extreme values. ST&E values above 70.8% of PME were excluded. These four data points represented 1.5% of the ST&E database and all fell under the missile commodity. PME values for the exclusions ranged from $2K to $30K, indicating smaller contracts. Figure 5 shows the ST&E distribution and its descriptive statistics. The ST&E CV is higher than SEPM at 182.1%. The descriptive statistics for ST&E by commodity type, contract type, contractor designation, and service are located in Appendix C.

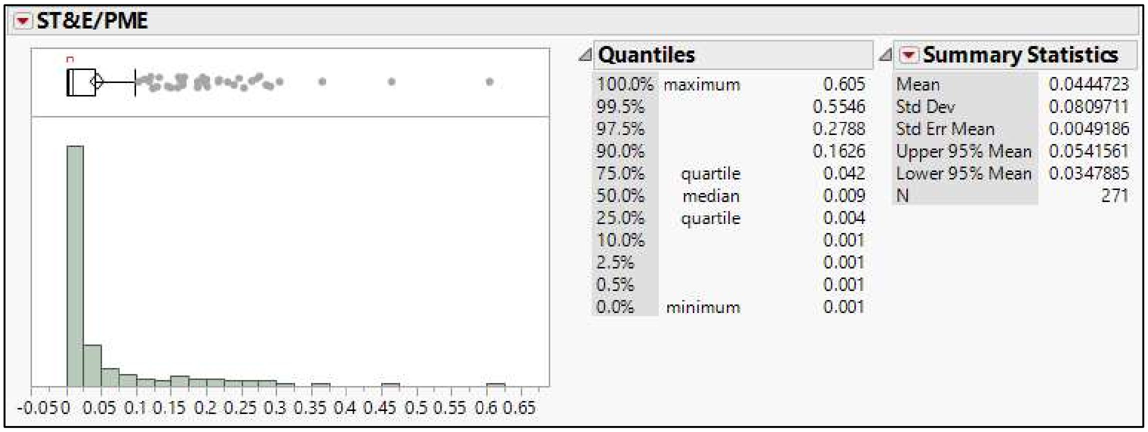


Figure 5. ST&E Descriptive Statistics

Training

The Training WBS element had 242 data points. Three data points were removed representing 1.2% of the Training data; all missile commodity. These points were more than three standard deviations away from the mean and had PME values of under $1.3K. Figure 6 shows the distribution and descriptive statistics for the 239 values analyzed for the Training WBS element. The calculated Training CV is lower than ST&E at 179%. The descriptive statistics for Training by commodity type, contract type, contractor designation, and service are located in Appendix C.

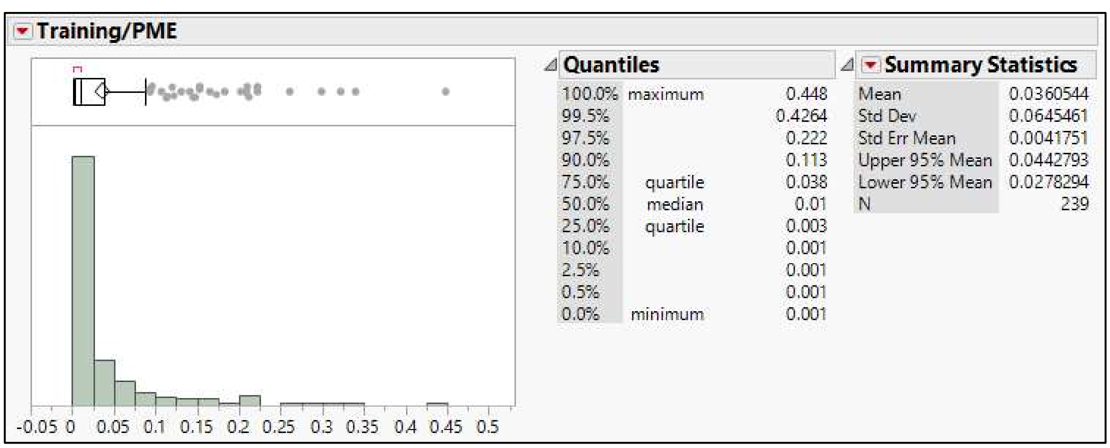
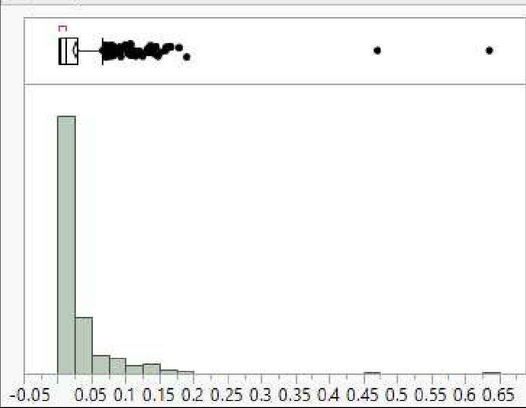


Figure 6. Training Descriptive Statistics

Data

The Data WBS element contained 536 values, or 51.9% of the total available data. No data points were excluded from Data. Four points lie outside three standard deviations, but there were no other criteria met for exclusion such as low dollar values or irrelevant contract types. Figure 7 shows the descriptive statistics for the Data WBS element. The Data CV is calculated at 176.9%. The descriptive statistics for Data by commodity type, contract type, contractor designation, and service are located in Appendix C.



Quantiles

100.0%	maximum	0.636
99.5%		0.278515
97.5%		0.141
90.0%		0.0736
75.0%	quartile	0.02875
50.0%	median	0.0115
25.0%	quartile	0.004
10.0%		0.002
2.5%		0.001
0.5%		0.001
0.0%	minimum	0.001

Summary Statistics

Mean	0.0264944
Std Dev	0.0468711
Std Err Mean	0.0020245
Upper 95% Mean	0.0304714
Lower 95% Mean	0.0225174
N	536

Figure 7. Data Descriptive Statistics

PSE

Peculiar Support Equipment (PSE) contained 361 data points or 34.9% of the gathered data. Values ranged from 0.1% to 6,131%. The 6,131% value (from the missile commodity) was excluded as it was well above other values and the document had a PME value of just $123. After excluding this value, 11 more values remained outside three standard deviations of the mean. None of these values were excluded. Figure 8 shows the descriptive statistics for PSE. The PSE calculated CV is 169.4%. The descriptive statistics for PSE by commodity type, contract type, contractor designation, and service are located in Appendix C.

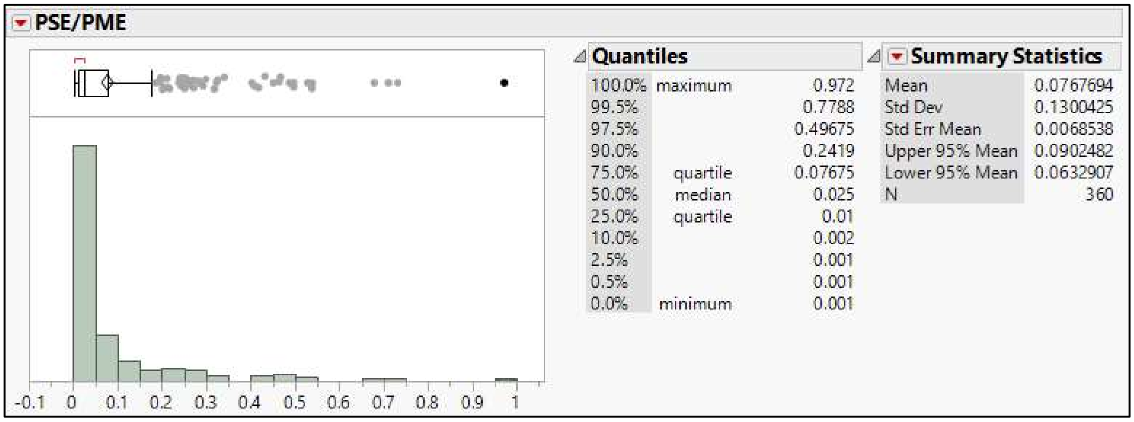


Figure 8. PSE Descriptive Statistics

CSE

Common Support Equipment (CSE) had significantly less data points than other WBS elements at 68 (6.6% of database). No values were excluded from the CSE analysis. The descriptive statistics for the CSE WBS element are shown in Figure 9. The calculated CV is 157.1%. The descriptive statistics for CSE by commodity type, contract type, contractor designation, and service are located in Appendix C.

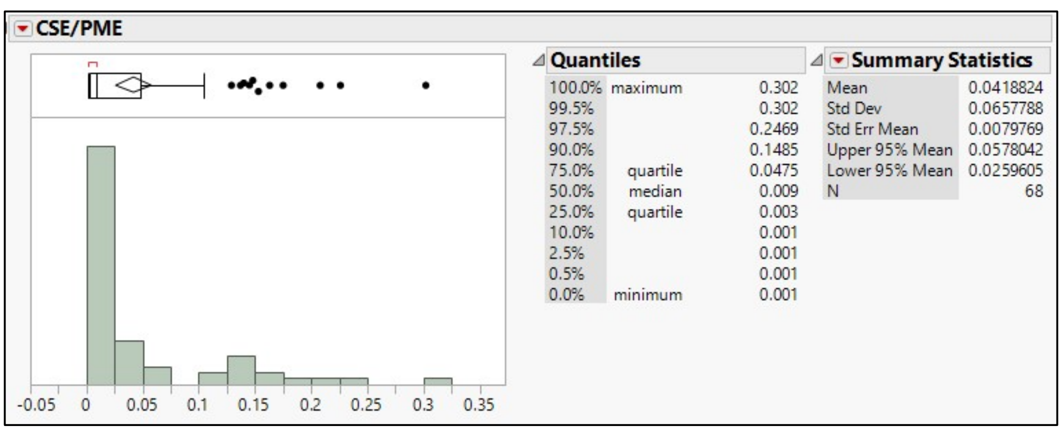


Figure 9. CSE Descriptive Statistics

Site Activation

Site Activation displayed limited data similar to CSE. Only 58 data points, or 5.6% of the total database, was able to be used for analysis. One extreme value beyond three standard deviations was excluded as the dollar amount was low with a PME value of $455. The Site Activation descriptive statistics are summarized in Figure 10. The CV is calculated at 143.7%. The descriptive statistics for Site Activation by commodity type, contract type, contractor designation, and service are located in Appendix C.

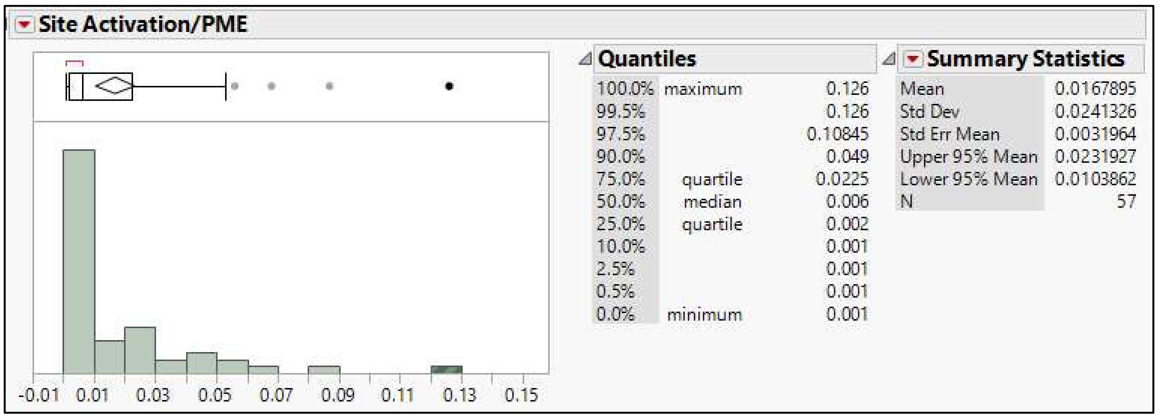


Figure 10. Site Activation Descriptive Statistics

Other

The Other WBS element is not a formal WBS element as outlined in MIL-STD-881D. It is primarily used to account for items not included within another WBS element, but should still be defined within the WBS. Therefore, this analysis discusses descriptive statistics only and does not include the "Other" element in future sections of the analysis. This element was created to provide flexibility within the systems WBS for elements that have not been identified within the other elements. 719 values (69.6%) existed within the database for this element. In order to remove documents potentially accounting for more data under the "Other" category than should have been, all values over three standard deviations away from the mean were removed. This resulted in 11 values being removed, or 1.5% of the Other database. Figure 11 displays the descriptive statistics and distribution for the Other WBS element. The calculated CV is 161.6%. The descriptive statistics for Other by commodity type, contract type, contractor designation, and service are located in Appendix C.

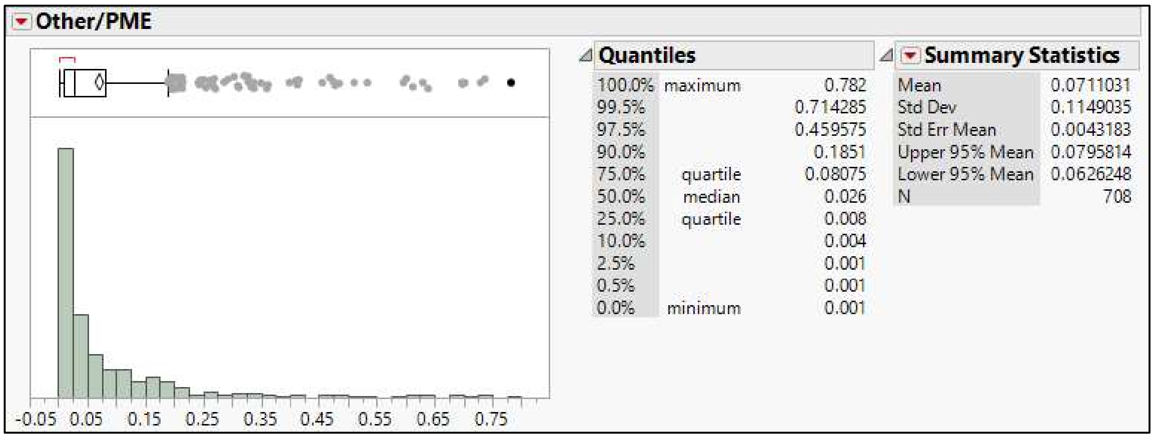


Figure 11. Other Descriptive Statistics

Spares

The Spares WBS element contained 322 values. The descriptive statistics and distribution for Spares is shown in Figure 12. Four values were more than three standard deviations away from the mean. An additional three values were greater than 50% factors (Spares/PME). All seven data points were removed to prevent documents from being included whose main purpose was to procure spares. The calculated CV is 130.9%. The descriptive statistics for Spares by commodity type, contract type, contractor designation, and service are located in Appendix C.

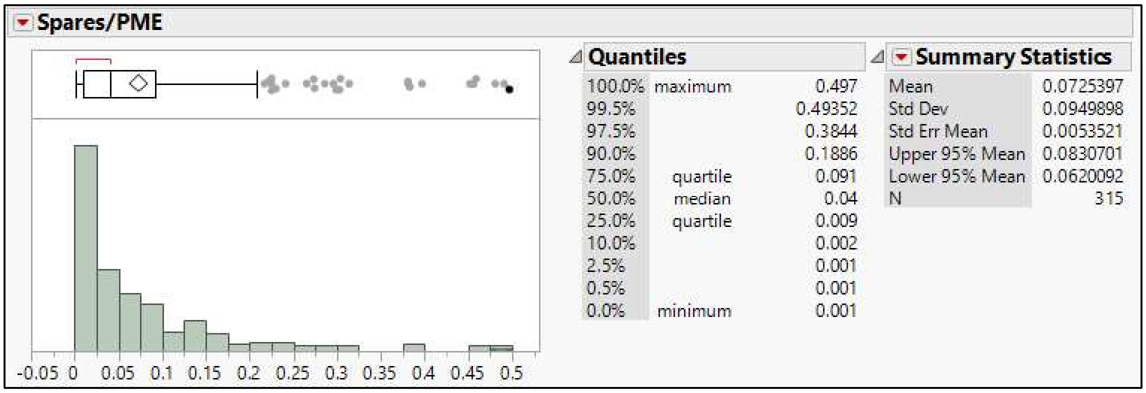


Figure 12. Spares Descriptive Statistics

Results by Category

This section first presents the Shapiro-Wilk test findings for each level II WBS element. The null hypothesis for the Shapiro-Wilk test assumes normality of the data for each WBS dataset described in the previous section. After determining non-normality for each dataset, non-parametric test results are discussed; in particular the Kruskal-Wallis test. The Kruskal-Wallis test is the non-parametric alternative to the one-way analysis of variance (ANOVA). Additionally, since histograms of the data (and subsets of the data) reveal a consistent right-skewed distribution shape, the Kruskal-Wallis test can be used to test the medians of data sets against each other for statistical differences among categories. The null hypothesis for the Kruskal-Wallis test states all group medians being tested are equal—i.e. the samples came from populations with the same distribution. An alpha of 0.05 was utilized for all statistical testing. The categories examined were commodity type, contract type, contractor type, and service.

Shapiro-Wilk Test Results

The Shapiro-Wilk test for normality found non-normality for each WBS dataset. This finding corroborates with visual histogram analysis of each distribution shape.

Figure 13 shows the results for SEPM. Since the P-value of <.0001 is less than the .05 alpha, the null hypothesis is rejected and we can conclude the data for the SEPM WBS element was not normally distributed.

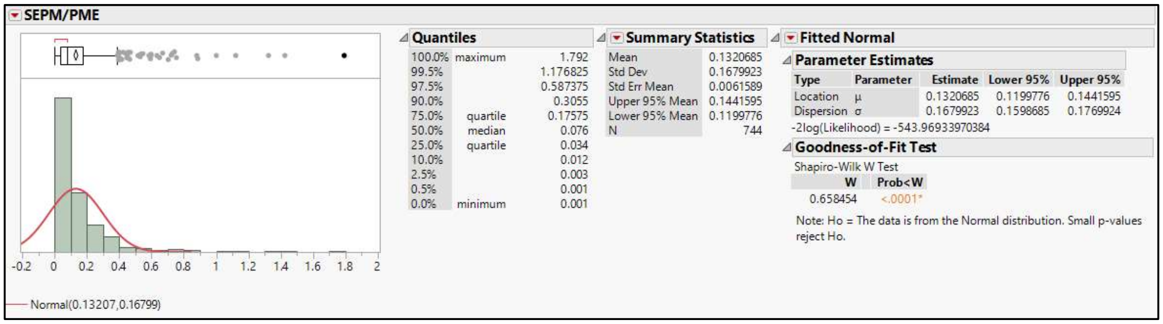


Figure 13. SEPM Shapiro-Wilk Test

The remaining WBS elements share the SEPM Shapiro-Wilk test results. This necessitated non-parametric testing when using the WBS element data for the commodity type, contract type, contractor type, and service categories. The Shapiro-Wilk test results for each remaining WBS element can be found in Appendix D.

Commodity Type

Performing the Kruskal-Wallis test exposed statistically significant differences between the level II WBS element median values within the commodity category. These differences were identified in the SEPM, Data, and Spares groups. Table 9 shows the Kruskal-Wallis test for each WBS element by commodity, the associated P-values and whether or not the null hypothesis is rejected when compared to an alpha (α) of .05.

Table 9. Kruskal-Wallis Results (Commodity Type)

WBS Element	Chi-Square	P-value	Null Hypothesis (.05 α)	N
SEPM	98.7633	<0.0001	**Reject**	744
ST&E	2.8587	0.4139	Fail to Reject	271
Training	2.9523	0.399	Fail to Reject	239
Data	37.1399	<0.0001	**Reject**	536
PSE	2.913	0.2309	Fail to Reject	360
CSE	1.1554	0.5612	Fail to Reject	68
Site Activation	0.5211	0.4791	Fail to Reject	57
Spares	14.8869	0.0006	**Reject**	315

Upon the discovery of statistically significant differences, the Steel-Dwass multiple comparison test was performed to identify which commodities exhibited them. Table 10 shows the significant differences that occurred for each WBS element by commodity type. The aircraft, missile, and UAV commodity types displayed statistically significant differences, while space and ship showed none. This could be because of the low N value of both the space and ship commodities; both with two data points each out of the total 1,033 data points. The test was rerun excluding space and ship commodities, but the results stayed the same. The differences in table 10 show that analysts should consider filtering the data to include only that commodity type when creating factors for SEPM, Data, and Spares. The JMP output for each test can be found in Appendix E.

Table 10. Commodity Differences

	Aircraft	Missile	UAV	Space	Ship
SEPM	2	1	1	0	0
ST&E	0	0	0	0	0
Training	0	0	0	0	0
Data	2	2	2	0	0
PSE	0	0	0	0	0
CSE	0	0	0	0	0
Site Activation	0	0	0	0	0
Spares	1	1	2	0	0

Contract Type

The Kruskal-Wallis test for the contract type category discovered one more statistical difference than the commodity type category. In addition to the SEPM, Data, and Spares WBS elements, the PSE category also rejected the null hypothesis as shown in Table 11.

Table 11. Kruskal-Wallis for Contract Type

WBS Element	Chi-Square	P-value	Null Hypothesis (.05 α)	N
SEPM	96.7487	<0.0001	**Reject**	744
ST&E	8.3239	0.1393	Fail to Reject	271
Training	1.5591	0.8161	Fail to Reject	239
Data	29.1159	<0.0001	**Reject**	536
PSE	28.2742	<0.0001	**Reject**	360
CSE	6.4868	0.1656	Fail to Reject	68
Site Activation	1.8907	0.864	Fail to Reject	57
Spares	27.3127	<0.0001	**Reject**	315

Conducting the Steel-Dwass multiple comparison test across contract types revealed significant differences and are broken down by contract type for each element in Table 12. SEPM (16) and PSE (12) record the most interactions with a combined 71.4% of total differences. Contract types did not display a huge difference in category differences ranging from 5-9 for each contract type. One limitation with the data on this test is that contracts with no data listed (no value) accounted for 49.2% of the data. Running this test including that category makes the results difficult to interpret. However, in the SEPM category, the No Value contracts showed statistical differences with FFP, FPI, FPAF, and MC contracts. This indicates that perhaps the contracts with no data were most similar to CPIF type contracts. These results show analysts may be able to use contract type (if known) to produce more accurate production factors in their cost estimates. The Steel-Dwass pairing results can be found in Appendix E.

Table 12. Contract Type Differences

	FFP	FPI	FPAF	CPIF	MC	No Value
SEPM	2	2	2	4	2	4
ST&E	0	0	0	0	0	0
Training	0	0	0	0	0	0
Data	2	2	0	0	2	2
PSE	1	2	3	2	2	2
CSE	0	0	0	0	0	0
Site Activation	0	0	0	0	0	0
Spares	2	1	0	2	0	1

Contract types can be more broadly referred to as fixed or cost type contracts. Thus, an analysis of these bucketed type contracts was performed to see if there were any differences in the results. The data set for each WBS element remains the same with the same exclusions previously mentioned. In addition, multiple contract (MC) types and data points with no value were excluded from this analysis in order to capture a true fixed vs cost comparison. This resulted in lower N values for each data set and, consequently, higher P-values in each test. Both the data and PSE categories moved from a rejection of the null to a failure to reject. The results of this fixed vs cost comparison are limited by the number of cost contracts in the dataset. A more robust dataset with a greater amount of contract type data could have provided more interesting results. The summary of original results compared to cost vs fixed types only is shown in table 13. The differences are bolded within the table. The descriptive statistics of the SEPM and Spares WBS elements (the only two showing statistically different median values) can be found in

Appendix E. On both occasions the cost type contracts have higher mean values (SEPM .2401 vs .0891, Spares .1269 vs .0713)

Table 13. Contract Type Analysis vs Fixed/Cost Analysis

	Original Results (Contract Type)				Fixed vs Cost Results			
WBS Element	**Chi-Square**	**P-value**	**Null Hypothesis (.05 α)**	**N**	**Chi-Square**	**P-value**	**Null Hypothesis (.05 α)**	**N**
SEPM	96.7487	<0.0001	Reject	744	19.1567	<0.0001	Reject	362
ST&E	8.3239	0.1393	Fail to Reject	271	1.1308	0.2902	Fail to Reject	112
Training	1.5591	0.8161	Fail to Reject	239	0.3438	0.5577	Fail to Reject	124
Data	29.1159	<0.0001	Reject	536	0.0822	0.7614	**Fail to Reject**	271
PSE	28.2742	<0.0001	Reject	360	1.5205	0.2186	**Fail to Reject**	197
CSE	6.4868	0.1656	Fail to Reject	68	0.0146	0.9038	Fail to Reject	11
Site Activation	1.8907	0.864	Fail to Reject	57	0.0533	0.8174	Fail to Reject	28
Spares	27.3127	<0.0001	Reject	315	8.6771	0.0032	Reject	175

Contractor Type

The Kruskal-Wallis test by contractor type showed just three differences between WBS elements. Only the elements SEPM, Training, and Data returned p-values less than the 0.05 alpha and led to a null hypothesis rejection. Table 14 summarizes the Kruskal-Wallis test results for contractor type.

Table 14. Kruskal-Wallis for Contractor Type

WBS Element	Chi-Square	P-value	Null Hypothesis (.05 α)	N
SEPM	6.1167	0.0134	**Reject**	744
ST&E	3.3601	0.0668	Fail to Reject	271
Training	7.899	0.0049	**Reject**	239
Data	19.3787	<0.0001	**Reject**	536
PSE	0.3153	0.5744	Fail to Reject	360
CSE	0.9668	0.3255	Fail to Reject	68
Site Activation	1.9396	0.1637	Fail to Reject	57
Spares	3.5588	0.0592	Fail to Reject	315

As shown, SEPM, Training, and Data required further analysis through the Steel-Dwass test. Only two statistical differences can be shown for each contractor type category; the only two designations being “prime” and “subcontractor.” Table 15 shows the significant interactions found by the Steel-Dwass multiple comparison test by contractor type. In the case of SEPM, subcontractors had higher factor values (.1604 vs .1297).

Table 15. Contractor Type Differences

	Prime	Sub
SEPM	1	1
ST&E	0	0
Training	1	1
Data	1	1
PSE	0	0
CSE	0	0
Site Activation	0	0
Spares	0	0

Estimates based on both prime and subcontractor data for the WBS elements that showed no statistical differences can incorporate a larger dataset (one including both prime and subcontractor data) and remain relatively accurate. Analysts must filter by contractor type for the SEPM, Training, and Data categories in order to avoid basing estimates on statistically different groups of values.

Service

The Kruskal-Wallis test results for the Service category revealed the most amount (five) of statistically different median values for the WBS elements. These included SEPM, Data, PSE, CSE, and Spares. Table 16 illustrates the p-values and resulting null hypothesis result for each element.

Table 16. Kruskal-Wallis for Service

WBS Element	Chi-Square	P-value	Null Hypothesis (.05 α)	N
SEPM	33.5998	<0.0001	**Reject**	744
ST&E	0.3816	0.8263	Fail to Reject	271
Training	1.1936	0.5506	Fail to Reject	239
Data	77.6738	<0.0001	**Reject**	536
PSE	16.9475	0.0002	**Reject**	360
CSE	18.422	<0.0001	**Reject**	68
Site Activation	0.0709	0.79	Fail to Reject	57
Spares	18.6375	<0.0001	**Reject**	315

The Steel-Dwass test identified a total of 18 significant interactions. Table 17 shows how many interactions each service had by WBS element. Statistical differences in the Data element occurred across all services. For SEPM, the Army (.189) was statistically different from the Air Force (.1084) and Navy (.1241) factors.

Table 17. Service Differences

	Air Force	Army	Navy
SEPM	1	2	1
ST&E	0	0	0
Training	0	0	0
Data	2	2	2
PSE	1	1	2
CSE	0	1	1
Site Activation	0	0	0
Spares	1	0	1

Category Summary

The four categories analyzed in this section emphasized varying degrees of differences in six WBS elements. The SEPM and Data WBS elements contain statistical differences in every category; commodity, contract type, contractor type, and service. Spares exhibited differences in three out of the four categories; all but contractor type. These should be considered when analysts are building an estimate. Other elements displayed some statistical differences between categories. The total category differences by WBS element are shown in Table 18. Analysts should be as specific as possible when estimating elements with a higher number of statistically significant categorical differences. A broader dataset can be used for WBS elements with few differences. Even where no statistical difference exists between categories, data should be refined as necessary to produce the most accurate estimate possible. It is interesting to note that the Engineering, Manufacturing, and Development (EMD) study done in 2019 (Markman et al.) showed differences in every ST&E WBS element test whereas this production study found nothing significant in the ST&E category. Table 18 also compares the production and EMD findings, but omits the development category findings contained in the EMD study (as this category does not exist in production).

Table 18. Total Category Differences

	Category Differences	
WBS Element	**Production**	**EMD**
SEPM	4	3
ST&E	0	4
Training	1	0
Data	4	1
PSE	2	2
CSE	1	0
Site Activation	0	1
Spares	3	0

Purpose Specific Analysis

The distributions and descriptive statistics of each WBS element dataset reveal large CV values in each category. The CV is calculated as the standard deviation divided by mean and expresses the dispersion (variability) of the datapoints within the dataset. Table 19 shows the CVs for each WBS element, ranging from 127.2% to 182.1%.

Table 19. Coefficient of Variation Summary

WBS Element	Mean	Std Dev	CV
SEPM	0.1321	0.1680	127.2%
ST&E	0.0445	0.0810	182.1%
Training	0.0361	0.0645	179.0%
Data	0.0265	0.0469	176.9%
PSE	0.0768	0.1300	169.4%
CSE	0.0419	0.0658	157.1%
Site Activation	0.0168	0.0241	143.7%
Other	0.0711	0.1149	161.6%
Spares	0.0725	0.0950	130.9%

High standard deviations in the dataset may have prevented the statistical analysis from identifying differences in instances where a cost analyst may have. This section presents results for a scenario where data was filtered down to lower levels to create a (more accurate) hypothetical cost estimate.

Scenario

This hypothetical scenario examined the SEPM WBS element after filtering down to aircraft MDAPs. This dataset contained 427 data points. Five were removed because they were more than three standard deviations away from the mean and relatively small dollar amounts (under $70K). The descriptive statistics for this scenario are shown in Figure 14.

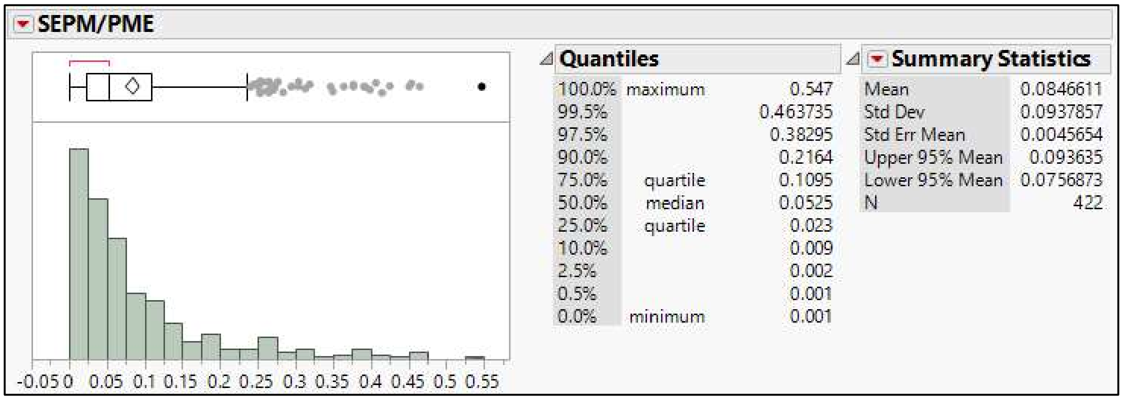


Figure 14. Scenario Descriptive Statistics

The mean and standard deviation in this scenario have dropped by almost half when compared to the entire SEPM dataset. When examining only 427 of the 749 available SEPM factors, the CV was 110.8%, a 16.4% decrease from the entire SEPM dataset. Table 20 shows the descriptive statistics for both data sets.

Table 20. SEPM Dataset (Aircraft vs. Entire) Descriptive Statistics

SEPM Dataset	N	Mean	Std Dev	CV
Entire Data	744	0.1321	0.1680	127.2%
Aircraft Data	422	0.0847	0.0938	110.8%

The lower CV shows less variability in the data and would produce a more accurate SEPM factor for aircraft MDAPs. The Kruskal-Wallis tests show significance for both contract type and contractor type, shown in figures 15 and 16 respectively. Service was not significantly different.

Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
CPIF	25	7564.50	5287.50	302.580	3.849
FFP	228	46368.0	48222.0	203.368	-1.484
FPAF	21	3363.00	4441.50	160.143	-1.979
FPI	62	13155.0	13113.0	212.177	0.047
MC	44	8315.50	9306.00	188.989	-1.293
No Value	42	10487.0	8883.00	249.690	2.138

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
24.2999	5	0.0002*

Figure 15. Scenario Kruskal-Wallis Test – Contract Type

Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Prime	403	83580.5	85234.5	207.396	-3.183
Sub	19	5672.50	4018.50	298.553	3.183

2-Sample Test, Normal Approximation

S	Z	Prob>|Z|
5672.5	3.18285	0.0015*

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
10.1367	1	0.0015*

Figure 16. Scenario Kruskal-Wallis Test – Contractor Type

The resulting p-values of 0.0002 and .0015 reject the null hypotheses and it can be concluded that differences exist between contract types and contractor types when calculating factors for SEPM. Therefore, the sample of data was refined further by filtering to FFP contracts and prime contractors. 221 data points remained. Five points were excluded due to being greater than three standard deviations away from the mean. The mean and standard deviation drop by 1.3% and 1.7% respectively. The calculated CV is now 107%. Figure 17 illustrates the distribution for the more specific dataset.

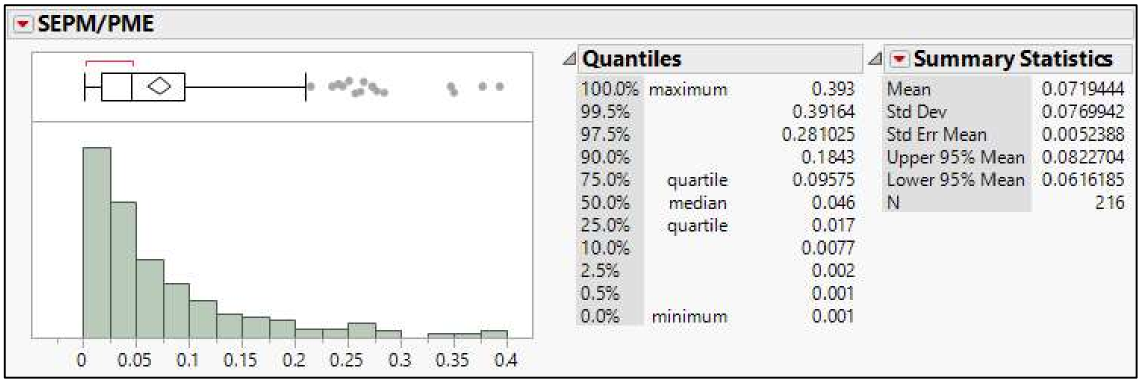


Figure 17. Scenario Descriptive Statistics – Specific Data

The CV remained high despite the small sample. The Kruskal-Wallis test revealed no significant differences between the service types. There may be remaining inapplicable data points, but only a specific analysis would be able to determine an inapplicability. For example, the dataset could remove rotary type aircraft or engine production that may be included in the aircraft commodity type data set. Specific aircraft type could be isolated as well. The more specific a database becomes for the creation of a composite production factor, the more likely that factor will be accurate for use in developing a cost estimate. Similar scenarios can be developed using this dataset, but the concept remains the same.

Chapter Summary

This chapter discussed the statistical analysis performed in this research and prefaces the results detailed in Chapter V. An overview of the dataset was provided to outline the key points of collection and analysis methodology. The descriptive statistics for each level II WBS element were presented. Additional statistics by commodity type, contract type, contractor type, and service are provided in Appendix C. Upon concluding non-normality of the datasets, the results of the two non-parametric tests utilized

(Kruskal-Wallis and Steel-Dwass) were outlined to highlight statistically significant differences in median values. A purpose specific analysis (scenario) was explored, which determined the more applicable the database is, the more accurate the composite factor becomes. Chapter V will address the results as they apply to the cost estimation field and discuss the use of the developed factors for future estimating purposes.

V. Conclusions and Recommendations

Chapter Overview

Chapter V outlays the conclusions drawn from the discussion and analysis conducted in Chapters I-IV. The research questions from Chapter I (shown again below) will be answered and findings presented. Limitations and potential future research opportunities are also discussed.

1. What are the standard production factors for MDAP programs with respect to the level II WBS elements?
2. What is the statistical difference in standard factors between differing commodity types with respect to the level II WBS elements?
3. What statistical differences exist between contract types utilized for MDAP procurement?
4. What differences are found in the standard factors when comparing prime and subcontractor data?
5. What statistical differences exist in factors between DoD service departments?

Research Questions Answered

Factor Development

The first research question reveals the production factors for each level II WBS element. Production factors calculated from the dataset for each WBS element are shown in Table 21—130 composite factors in total. Due to low N values in some categories, 14 factors could not be calculated. These represent mean values in the respective categories. The SEPM WBS element was the highest factor in most cases.

Table 21. Factors by Type (Mean Values)

	Standard Factors of Production								
	SEPM	ST&E	Training	Data	PSE	CSE	Site Act.	Other	Spares
Commodity Type									
Aircraft	0.0916	0.0391	0.0357	0.0295	0.0849	0.0707	0.017	0.0801	0.0712
Missile	0.1833	0.0515	0.0374	0.0208	0.0584	0.0284	0.015	0.0583	0.0497
UAV	0.1678	0.0073	0.042	0.0021	0.0633	0.021	N/A	0.0297	0.2157
Space	0.601	N/A	N/A	N/A	N/A	N/A	N/A	0.1085	N/A
Ship	0.441	0.002	0.002	0.058	N/A	N/A	N/A	0.307	N/A
Contract Type									
FFP	0.0891	0.0419	0.0263	0.0278	0.0733	0.0057	0.018	0.0758	0.051
FPI	0.1011	0.043	0.0345	0.0362	0.0989	0.004	0.0247	0.0654	0.1245
FPAF	0.046	0.001	0.0071	0.0159	0.0083	N/A	0.002	0.123	0.0822
CPIF	0.2401	0.04	0.0273	0.0268	0.1165	0.008	0.0338	0.061	0.1269
MC	0.0648	0.0243	0.0403	0.0124	0.0145	0.0133	0.0146	0.0402	0.0818
None Listed	0.1752	0.0502	0.0461	0.0263	0.0804	0.0516	0.011	0.0731	0.0605
Contractor Type									
Prime	0.1297	0.045	0.0372	0.0275	0.0776	0.041	0.0162	0.0727	0.0735
Subcontractor	0.1604	0.0381	0.0025	0.0068	0.0583	0.07	0.032	0.0487	0.014
Service									
Air Force	0.1084	0.0383	0.027	0.022	0.0623	0.0859	0.0181	0.0814	0.0976
Army	0.189	0.0527	0.0241	0.0053	0.0578	0.1075	N/A	0.0799	0.1312
Navy (Inc Marines)	0.1241	0.0438	0.0487	0.0343	0.0977	0.0105	0.0157	0.0598	0.0541

Statistical Analysis Results

Research questions two through five uncover any statistical differences between the level II WBS elements with respect to commodity type, contract type, contractor type, and service. A summary table for each research question details the non-parametric statistic test results for each category. All four categories had anywhere from three to five statistical differences between WBS elements. The values displayed in the corresponding category table represent the number of differences each category registered based on the Steel-Dwass multiple comparison test.

Commodity Type

Differences were identified within the SEPM, Data, and Spares categories in the aircraft, missile, and UAV commodity types. Estimates in these areas would likely be more accurate when filtering out the statistically different category data. WBS elements with no statistically different commodity types can likely use a broad dataset and remain accurate. The differences for each level II WBS element by commodity type revealed by the Steel-Dwass test are summarized in table 22.

Table 22. Commodity Differences

	Aircraft	Missile	UAV	Space	Ship
SEPM	2	1	1	0	0
ST&E	0	0	0	0	0
Training	0	0	0	0	0
Data	2	2	2	0	0
PSE	0	0	0	0	0
CSE	0	0	0	0	0
Site Activation	0	0	0	0	0
Spares	1	1	2	0	0

Contract Type

SEPM and PSE recorded the most interactions with a combined 71.4% of total differences. Contract types did not display a huge difference in category differences ranging from 5-9 for each contract type. In the SEPM category, "No Value" contracts showed statistical differences with FFP, FPI, FPAF, and MC contracts. This indicates that contracts with no data may be most similar to CPIF type contracts—at least within this dataset. These results suggest analysts can also use contract type (if known) to create more accurate factors in their cost estimates. The differences for each level II WBS element by contract type revealed by the Steel-Dwass test are summarized in table 23.

Table 23. Contract Type Differences

	FFP	FPI	FPAF	CPIF	MC	No Value
SEPM	2	2	2	4	2	4
ST&E	0	0	0	0	0	0
Training	0	0	0	0	0	0
Data	2	2	0	0	2	2
PSE	1	2	3	2	2	2
CSE	0	0	0	0	0	0
Site Activation	0	0	0	0	0	0
Spares	2	1	0	2	0	1

Contractor Type

Only the elements SEPM, Training, and Data displayed statistically significant differences based on prime vs subcontractor data. Cost estimates based on both prime and subcontractor data for the WBS elements that showed no statistical differences can retain an unfiltered (broader) dataset while retaining its accuracy. Analysts should differentiate by contractor type for the SEPM, Training, and Data categories to avoid using statistically different data when computing a factor. The differences revealed by the Steel-Dwass tests are summarized in table 24.

Table 24. Contractor Type Differences

	Prime	Sub
SEPM	1	1
ST&E	0	0
Training	1	1
Data	1	1
PSE	0	0
CSE	0	0
Site Activation	0	0
Spares	0	0

Service

The Service category revealed five statistically different median values for the WBS elements; SEPM, Data, PSE, CSE, and Spares. All services in the Data WBS element exhibited statistically significant differences. The Steel-Dwass test results are summarized in table 25.

Table 25. Service Differences

	Air Force	Army	Navy
SEPM	1	2	1
ST&E	0	0	0
Training	0	0	0
Data	2	2	2
PSE	1	1	2
CSE	0	1	1
Site Activation	0	0	0
Spares	1	0	1

Category Summary

Each of the four categories exhibited statistical differences in at least three, but no more than five, WBS elements. Descriptive statistics of each WBS element showed high standard deviations and coefficient of variation (CV) values which could have negatively impacted the power of the hypothesis testing performed. Low power in hypothesis testing results in a higher probability of a type II error—i.e. not rejecting a false null hypothesis. The high standard deviations in the data suggest that each MDAP has unique properties. Analysts must be familiar with these differences between programs to create data inclusion criteria when creating factors that result in accurate cost estimating. The realities of cost analysts possessing such knowledge are limited in most cases. For this reason, the generic cost factors calculated in this research represent a starting point for refinement based on the program being estimated and the knowledge of it. Given the analogy factor method is typically used earlier in a program's lifecycle, it is appropriate that there is little knowledge or data of the MDAP being estimated. Under these circumstances broad datasets are suitable, but statistically different categories should be filtered out as more information becomes available.

The benefit of a dataset with direct application to the MDAP being estimated was shown through an example scenario. Under the scenario, data in the SEPM category was filtered down by commodity type (aircraft), contract type (FFP), and contractor type (prime). This resulted in a 45.5% decrease in the production factor calculated and a 20.2% drop in the CV—all while losing 528 data points (71% of the available data). Service became an insignificant category when tailoring the data to a specific program. The scenario shows a factor calculated with the entire dataset would have been inaccurate. Cost estimators can use similar statistical and practical analysis to logically determine exclusion criteria to avoid this inaccuracy. Table 26 shows the summary of the scenario in which the data was filtered to a more specific program.

Table 26. Scenario Summary

SEPM Dataset	N	Mean	Std Dev	CV
Entire Data	744	0.1321	0.1680	127.2%
Aircraft Data	422	0.0847	0.0938	110.8%
Specific Data	216	0.0719	0.0770	107.0%

Significance of Results

This research represents the first known Department of Defense (DoD) MDAP production factor statistical analysis. Previous factor studies discussed in Chapter II (Blair, 1988,;Wren, 1998; Otte, 2015) established factors specifically for aircraft and the

Engineering, Manufacturing, and Development (EMD) lifecycle phase. These were primarily for Air Force Lifecycle Management Center (AFLCMC) use, but did branch out for use in other Air Force program offices. Data used in these studies was extremely limited in scope. In 2019, Markman et al. compiled a large database spanning 102 MDAPs for the EMD lifecycle phase. This data facilitated research that led to 443 unique program factors branching outside of the aircraft commodity. The research conducted in this study was tailored to build on Markman et al. (2019), but in the production lifecycle phase of MDAPs.

1,033 Cost Data Summary Reports (CDSRs), or 1921s, were compiled into a single database and provides cost analysts a point of origin to build production factors. This allowed for the creation of 3,330 unique factors (each 1921 had multiple WBS factors) and 130 composite factors when averaged across the WBS elements by commodity type, contract type, contractor type, and service. Two factors were also created during the scenario resulting in a total of 3,462 factors. Table 27 shows the breakdown of created factors by WBS, composite, and scenario. The descriptive statistics for each level II WBS element and the summary factor table allow analysts to produce an initial estimate quickly with minimum program data. Upon establishing this initial estimate, the analyst can perform statistical and practical analysis to generate a more accurate factor for their unique estimating scenario. This process can be repeated as more information or data becomes available to the analyst.

Table 27. Factors Created

SEPM	749
ST&E	275
Training	242
Data	536
PSE	361
CSE	68
Site Activation	58
Other	719
Spares	322
Composite Factors	130
Scenario Factors	2
Total	**3462**

Limitations

The data source for CDSRs presented some limitations in the analysis. The Cost Assessment Data Enterprise (CADE) system was utilized for all data collection. The CADE database only contains Acquisition Category (ACAT) I programs. Thus, ACAT II and III programs were excluded in this research. CADE consists of 202 MDAP programs with 119 programs containing production data. The electronic automated software, ordnance, surface vehicle, and system of system commodities were excluded in order to keep the analysis relevant to the Air Force; thus, reducing the potential number of programs from 119 to 75. The ship and space commodities presented challenges in data point creation as the 1921s were either in .xml format or not final 1921s with complete program cost data. This resulted in a low number of data points for both ship and space (two each). These low N values make it difficult to perform hypothesis testing and draw meaningful conclusions.

Prior to conducting this study, data had already been compiled outside of CADE in the AFLCMC/FZC cost library. This is known as legacy data and is primarily from the

1970s and 1980s. This data is not found within CADE, but resulted in a significant portion of the overall dataset in this study. While previous production data has been used to create factors prior to this study, no known statistical analysis has been performed. The approach taken in this factor development study hinges upon cost data reporting requirements and availability of data. During the data collection phase, it was apparent there is no consistency in formatting or separating costs into the correct WBS element. Studies such as this could be made easier to accomplish and update with stricter enforcement and better practices when it comes to cost data reporting requirements.

Recommendations for Future Research

This research can be expanded to include more production data points for a wider variety of MDAPs. The production data available within CADE is vast and data collection for the .xml format is possible, albeit time consuming. Initial and interim 1921s could be collected to monitor how factors change throughout a program's life. Including the omitted commodity types is another potential addition to this production factor research. Production factors could be updated at any point in the future using the more robust dataset utilizing the same methodology outlined in this study. Additionally, the data could be analyzed for time period trends (decades or otherwise). This analysis was done at the document level. Documents could be rolled up and factors calculated at the program level for a potentially different look at production factors.

Summary

This study utilized data from the CADE system and the previously built AFLCMC/FZC cost data library database to centralize 1,033 CDSRs over 145 MDAPs and create 3,462 unique production factors spanning multiple commodity types, contract types, contractor types, and services for each level II WBS element. The analogy/factor cost estimating technique relies heavily upon the accessibility of useable data points. CADE is making cost data centralization possible. This allows cost estimators to calculate their own unique factors with the highest accuracy given the available data and information they have on their program. The dataset built in this study offers analysts a point of origin to refine the data and apply statistical and practical methods to their estimate. An increased emphasis in efficient government spending and accountability has heightened the demand for accurate cost estimating in the DoD. This research provides the analyst a way in which to use historical data to more accurately predict future MDAP costs.

Appendix A – DD Form 1921 Example

SECURITY CLASSIFICATION **Unclassified**

COST DATA SUMMARY REPORT

Form Approved OMB No. 0704-0188

The public reporting burden for this collection of information is estimated to average 8 hours per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing the burden, to Department of Defense, Washington Headquarters Services, Executive Services Directorate (0704-0188). Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to any penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.
PLEASE DO NOT RETURN YOUR COMPLETED FORM TO THE ABOVE ORGANIZATION.

1. PROGRAM a. MDAP: b. PHASE:	**2. PRIME MISSION PRODUCT**	**3. CONTRACTOR TYPE** (X one) ☐ PRIME / ASSOCIATE ☐ DIRECT-REPORTING SUBCONTRACTOR	**4. NAME/ADDRESS** (Include ZIP Code)	**5. APPROVED PLAN NUMBER**
6. CUSTOMER (DIRECT-REPORTING SUBCONTRACTOR USE ONLY)	**7. CONTRACT TYPE** / **8. CONTRACT PRICE**	**9. CONTRACT CEILING**	**10. TYPE ACTION** a. CONTRACT NO.: b. LATEST MODIFICATION:	c. SOLICITATION NO.: d. NAME:
11. PERIOD OF PERFORMANCE a. START DATE *(YYYYMMDD):* b. END DATE *(YYYYMMDD):*	**12. APPROPRIATION** ☐ RDT&E ☐ PROCUREMENT ☐ O&M	**13. REPORT CYCLE** ☐ INITIAL ☐ INTERIM ☐ FINAL	**14. SUBMISSION NUMBER** / **15. RESUBMISSION NUMBER**	**16. REPORT AS OF** *(YYYYMMDD)*
17. NAME (Last, First, Middle Initial)	**18. DEPARTMENT**	**19. TELEPHONE NUMBER** (Include Area Code)	**20. EMAIL ADDRESS**	**21. DATE PREPARED** *(YYYYMMDD)*

WBS ELEMENT CODE	WBS REPORTING ELEMENTS	NUMBER OF UNITS TO DATE	COSTS INCURRED TO DATE			NUMBER OF UNITS AT COMPLETION	COSTS INCURRED AT COMPLETION		
			NONRECURRING	RECURRING	TOTAL		NONRECURRING	RECURRING	TOTAL
A	B	C	D	E	F	G	H	I	J
1.0	Aircraft System	17	$202.6	$78,188.2	$78,390.8	17	$202.6	$78,188.2	$78,390.8
1.1	Air Vehicle	17	$0.0	$55,884.7	$55,884.7	17	$0.0	$55,884.7	$55,884.7
1.1.1	Airframe	17	$0.0	$21,400.1	$21,400.1	17	$0.0	$21,400.1	$21,400.1
1.1.1.1	Airframe Integration, Assembly, Test and Checkout	17	$0.0	$6,693.7	$6,693.7	17	$0.0	$6,693.7	$6,693.7
1.1.1.1.1	Kit Installation	17	$0.0	$5,609.1	$5,609.1	17	$0.0	$5,609.1	$5,609.1
1.1.1.1.2	Idle Time	0	$0.0	$1,084.6	$1,084.6	0	$0.0	$1,084.6	$1,084.6
1.1.1.2	Fuselage	0	$0.0	$14,706.4	$14,706.4	17	$0.0	$14,706.4	$14,706.4
1.1.1.3	Wing	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.1.4	Empennage	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.1.5	Nacelle	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.1.6	Other Airframe Components	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.2	Propulsion	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.3	Vehicle Subsystems	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.4	Avionics	17	$0.0	$34,484.6	$34,484.6	17	$0.0	$34,484.6	$34,484.6
1.1.4.1	Avionics Integration, Assembly, Test, and Checkout	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.4.2	Communication/Identification	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.4.3	Navigation/Guidance	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.4.4	Mission Computer/Processing	17	$0.0	$34,484.6	$34,484.6	17	$0.0	$34,484.6	$34,484.6
1.1.4.4.1	Integrated Processing Unit (IPU)	17	$0.0	$23,149.0	$23,149.0	17	$0.0	$23,149.0	$23,149.0
1.1.4.4.2	Direct Drive Unit	17	$0.0	$11,335.6	$11,335.6	17	$0.0	$11,335.6	$11,335.6
1.1.4.5	Fire Control	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.4.6	Data Display and Controls	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.4.7	Survivability	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.4.8	Reconnaissance	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.4.9	Automatic Flight Control	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.4.10	Health Monitoring System	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.4.11	Stores Management	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.4.12	Avionics Software Release	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.4.13	Other Avionics Subsystems	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.5	Armament/Weapons Delivery	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.6	Auxiliary Equipment	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.7	Furnishings and Equipment	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.8	Air Vehicle Software Release	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.1.9	Air Vehicle Integration, Assembly, Test, and Checkout	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.2	System Engineering	0	$0.0	$4,236.4	$4,236.4	0	$0.0	$4,236.4	$4,236.4
1.3	Program Management	0	$16.8	$10,539.6	$10,556.4	0	$16.8	$10,539.6	$10,556.4
1.4	System Test and Evaluation	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.5	Training	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.6	Data	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.7	Peculiar Support Equipment	0	$1.6	$678.9	$680.5	0	$1.6	$678.9	$680.5
1.8	Common Support Equipment	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.9	Operational/Site Activation	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.10	Industrial Facilities	0	$0.0	$0.0	$0.0	0	$0.0	$0.0	$0.0
1.11	Initial Spares and Repair Parts	0	$184.2	$6,848.6	$7,032.9	0	$184.2	$6,848.6	$7,032.9
	Subtotal Cost		$202.6	$78,188.2	$78,390.8		$202.6	$78,188.2	$78,390.8
	Reporting Contractor G&A		$0.0	$0.0	$4,688.8		$0.0	$0.0	$4,688.8
	Reporting Contractor Undistributed Budget		$0.0	$0.0	$0.0		$0.0	$0.0	$0.0
	Reporting Contractor Management Reserve		$0.0	$0.0	$0.0		$0.0	$0.0	$0.0
	Reporting Contractor FCCM		$0.0	$0.0	$77.9		$0.0	$0.0	$77.9
	Total Cost		$0.0	$0.0	$83,157.5		$0.0	$0.0	$83,157.5
	Reporting Contractor Profit/Loss or Fee		$0.0	$0.0	$28,728.9		$0.0	$0.0	$28,728.9
	Total Price		$0.0	$0.0	$111,886.4		$0.0	$0.0	$111,886.4

22. REMARKS

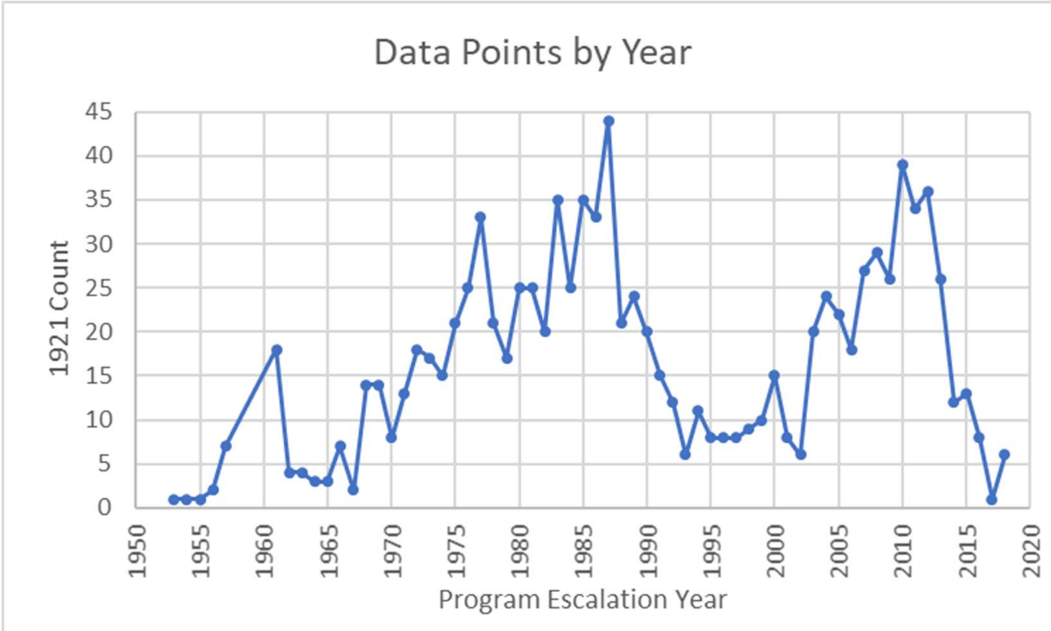
DD FORM 1921, 20070416 PREVIOUS EDITION IS OBSOLETE. SECURITY CLASSIFICATION **Unclassified**

Appendix B – Dataset

Dataset Programs

Mission Design Series (MDS)	1921s
A-10A	9
A-3A/B	4
A-4A	3
A-4B	3
A-4C	5
A-4E	5
A-5A/RA-5C	4
A-6A	9
A-6E	22
A-6E, EA-6A	6
A-7A	1
A-7A/B	4
A-7B	2
A-7D	8
A-7E	10
AGM-114 A/B	1
AGM-114L	7
AGM-154A	5
AGM-154C	3
AGM-154C-1	3
AGM-45	11
AGM-65A	3
AGM-65D	8
AGM-86B	4
AGM-88A	5
AGM-88B	3
AGM-88C	1
AH-1Z	9
AIM-120 A/B	18
AIM-120 B/C	3
AIM-120C	1
AIM-120D	6
AIM-54A	11
AIM-54C	11
AIM-7E	3
AIM-7E/7H	1
AIM-7E-2	1
AIM-7F	17
AIM-7M	15
AIM-7P	2
AIM-9L	5
AIM-9M	12
AIM-9X	9
AV-8B	6
B-1A	1
B-1B	18
B-2A	5
B-47A/B/C/E	3
B-52A/B/C/D	5
B-58A	4
B-66B	4
BAT	4
C-130J	11
C-141A	3
C-17A	11
C-23A	1
C-26A	1
C-26B	3
C-27A	2
C-29A	1
C-5A	12
C-5B	5
C-5M	8
DSU-15/B	18
E/F-111A	2
E-3A	9
E-3G	10
E-6A	5
E-8C	10
EA-18G	28
EA-6B	11
EELV	1
ES-3A	1
F/A-18A	17
F/A-18A/B	14
F/A-18C/D	8
F/A-18E/F	15
F-107	3
F-111A	1
F-111B	3
F-117A	10
F-14A	40
F-14D	3
F-15A/B	6
F-15C/D	13
F-15E	6
F-16A/B	5
F-16A/B Blk25	3
F-16C/D	12
F-22A	25
F-35A	11
F-35B	5
F-4B	6
F-5E	9
FB-111A	2
FB-111D	2
FGM-148	21
FGM-77	3
HC-130J	2
HELLFIRE ES	1
HELLFIRE Facilities	1
HIMARS	23
JAGM	1
KC-130J	3
KC-135A	7
LCS	1
M-26	9
M-30	40
MC-130J	2
MGM-140	10
MH-60R	22
MH-60S	9
MIDS	2
MIM-104	4
MIM-104A	5
MIM-104F	23
MLRS-ER	4
MQ-1B	4
MQ-1C	4
MQ-9A	5
Multiple	23
OPTIC T/D	3
OV-10D	1
P-3B/C	6
P-3C	9
P-8A	6
RIM-162	2
RIM-66C	1
RQ-4A/B	9
S-3A	9
S-3B	4
SM-6	2
SM-II	9
SM-III	1
SSGN Trident	1
T-1A	6
T-38A	5
T-39A	3
T-3A	3
T-45TS	9
T-46A	1
TA-4F	3
TA-4J	5
UH-1Y	10
WGS	1
Total	**1033**

Data Points by Year



Appendix C – Descriptive Statistics by Level II WBS Element

SEPM Descriptive Statistics									
	Mean	**Std Dev**	**CV**	**N**	**Max**	**75%**	**Median**	**25%**	**Min**
Commodity Type									
Aircraft	0.0916	0.1135	1.2391	427	0.742	0.115	0.054	0.024	0.001
Missile	0.1833	0.2094	1.1424	291	1.792	0.245	0.132	0.05	0.001
UAV	0.1678	0.07685	0.4580	22	0.345	0.2245	0.1465	0.115	0.012
Space	0.601	0.5657	0.9413	2	1.001	1.001	0.601	0.201	0.201
Ship	0.441	0.4426	1.0036	2	0.754	0.754	0.441	0.128	0.128
Contract Type									
FFP	0.0891	0.1135	1.2738	237	0.729	0.1145	0.05	0.0205	0.001
FPI	0.1011	0.0949	0.9387	75	0.399	0.138	0.069	0.027	0.005
FPAF	0.046	0.0486	1.0565	21	0.23	0.059	0.027	0.022	0.009
CPIF	0.2401	0.245	1.0204	29	1.001	0.336	0.155	0.0595	0.005
MC	0.0648	0.0601	0.9275	48	0.265	0.09425	0.0515	0.0158	0.002
No Value	0.1752	0.2015	1.1501	334	1.792	0.2403	0.1205	0.05	0.001
Contractor Type									
Prime	0.1297	0.1691	1.3038	686	1.792	0.174	0.0735	0.032	0.001
Subcontractor	0.1604	0.1522	0.9489	58	0.669	0.2358	0.1065	0.047	0.024
Service									
Air Force	0.1084	0.1297	1.1965	262	1.001	0.143	0.0635	0.0248	0.001
Army	0.189	0.2188	1.1577	155	1.792	0.263	0.143	0.048	0.012
Navy (Inc Marines)	0.1241	0.1618	1.3038	327	1.425	0.154	0.07	0.031	0.001

ST&E Descriptive Statistics									
	Mean	**Std Dev**	**CV**	**N**	**Max**	**75%**	**Median**	**25%**	**Min**
Commodity Type									
Aircraft	0.0391	0.0622	1.5908	139	0.292	0.046	0.009	0.004	0.001
Missile	0.0515	0.098	1.9029	128	0.605	0.041	0.009	0.004	0.001
UAV	0.0073	0.0085	1.1644	3	0.017	0.017	0.004	0.001	0.001
Space	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Ship	0.002	N/A	N/A	1	0.002	0.002	0.002	0.002	0.002
Contract Type									
FFP	0.0419	0.0642	1.5322	75	0.273	0.052	0.008	0.003	0.001
FPI	0.043	0.0525	1.2209	28	0.188	0.0528	0.0225	0.007	0.001
FPAF	0.001	N/A	N/A	1	0.001	0.001	0.001	0.001	0.001
CPIF	0.04	0.0846	2.1150	8	0.247	0.031	0.0045	0.0013	0.001
MC	0.0243	0.0599	2.4650	23	0.292	0.021	0.006	0.003	0.001
No Value	0.0502	0.096	1.9124	136	0.605	0.0405	0.009	0.004	0.001
Contractor Type									
Prime	0.045	0.0836	1.8578	251	0.605	0.041	0.008	0.003	0.001
Subcontractor	0.0381	0.0343	0.9003	20	0.13	0.0518	0.035	0.0065	0.001
Service									
Air Force	0.0383	0.0643	1.6789	78	0.292	0.0373	0.0105	0.003	0.001
Army	0.0527	0.104	1.9734	69	0.605	0.044	0.007	0.003	0.001
Navy (Inc Marines)	0.0438	0.0759	1.7329	124	0.465	0.045	0.009	0.004	0.001

Training Descriptive Statistics									
	Mean	**Std Dev**	**CV**	**N**	**Max**	**75%**	**Median**	**25%**	**Min**
Commodity Type									
Aircraft	0.0357	0.0644	1.8039	169	0.448	0.036	0.01	0.002	0.001
Missile	0.0374	0.0662	1.7701	68	0.34	0.045	0.009	0.004	0.001
UAV	0.042	N/A	N/A	1	0.042	0.042	0.042	0.042	0.042
Space	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Ship	0.002	N/A	N/A	1	0.002	0.002	0.002	0.002	0.002
Contract Type									
FFP	0.0263	0.0454	1.7262	75	0.212	0.03	0.007	0.002	0.001
FPI	0.0345	0.0609	1.7652	33	0.222	0.0295	0.008	0.001	0.001
FPAF	0.0071	0.0059	0.8310	7	0.017	0.012	0.005	0.001	0.001
CPIF	0.0273	0.0406	1.4872	9	0.114	0.0505	0.002	0.001	0.001
MC	0.0403	0.0725	1.7990	15	0.261	0.039	0.01	0.002	0.001
No Value	0.0461	0.0785	1.7028	100	0.448	0.056	0.013	0.004	0.001
Contractor Type									
Prime	0.0372	0.0653	1.7554	231	0.448	0.038	0.01	0.003	0.001
Subcontractor	0.0025	0.0013	0.5200	8	0.004	0.004	0.002	0.0013	0.001
Service									
Air Force	0.027	0.0415	1.5370	93	0.209	0.029	0.012	0.002	0.001
Army	0.0241	0.057	2.3651	41	0.34	0.0155	0.006	0.004	0.001
Navy (Inc Marines)	0.0487	0.0805	1.6530	105	0.448	0.06	0.01	0.002	0.001

Data Descriptive Statistics									
	Mean	**Std Dev**	**CV**	**N**	**Max**	**75%**	**Median**	**25%**	**Min**
Commodity Type									
Aircraft	0.0295	0.0478	1.6203	361	0.636	0.033	0.014	0.005	0.001
Missile	0.0208	0.0454	2.1827	167	0.471	0.021	0.006	0.002	0.001
UAV	0.0021	0.0011	0.5238	7	0.004	0.003	0.002	0.001	0.001
Space	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Ship	0.058	N/A	N/A	1	0.058	0.058	0.058	0.058	0.058
Contract Type									
FFP	0.0278	0.0359	1.2914	172	0.165	0.031	0.015	0.0043	0.001
FPI	0.0362	0.0352	0.9724	60	0.134	0.0553	0.0235	0.0063	0.001
FPAF	0.0159	0.0255	1.6038	21	0.125	0.0135	0.01	0.0075	0.001
CPIF	0.0268	0.0239	0.8918	18	0.082	0.045	0.0225	0.0048	0.001
MC	0.0124	0.0229	1.8468	38	0.141	0.012	0.007	0.004	0.001
No Value	0.0263	0.0604	2.2966	227	0.636	0.024	0.009	0.003	0.001
Contractor Type									
Prime	0.0275	0.0478	1.7382	510	0.636	0.03	0.012	0.004	0.001
Subcontractor	0.0068	0.0106	1.5588	26	0.052	0.007	0.0025	0.002	0.001
Service									
Air Force	0.022	0.0508	2.3091	221	0.636	0.023	0.009	0.003	0.001
Army	0.0053	0.0062	1.1698	51	0.027	0.006	0.003	0.001	0.001
Navy (Inc Marines)	0.0343	0.0462	1.3469	264	0.471	0.04	0.019	0.007	0.001

PSE Descriptive Statistics									
	Mean	**Std Dev**	**CV**	**N**	**Max**	**75%**	**Median**	**25%**	**Min**
Commodity Type									
Aircraft	0.0849	0.1385	1.6313	248	0.972	0.0885	0.025	0.009	0.001
Missile	0.0584	0.1115	1.9092	101	0.711	0.0575	0.02	0.01	0.001
UAV	0.0633	0.056	0.8847	11	0.217	0.098	0.042	0.021	0.011
Space	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Ship	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Contract Type									
FFP	0.0733	0.1198	1.6344	117	0.732	0.067	0.025	0.0095	0.001
FPI	0.0989	0.1096	1.1082	57	0.452	0.147	0.051	0.0135	0.001
FPAF	0.0083	0.0046	0.5542	12	0.017	0.0118	0.0085	0.004	0.001
CPIF	0.1165	0.151	1.2961	11	0.497	0.217	0.042	0.025	0.002
MC	0.0145	0.0127	0.8759	16	0.038	0.0253	0.013	0.0025	0.001
No Value	0.0804	0.1511	1.8794	147	0.972	0.073	0.022	0.01	0.001
Contractor Type									
Prime	0.0776	0.1318	1.6985	345	0.972	0.077	0.024	0.0095	0.001
Subcontractor	0.0583	0.0794	1.3619	15	0.323	0.059	0.042	0.012	0.002
Service									
Air Force	0.0623	0.1206	1.9358	143	0.972	0.051	0.021	0.009	0.001
Army	0.0578	0.1274	2.2042	62	0.711	0.0568	0.0145	0.006	0.001
Navy (Inc Marines)	0.0977	0.1371	1.4033	155	0.732	0.116	0.034	0.016	0.001

CSE Descriptive Statistics									
	Mean	**Std Dev**	**CV**	**N**	**Max**	**75%**	**Median**	**25%**	**Min**
Commodity Type									
Aircraft	0.0707	0.0893	1.2631	22	0.302	0.1413	0.013	0.0025	0.001
Missile	0.0284	0.047	1.6549	44	0.208	0.037	0.0085	0.003	0.001
UAV	0.021	0.0184	0.8762	2	0.034	0.034	0.021	0.008	0.008
Space	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Ship	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Contract Type									
FFP	0.0057	0.006	1.0526	6	0.017	0.0095	0.004	0.001	0.001
FPI	0.004	0.0036	0.9000	3	0.008	0.008	0.003	0.001	0.001
FPAF	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
CPIF	0.008	0.0099	1.2375	2	0.015	0.015	0.008	0.001	0.001
MC	0.0133	0.0144	1.0827	4	0.034	0.0283	0.009	0.0025	0.001
No Value	0.0516	0.0716	1.3876	53	0.302	0.085	0.012	0.003	0.001
Contractor Type									
Prime	0.041	0.0658	1.6049	66	0.302	0.0445	0.0085	0.003	0.001
Subcontractor	0.07	0.0834	1.1914	2	0.129	0.129	0.07	0.011	0.011
Service									
Air Force	0.0859	0.0925	1.0768	18	0.302	0.147	0.0675	0.0025	0.001
Army	0.1075	0.0628	0.5842	8	0.208	0.1593	0.099	0.0505	0.039
Navy (Inc Marines)	0.0105	0.0124	1.1810	42	0.052	0.0133	0.0065	0.002	0.001

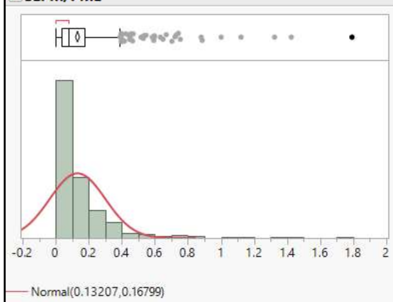
Site Activation Descriptive Statistics									
	Mean	**Std Dev**	**CV**	**N**	**Max**	**75%**	**Median**	**25%**	**Min**
Commodity Type									
Aircraft	0.017	0.025	1.4706	52	0.126	0.0208	0.006	0.002	0.001
Missile	0.015	0.0141	0.9400	5	0.034	0.03	0.008	0.0035	0.003
UAV	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Space	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Ship	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Contract Type									
FFP	0.018	0.0198	1.1000	20	0.068	0.0278	0.0075	0.0023	0.001
FPI	0.0247	0.0283	1.1457	3	0.056	0.056	0.017	0.001	0.001
FPAF	0.002	N/A	N/A	1	0.002	0.002	0.002	0.002	0.002
CPIF	0.0338	0.0615	1.8195	4	0.126	0.0958	0.004	0.0015	0.001
MC	0.0146	0.0225	1.5411	19	0.087	0.013	0.006	0.002	0.001
No Value	0.011	0.0111	1.0091	10	0.034	0.02	0.005	0.0038	0.003
Contractor Type									
Prime	0.0162	0.0242	1.4938	55	0.126	0.021	0.006	0.002	0.001
Subcontractor	0.032	0.0212	0.6625	2	0.047	0.047	0.032	0.017	0.017
Service									
Air Force	0.0181	0.0286	1.5801	25	0.126	0.0205	0.006	0.002	0.001
Army	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Navy (Inc Marines)	0.0157	0.0204	1.2994	32	0.087	0.0255	0.0065	0.0023	0.001

Other Descriptive Statistics									
	Mean	**Std Dev**	**CV**	**N**	**Max**	**75%**	**Median**	**25%**	**Min**
Commodity Type									
Aircraft	0.0801	0.1208	1.5081	415	0.782	0.11	0.032	0.008	0.001
Missile	0.0583	0.1019	1.7479	269	0.697	0.055	0.023	0.009	0.001
UAV	0.0297	0.0672	2.2626	20	0.312	0.0248	0.018	0.0053	0.002
Space	0.1085	0.1351	1.2452	2	0.204	0.204	0.1085	0.013	0.013
Ship	0.307	0.4313	1.4049	2	0.612	0.612	0.307	0.002	0.002
Contract Type									
FFP	0.0758	0.1004	1.3245	232	0.737	0.105	0.0425	0.009	0.001
FPI	0.0654	0.1259	1.9251	64	0.782	0.0768	0.0115	0.0043	0.001
FPAF	0.123	0.0243	0.1976	9	0.155	0.1475	0.113	0.101	0.096
CPIF	0.061	0.129	2.1148	28	0.612	0.0588	0.0185	0.0043	0.001
MC	0.0402	0.0945	2.3507	51	0.63	0.028	0.011	0.006	0.001
No Value	0.0731	0.1247	1.7059	324	0.729	0.0725	0.026	0.01	0.001
Contractor Type									
Prime	0.0727	0.116	1.5956	662	0.782	0.0835	0.026	0.008	0.001
Subcontractor	0.0487	0.0965	1.9815	46	0.601	0.0555	0.0225	0.003	0.001
Service									
Air Force	0.0814	0.132	1.6216	243	0.737	0.106	0.027	0.008	0.001
Army	0.0799	0.1239	1.5507	137	0.697	0.0865	0.033	0.0085	0.001
Navy (Inc Marines)	0.0598	0.095	1.5886	328	0.782	0.073	0.022	0.008	0.001

Spares Descriptive Statistics									
	Mean	**Std Dev**	**CV**	**N**	**Max**	**75%**	**Median**	**25%**	**Min**
Commodity Type									
Aircraft	0.0712	0.0932	1.3090	228	0.497	0.0948	0.0425	0.007	0.001
Missile	0.0497	0.0517	1.0402	73	0.225	0.0735	0.037	0.012	0.001
UAV	0.2157	0.165	0.7650	14	0.481	0.385	0.1525	0.0623	0.022
Space	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Ship	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Contract Type									
FFP	0.051	0.0743	1.4569	107	0.456	0.064	0.02	0.003	0.001
FPI	0.1245	0.1419	1.1398	39	0.481	0.16	0.074	0.02	0.001
FPAF	0.08222	0.0626	0.7614	9	0.241	0.081	0.065	0.059	0.017
CPIF	0.1269	0.1026	0.8085	20	0.383	0.19	0.1245	0.0333	0.001
MC	0.0818	0.1006	1.2298	37	0.381	0.0955	0.056	0.0035	0.002
No Value	0.0605	0.0801	1.3240	103	0.497	0.083	0.038	0.011	0.001
Contractor Type									
Prime	0.0735	0.0954	1.2980	310	0.497	0.0923	0.0415	0.009	0.001
Subcontractor	0.014	0.0155	1.1071	5	0.037	0.03	0.005	0.0025	0.002
Service									
Air Force	0.0976	0.1053	1.0789	116	0.481	0.1363	0.0595	0.0223	0.001
Army	0.1312	0.1751	1.3346	10	0.452	0.3173	0.0395	0.0058	0.003
Navy (Inc Marines)	0.0541	0.077	1.4233	189	0.497	0.074	0.027	0.007	0.001

Appendix D – Shapiro-Wilk Test Results by Level II WBS Element

SEPM/PME



Quantiles

100.0%	maximum	1.792
99.5%		1.176825
97.5%		0.587375
90.0%		0.3055
75.0%	quartile	0.17575
50.0%	median	0.076
25.0%	quartile	0.034
10.0%		0.012
2.5%		0.003
0.5%		0.001
0.0%	minimum	0.001

Summary Statistics

Mean	0.1320685
Std Dev	0.1679923
Std Err Mean	0.0061589
Upper 95% Mean	0.1441595
Lower 95% Mean	0.1199776
N	744

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	μ	0.1320685	0.1199776	0.1441595
Dispersion	σ	0.1679923	0.1598685	0.1769924

-2log(Likelihood) = -543.96933970384

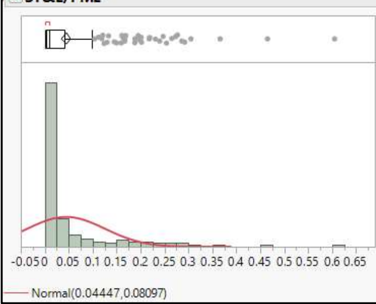
Goodness-of-Fit Test

Shapiro-Wilk W Test

W	Prob<W
0.658454	<.0001*

Note: Ho = The data is from the Normal distribution. Small p-values reject Ho.

ST&E/PME



Quantiles

100.0%	maximum	0.605
99.5%		0.5546
97.5%		0.2788
90.0%		0.1626
75.0%	quartile	0.042
50.0%	median	0.009
25.0%	quartile	0.004
10.0%		0.001
2.5%		0.001
0.5%		0.001
0.0%	minimum	0.001

Summary Statistics

Mean	0.0444723
Std Dev	0.0809711
Std Err Mean	0.0049186
Upper 95% Mean	0.0541561
Lower 95% Mean	0.0347885
N	271

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	μ	0.0444723	0.0347885	0.0541561
Dispersion	σ	0.0809711	0.0746797	0.0884292

-2log(Likelihood) = -594.340434358534

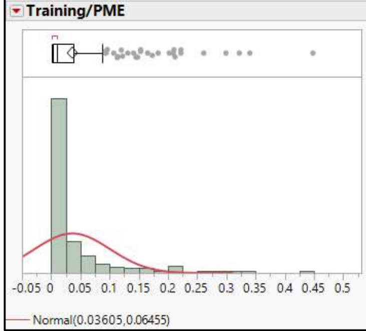
Goodness-of-Fit Test

Shapiro-Wilk W Test

W	Prob<W
0.577435	<.0001*

Note: Ho = The data is from the Normal distribution. Small p-values reject Ho.

Training/PME



Quantiles

100.0%	maximum	0.448
99.5%		0.4264
97.5%		0.222
90.0%		0.113
75.0%	quartile	0.038
50.0%	median	0.01
25.0%	quartile	0.003
10.0%		0.001
2.5%		0.001
0.5%		0.001
0.0%	minimum	0.001

Summary Statistics

Mean	0.0360544
Std Dev	0.0645461
Std Err Mean	0.0041751
Upper 95% Mean	0.0442793
Lower 95% Mean	0.0278294
N	239

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	μ	0.0360544	0.0278294	0.0442793
Dispersion	σ	0.0645461	0.0592318	0.0709162

-2log(Likelihood) = -632.646686295779

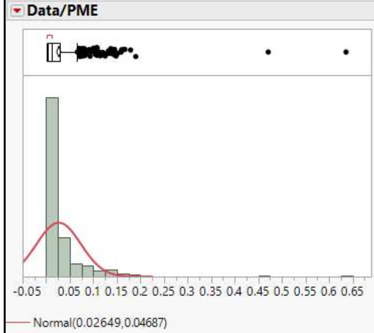
Goodness-of-Fit Test

Shapiro-Wilk W Test

W	Prob<W
0.581842	<.0001*

Note: Ho = The data is from the Normal distribution. Small p-values reject Ho.

Data/PME



Quantiles

100.0%	maximum	0.636
99.5%		0.278515
97.5%		0.141
90.0%		0.0736
75.0%	quartile	0.02875
50.0%	median	0.0115
25.0%	quartile	0.004
10.0%		0.002
2.5%		0.001
0.5%		0.001
0.0%	minimum	0.001

Summary Statistics

Mean	0.0264944
Std Dev	0.0468711
Std Err Mean	0.0020245
Upper 95% Mean	0.0304714
Lower 95% Mean	0.0225174
N	536

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	μ	0.0264944	0.0225174	0.0304714
Dispersion	σ	0.0468711	0.0442232	0.0498588

-2log(Likelihood) = -1760.59716177397

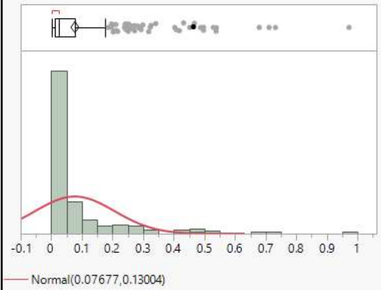
Goodness-of-Fit Test

Shapiro-Wilk W Test

W	Prob<W
0.495865	<.0001*

Note: Ho = The data is from the Normal distribution. Small p-values reject Ho.

PSE/PME



Quantiles

100.0%	maximum	0.972
99.5%		0.7788
97.5%		0.49675
90.0%		0.2419
75.0%	quartile	0.07675
50.0%	median	0.025
25.0%	quartile	0.01
10.0%		0.002
2.5%		0.001
0.5%		0.001
0.0%	minimum	0.001

Summary Statistics

Mean	0.0767694
Std Dev	0.1300425
Std Err Mean	0.0068538
Upper 95% Mean	0.0902482
Lower 95% Mean	0.0632907
N	360

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	μ	0.0767694	0.0632907	0.0902482
Dispersion	σ	0.1300425	0.1211866	0.1403055

-2log(Likelihood) = -448.087653553563

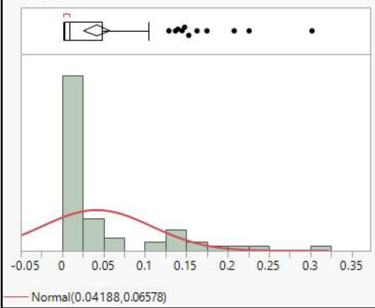
Goodness-of-Fit Test

Shapiro-Wilk W Test

W	Prob<W
0.595379	<.0001*

Note: Ho = The data is from the Normal distribution. Small p-values reject Ho.

CSE/PME



Quantiles

100.0%	maximum	0.302
99.5%		0.302
97.5%		0.2469
90.0%		0.1485
75.0%	quartile	0.0475
50.0%	median	0.009
25.0%	quartile	0.003
10.0%		0.001
2.5%		0.001
0.5%		0.001
0.0%	minimum	0.001

Summary Statistics

Mean	0.0418824
Std Dev	0.0657788
Std Err Mean	0.0079769
Upper 95% Mean	0.0578042
Lower 95% Mean	0.0259605
N	68

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	μ	0.0418824	0.0259605	0.0578042
Dispersion	σ	0.0657788	0.0562817	0.0791618

-2log(Likelihood) = -178.142586896598

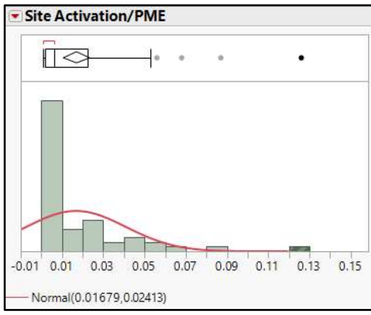
Goodness-of-Fit Test

Shapiro-Wilk W Test

W	Prob<W
0.668859	<.0001*

Note: Ho = The data is from the Normal distribution. Small p-values reject Ho.

Site Activation/PME



Quantiles

100.0%	maximum	0.126
99.5%		0.126
97.5%		0.10845
90.0%		0.049
75.0%	quartile	0.0225
50.0%	median	0.006
25.0%	quartile	0.002
10.0%		0.001
2.5%		0.001
0.5%		0.001
0.0%	minimum	0.001

Summary Statistics

Mean	0.0167895
Std Dev	0.0241326
Std Err Mean	0.0031964
Upper 95% Mean	0.0231927
Lower 95% Mean	0.0103862
N	57

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	μ	0.0167895	0.0103862	0.0231927
Dispersion	σ	0.0241326	0.0203741	0.0296046

-2log(Likelihood) = -263.798750636118

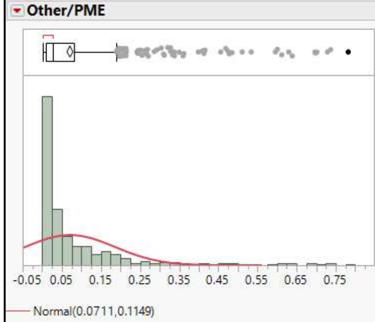
Goodness-of-Fit Test

Shapiro-Wilk W Test

W	Prob<W
0.679481	<.0001*

Note: Ho = The data is from the Normal distribution. Small p-values reject Ho.

Other/PME



Quantiles

100.0%	maximum	0.782
99.5%		0.714285
97.5%		0.459575
90.0%		0.1851
75.0%	quartile	0.08075
50.0%	median	0.026
25.0%	quartile	0.008
10.0%		0.004
2.5%		0.001
0.5%		0.001
0.0%	minimum	0.001

Summary Statistics

Mean	0.0711031
Std Dev	0.1149035
Std Err Mean	0.0043183
Upper 95% Mean	0.0795814
Lower 95% Mean	0.0626248
N	708

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	μ	0.0711031	0.0626248	0.0795814
Dispersion	σ	0.1149035	0.1092143	0.1212227

-2log(Likelihood) = -1055.52904099828

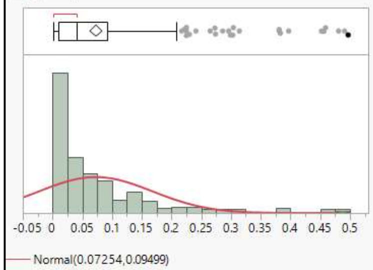
Goodness-of-Fit Test

Shapiro-Wilk W Test

W	Prob<W
0.607052	<.0001*

Note: Ho = The data is from the Normal distribution. Small p-values reject Ho.

Spares/PME



Quantiles

100.0%	maximum	0.497
99.5%		0.49352
97.5%		0.3844
90.0%		0.1886
75.0%	quartile	0.091
50.0%	median	0.04
25.0%	quartile	0.009
10.0%		0.002
2.5%		0.001
0.5%		0.001
0.0%	minimum	0.001

Summary Statistics

Mean	0.0725397
Std Dev	0.0949898
Std Err Mean	0.0053521
Upper 95% Mean	0.0830701
Lower 95% Mean	0.0620092
N	315

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	μ	0.0725397	0.0620092	0.0830701
Dispersion	σ	0.0949898	0.0881061	0.1030494

-2log(Likelihood) = -590.079447756383

Goodness-of-Fit Test

Shapiro-Wilk W Test

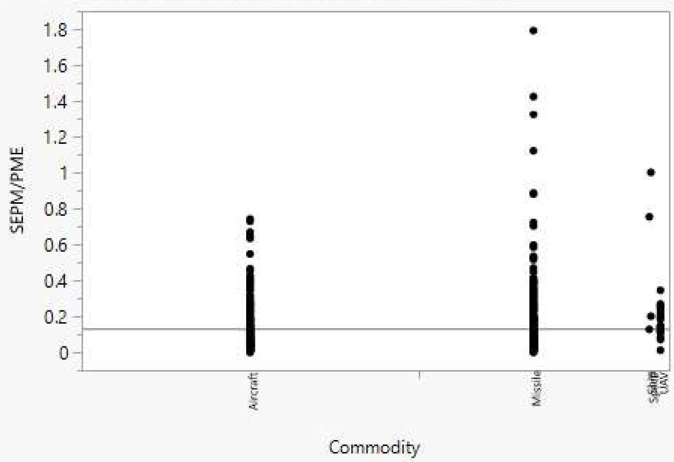
W	Prob<W
0.723011	<.0001*

Note: Ho = The data is from the Normal distribution. Small p-values reject Ho.

Appendix E – Kruskal-Wallis and Steel-Dwass and Results

Kruskal-Wallis and Steel-Dwass Results by Commodity

Oneway Analysis of SEPM/PME By Commodity



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Aircraft	427	130947	159058	306.667	-9.697
Missile	291	132217	108398	454.352	8.326
Ship	2	1226.00	745.000	613.000	1.583
Space	2	1336.00	745.000	668.000	1.945
UAV	22	11414.5	8195.00	518.841	3.242

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
98.7633	4	<.0001*

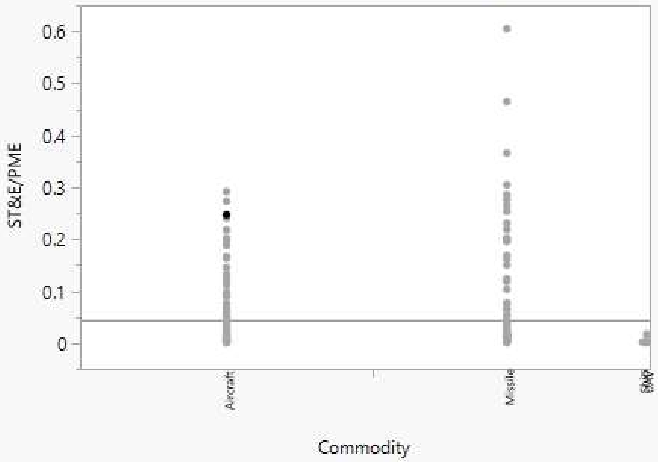
Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
2.72777	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Space	Aircraft	189.634	87.87222	2.15807	0.1958	0.229500	.	.
Ship	Aircraft	169.540	87.87222	1.92940	0.3016	0.126000	.	.
Missile	Aircraft	142.205	15.76625	9.01959	<.0001*	0.056000	0.036000	0.0800000
UAV	Aircraft	133.041	28.36730	4.68996	<.0001*	0.095000	0.052000	0.1350000
Space	Missile	99.429	60.11460	1.65399	0.4628	0.190500	.	.
Ship	Missile	68.719	60.11462	1.14313	0.7835	0.116500	.	.
UAV	Missile	22.294	20.01027	1.11414	0.7992	0.029000	-0.048000	0.0860000
Space	Ship	0.500	1.29099	0.38730	0.9952	0.160000	.	.
UAV	Ship	-3.545	5.22006	-0.67920	0.9610	-0.262500	.	.
UAV	Space	-7.364	5.22006	-1.41064	0.6208	-0.422500	.	.

Excluded Rows 5

Oneway Analysis of ST&E/PME By Commodity



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Aircraft	139	19089.0	18904.0	137.331	0.286
Missile	128	17474.5	17408.0	136.520	0.103
Ship	1	40.500	136.000	40.500	-1.216
UAV	3	252.000	408.000	84.000	-1.153

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
2.8587	3	0.4139

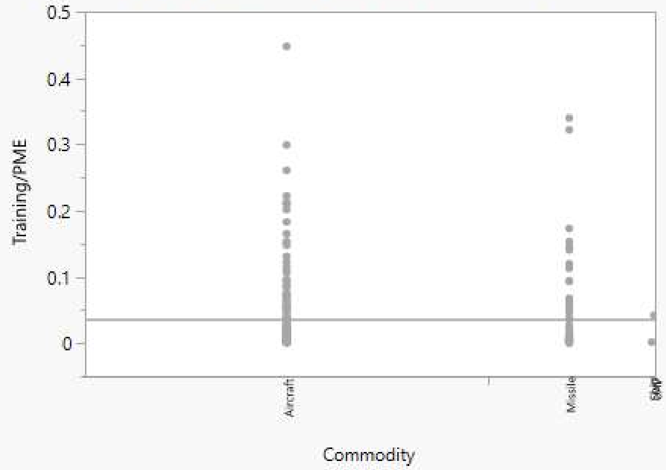
Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
2.56903	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
UAV	Ship	0.0000	1.49071	0.00000	1.0000	0.002000	.	.
Missile	Aircraft	-0.7653	9.44754	-0.08101	0.9998	0.000000	-0.003000	0.0040000
UAV	Missile	-25.2448	22.13484	-1.14050	0.6644	-0.005000	-0.237000	0.0150000
UAV	Aircraft	-27.7530	23.97435	-1.15761	0.6537	-0.005000	-0.171000	0.0140000
Ship	Missile	-43.3359	37.46517	-1.15670	0.6542	-0.007000	.	.
Ship	Aircraft	-51.3669	40.65329	-1.26354	0.5862	-0.007000	.	.

Excluded Rows 4

Oneway Analysis of Training/PME By Commodity



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Aircraft	169	19817.0	20280.0	117.260	-0.953
Missile	68	8629.00	8160.00	126.897	0.974
Ship	1	48.000	120.000	48.000	-1.039
UAV	1	186.000	120.000	186.000	0.952

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
2.9523	3	0.3990

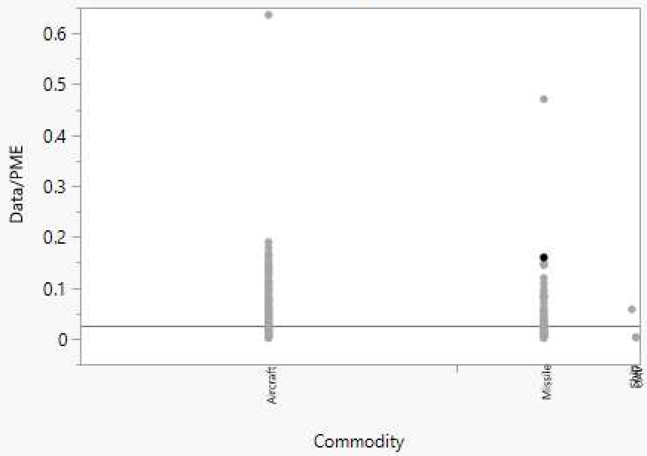
Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
2.56903	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
UAV	Aircraft	48.2840	49.14327	0.98252	0.7594	0.032000	.	.
UAV	Missile	16.7426	20.15966	0.83050	0.8400	0.033000	.	.
Missile	Aircraft	9.4041	9.82161	0.95749	0.7736	0.001000	-0.004000	0.0040000
UAV	Ship	0.0000	1.00000	0.00000	1.0000	0.040000	.	.
Ship	Missile	-29.4265	20.15855	-1.45975	0.4621	-0.007000	.	.
Ship	Aircraft	-41.7456	49.13752	-0.84957	0.8307	-0.008000	.	.

Excluded Rows 3

Oneway Analysis of Data/PME By Commodity



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Aircraft	361	105782	96928.5	293.024	5.270
Missile	167	37189.0	44839.5	222.689	-4.612
Ship	1	469.000	268.500	469.000	1.294
UAV	7	476.500	1879.50	68.071	-3.449

1-Way Test, ChiSquare Approximation

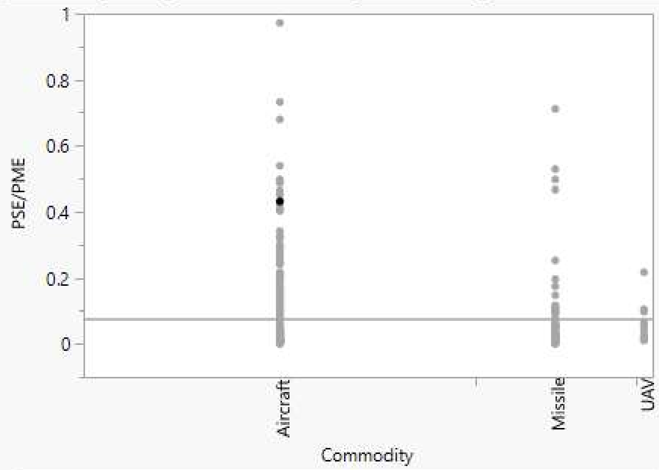
ChiSquare	DF	Prob>ChiSq
37.1399	3	<.0001*

Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
2.56903	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Ship	Aircraft	129.357	104.7312	1.23514	0.6044	0.044000	.	.
Ship	Missile	67.401	48.6184	1.38633	0.5079	0.052000	.	.
UAV	Ship	-3.429	2.5395	-1.35011	0.5309	-0.056000	.	.
UAV	Missile	-53.287	19.3538	-2.75329	0.0301*	-0.004000	-0.022000	0.000000
Missile	Aircraft	-69.548	14.2641	-4.87576	<.0001*	-0.005000	-0.008000	-0.002000
UAV	Aircraft	-151.525	40.5693	-3.73497	0.0011*	-0.012000	-0.035000	-0.002000

Oneway Analysis of PSE/PME By Commodity



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Aircraft	248	45419.5	44764.0	183.143	0.717
Missile	101	17130.0	18230.5	169.604	-1.240
UAV	11	2430.50	1985.50	220.955	1.308

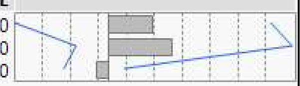
1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
2.9313	2	0.2309

Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

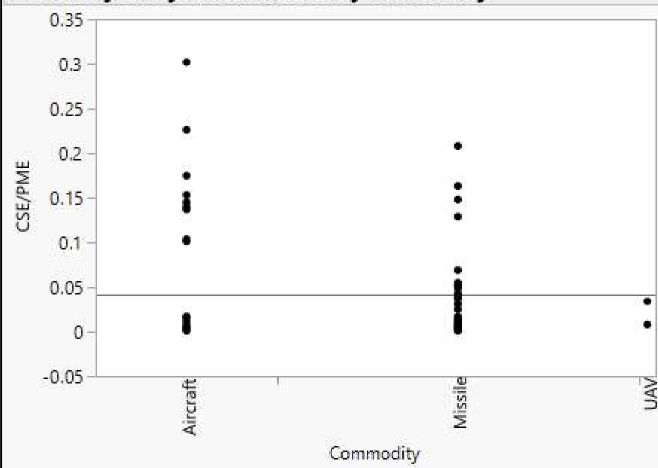
q*	Alpha
2.34370	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
UAV	Aircraft	25.5392	23.07438	1.10682	0.5098	0.011000	-0.023000	0.0410000
UAV	Missile	17.6418	10.30718	1.71160	0.2008	0.016000	-0.008000	0.0460000
Missile	Aircraft	-12.8813	11.90505	-1.08200	0.5252	-0.003000	-0.011000	0.0040000



Excluded Rows 1

Oneway Analysis of CSE/PME By Commodity



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Aircraft	22	832.000	759.000	37.8182	0.954
Missile	44	1435.00	1518.00	32.6136	-1.062
UAV	2	79.000	69.000	39.5000	0.346

1-Way Test, ChiSquare Approximation

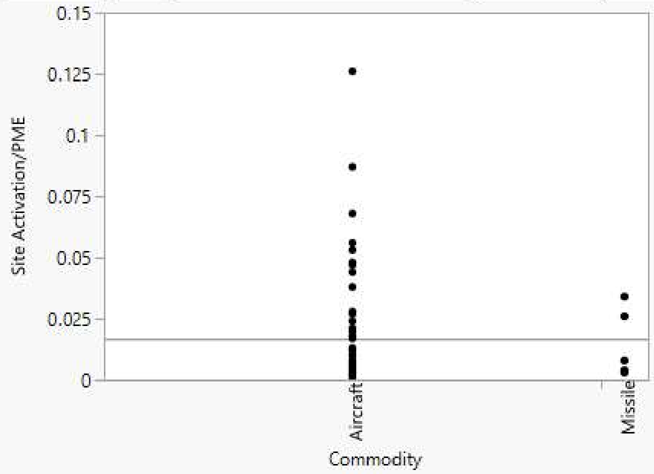
ChiSquare	DF	Prob>ChiSq
1.1554	2	0.5612

Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
2.34370	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
UAV	Missile	4.44318	9.680267	0.45899	0.8904	0.005000	.	.
UAV	Aircraft	0.27273	5.197293	0.05247	0.9985	0.001000	.	.
Missile	Aircraft	-5.01136	4.994612	-1.00335	0.5747	-0.004000	-0.096000	0.0030000

Oneway Analysis of Site Activation/PME By Commodity



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Aircraft	52	1482.50	1508.00	28.5096	-0.708
Missile	5	170.500	145.000	34.1000	0.708

2-Sample Test, Normal Approximation

S	Z	Prob>|Z|
170.5	0.70771	0.4791

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
0.5211	1	0.4704

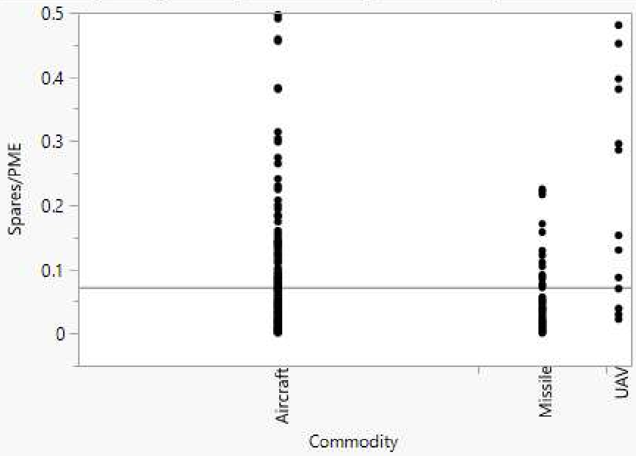
Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
1.95996	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Missile	Aircraft	5.480769	7.744371	0.7077101	0.4791	0.0020000	-0.013000	0.0210000

Excluded Rows 1

Oneway Analysis of Spares/PME By Commodity



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Aircraft	228	35211.0	36024.0	154.434	-1.125
Missile	73	11064.5	11534.0	151.568	-0.688
UAV	14	3494.50	2212.00	249.607	3.850

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
14.8869	2	0.0006*

Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

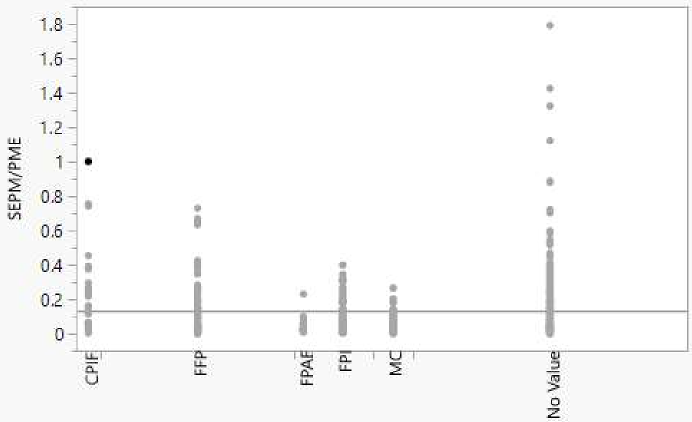
q*	Alpha
2.34370	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
UAV	Aircraft	70.9624	19.26490	3.68351	0.0007*	0.112000	0.029000	0.2590000
UAV	Missile	29.4114	7.36783	3.99187	0.0002*	0.120500	0.037000	0.2770000
Missile	Aircraft	-2.2244	11.69997	-0.19012	0.9803	-0.001000	-0.017000	0.0080000

Excluded Rows 7

Kruskal-Wallis and Steel-Dwass Results by Contract Type

Oneway Analysis of SEPM/PME By Contract Type



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
CPIF	29	14323.5	10802.5	493.914	3.103
FFP	237	71192.5	88282.5	300.390	-6.257
FPAF	21	4407.50	7822.50	209.881	-3.517
FPI	75	25986.5	27937.5	346.487	-1.105
MC	48	12975.5	17880.0	270.323	-3.405
No Value	334	148255	124415	443.876	8.176

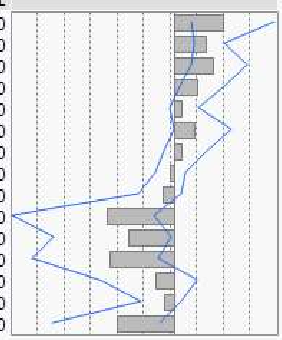
1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
96.7487	5	<.0001*

Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

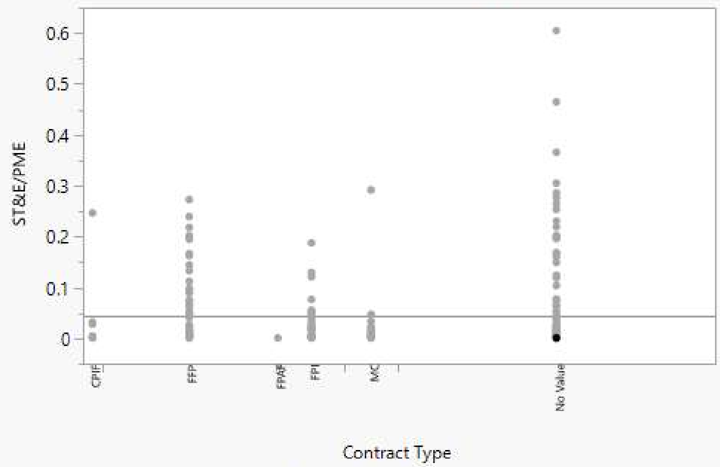
q*	Alpha
2.84970	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
No Value	FPAF	114.057	23.08722	4.94025	<.0001*	0.077500	0.025000	0.156000
No Value	FFP	109.886	14.01158	7.84249	<.0001*	0.051000	0.031000	0.078000
No Value	MC	88.995	17.04392	5.22152	<.0001*	0.062000	0.026000	0.114000
No Value	FPI	55.244	15.10477	3.65736	0.0035*	0.037000	0.008000	0.077000
FPI	FFP	20.519	11.95104	1.71693	0.5204	0.012000	-0.008000	0.037000
FPI	FPAF	17.798	6.87640	2.58829	0.1001	0.032000	-0.002000	0.089000
MC	FPAF	6.092	5.24699	1.16110	0.8553	0.012000	-0.018000	0.050000
MC	FFP	-11.812	13.04405	-0.90558	0.9452	-0.006000	-0.030000	0.017000
MC	FPI	-13.615	6.58889	-2.06642	0.3050	-0.019000	-0.057000	0.009000
FPAF	CPIF	-17.980	4.17642	-4.30520	0.0002*	-0.107000	-0.256000	-0.032000
FPI	CPIF	-20.441	6.59594	-3.09909	0.0238*	-0.073000	-0.191000	-0.007000
MC	CPIF	-21.407	5.25975	-4.07003	0.0007*	-0.102000	-0.226000	-0.027000
No Value	CPIF	-28.763	20.31361	-1.41597	0.7174	-0.029000	-0.120000	0.034000
FPAF	FFP	-28.978	16.98891	-1.70568	0.5279	-0.017000	-0.054000	0.009000
FFP	CPIF	-66.471	15.13383	-4.39221	0.0002*	-0.090000	-0.193000	-0.025000



Excluded Rows 5

Oneway Analysis of ST&E/PME By Contract Type



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
CPIF	8	875.000	1088.00	109.375	-0.974
FFP	75	10114.5	10200.0	134.860	-0.147
FPAF	1	14.500	136.000	14.500	-1.549
FPI	28	4560.00	3808.00	162.857	1.916
MC	23	2646.00	3128.00	115.043	-1.341
No Value	136	18646.0	18496.0	137.103	0.232

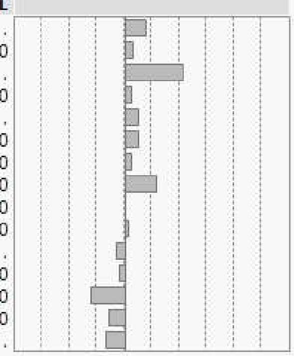
1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
8.3239	5	0.1393

Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

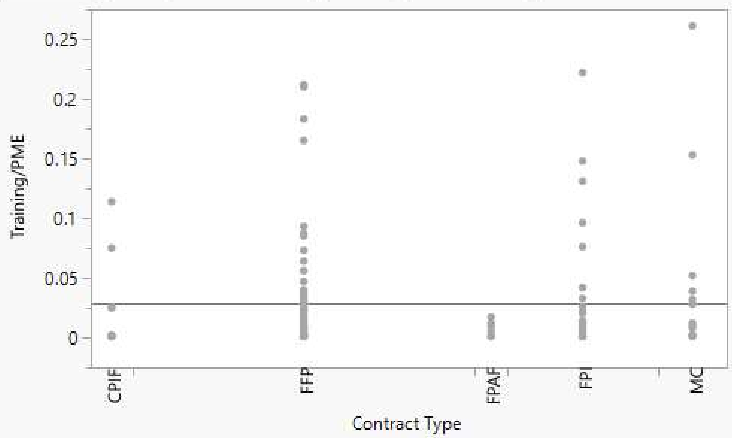
q*	Alpha
2.84970	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
No Value	FPAF	60.9449	39.77617	1.53219	0.6434	0.008000	.	.
No Value	CPIF	14.5588	15.15100	0.96092	0.9302	0.003000	-0.025000	0.0380000
FPI	FPAF	13.4643	8.66114	1.55456	0.6287	0.021500	.	.
No Value	MC	12.5807	10.36575	1.21368	0.8304	0.002000	-0.003000	0.0150000
MC	FPAF	9.9130	7.18694	1.37931	0.7396	0.005000	.	.
FPI	FFP	9.6133	6.60991	1.45438	0.6934	0.005000	-0.007000	0.0230000
FFP	CPIF	7.9542	8.94817	0.88892	0.9493	0.002000	-0.026000	0.0600000
FPI	CPIF	6.1875	4.22040	1.46609	0.6860	0.012000	-0.026000	0.0540000
No Value	FFP	2.1100	8.76885	0.24062	0.9999	0.000000	-0.004000	0.0050000
MC	CPIF	1.3478	3.71802	0.36251	0.9992	0.001000	-0.029000	0.0200000
FPAF	CPIF	-2.8125	2.85591	-0.98480	0.9229	-0.003500	.	.
MC	FFP	-6.8742	6.76528	-1.01610	0.9128	-0.002000	-0.025000	0.0040000
MC	FPI	-10.3346	4.17922	-2.47286	0.1322	-0.013000	-0.041000	0.0010000
No Value	FPI	-15.9995	9.84341	-1.62540	0.5816	-0.006000	-0.022000	0.0040000
FPAF	FFP	-33.9467	22.19098	-1.52975	0.6450	-0.007000	.	.



Excluded Rows 4

Oneway Analysis of Training/PME By Contract Type



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
CPIF	9	556.500	630.000	61.8333	-0.629
FFP	75	5412.00	5250.00	72.1600	0.687
FPAF	7	399.000	490.000	57.0000	-0.877
FPI	33	2250.50	2310.00	68.1970	-0.294
MC	15	1112.00	1050.00	74.1333	0.420

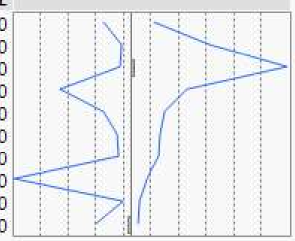
1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
1.5591	4	0.8161

Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
2.72777	0.05

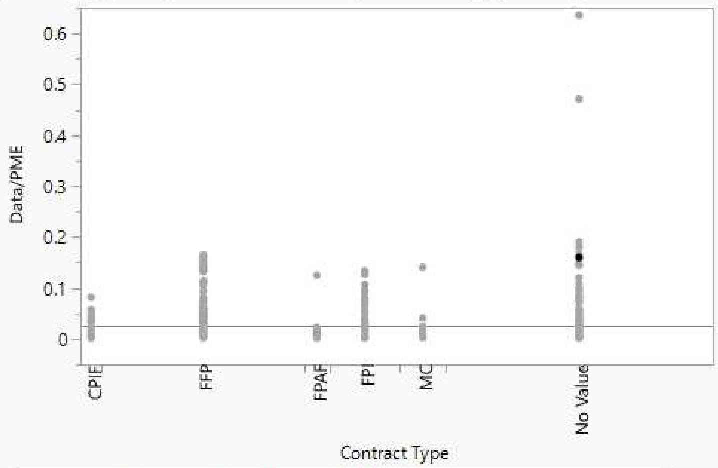
Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
FFP	CPIF	5.97333	8.565614	0.697362	0.9571	0.001000	-0.024000	0.0220000
FPI	FPAF	3.11688	4.806848	0.648426	0.9670	0.001000	-0.008000	0.0710000
MC	FPAF	2.61905	2.950460	0.887674	0.9016	0.003000	-0.009000	0.1410000
MC	CPIF	2.22222	2.938336	0.756286	0.9429	0.001000	-0.063000	0.0510000
FPI	CPIF	1.97980	4.537381	0.436331	0.9925	0.000000	-0.025000	0.0310000
MC	FPI	1.93939	4.314999	0.449454	0.9916	0.000000	-0.013000	0.0270000
MC	FFP	1.20000	7.361424	0.163012	0.9998	0.000000	-0.011000	0.0250000
FPAF	CPIF	-0.50794	2.334920	-0.217539	0.9995	0.000000	-0.105000	0.0150000
FPI	FFP	-3.12000	6.510484	-0.479227	0.9893	0.000000	-0.007000	0.0080000
FPAF	FFP	-8.82476	9.378818	-0.940925	0.8809	-0.002000	-0.031000	0.0060000



Missing Rows 100

Excluded Rows 3

Oneway Analysis of Data/PME By Contract Type



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
CPIF	18	5487.50	4833.00	304.861	1.014
FFP	172	49958.5	46182.0	290.456	2.258
FPAF	21	5282.50	5638.50	251.548	-0.512
FPI	60	20254.5	16110.0	337.575	3.669
MC	38	7842.00	10203.0	206.368	-2.568
No Value	227	55091.0	60949.5	242.692	-3.310

1-Way Test, ChiSquare Approximation

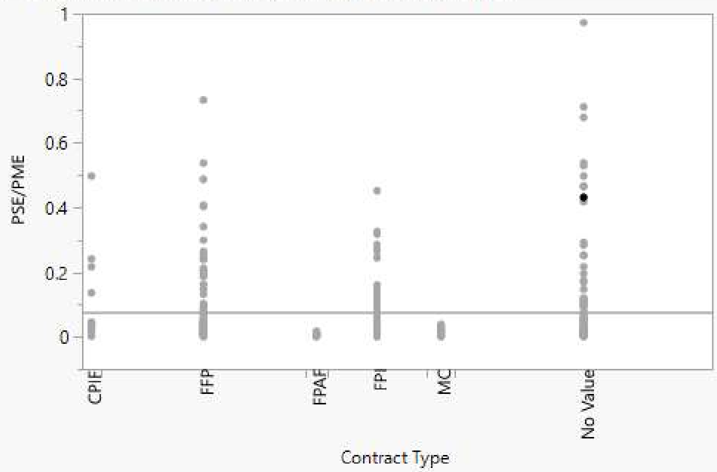
ChiSquare	DF	Prob>ChiSq
29.1159	5	<.0001*

Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
2.84970	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
FPI	FFP	21.7163	10.05705	2.15931	0.2571	0.005000	-0.002000	0.017000
FPI	FPAF	15.4929	5.96019	2.59939	0.0973	0.013000	-0.001000	0.032000
No Value	MC	14.4389	13.40311	1.07728	0.8906	0.001000	-0.002000	0.008000
FPI	CPIF	4.7306	6.08668	0.77720	0.9714	0.004000	-0.016000	0.028000
FPAF	CPIF	-5.4167	3.65231	-1.48308	0.6752	-0.011000	-0.033000	0.006000
FFP	CPIF	-6.7506	13.61338	-0.49588	0.9963	-0.002000	-0.021000	0.011000
No Value	FPAF	-7.5175	16.33030	-0.46034	0.9974	-0.001000	-0.007000	0.008000
MC	FPAF	-8.2068	4.65475	-1.76309	0.4899	-0.003000	-0.008000	0.002000
MC	CPIF	-10.6023	4.65589	-2.27719	0.2033	-0.013000	-0.033000	0.001000
FPAF	FFP	-16.9650	12.90087	-1.31503	0.7769	-0.004000	-0.017000	0.004000
MC	FPI	-24.5645	5.88935	-4.17100	0.0004*	-0.015000	-0.030000	-0.003000
No Value	CPIF	-25.5733	17.31846	-1.47665	0.6793	-0.006000	-0.024000	0.004000
MC	FFP	-34.5877	10.88233	-3.17833	0.0185*	-0.007000	-0.016000	-0.001000
No Value	FFP	-35.3381	11.64297	-3.03515	0.0290*	-0.003000	-0.008000	0.000000
No Value	FPI	-48.4233	12.02853	-4.02571	0.0008*	-0.011000	-0.021000	-0.002000

Oneway Analysis of PSE/PME By Contract Type



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
CPIF	11	2502.00	1985.50	227.455	1.519
FFP	117	21420.5	21118.5	183.081	0.326
FPAF	12	936.500	2166.00	78.042	-3.469
FPI	57	12310.5	10288.5	215.974	2.805
MC	16	1744.00	2888.00	109.000	-2.811
No Value	147	26066.5	26533.5	177.323	-0.481

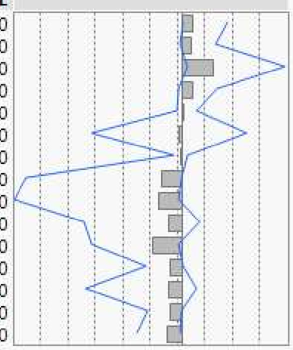
1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
28.2742	5	<.0001*

Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

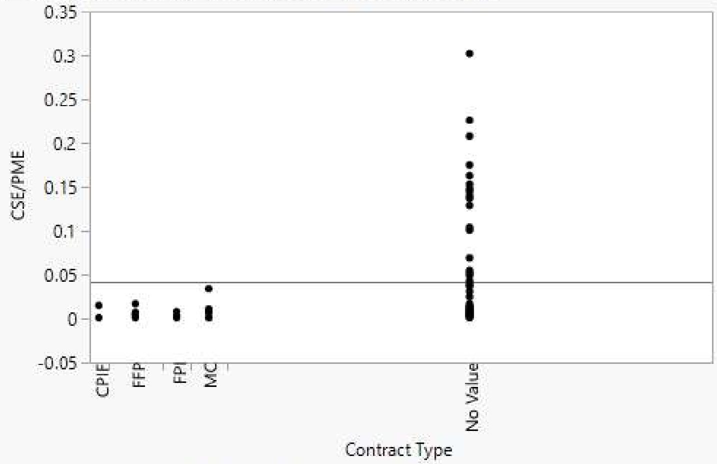
q*	Alpha
2.84970	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
No Value	FPAF	45.1131	13.81734	3.26496	0.0140*	0.015000	0.002000	0.063000
No Value	MC	30.3892	12.41848	2.44710	0.1403	0.013000	-0.002000	0.048000
FPI	FPAF	23.7061	6.36769	3.72288	0.0027*	0.044500	0.007000	0.143000
FPI	FFP	17.1808	8.13461	2.11207	0.2809	0.015000	-0.004000	0.050000
MC	FPAF	2.9896	3.13360	0.95404	0.9322	0.004000	-0.007000	0.021000
FPI	CPIF	-1.3014	6.50956	-0.19993	1.0000	-0.003000	-0.126000	0.091000
No Value	FFP	-4.4898	9.45725	-0.47475	0.9970	-0.001000	-0.011000	0.008000
MC	CPIF	-9.0511	3.10597	-2.91411	0.0416*	-0.028500	-0.216000	0.000000
FPAF	CPIF	-9.4091	2.82831	-3.32676	0.0113*	-0.033000	-0.232000	-0.005000
FFP	CPIF	-15.8135	11.69593	-1.35205	0.7557	-0.017000	-0.135000	0.025000
MC	FPI	-20.4912	5.99780	-3.41646	0.0083*	-0.041000	-0.125000	-0.005000
No Value	FPI	-21.4980	9.20780	-2.33476	0.1801	-0.016000	-0.050000	0.002000
No Value	CPIF	-22.4737	14.29693	-1.57193	0.6172	-0.018000	-0.134000	0.021000
MC	FFP	-29.0938	10.26874	-2.83324	0.0524	-0.015000	-0.047000	0.000000
FPAF	FFP	-38.3141	11.32792	-3.38227	0.0094*	-0.019000	-0.061000	-0.002000



Excluded Rows 1

Oneway Analysis of CSE/PME By Contract Type



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
CPIF	2	48.500	69.000	24.2500	-0.728
FFP	6	129.000	207.000	21.5000	-1.681
FPI	3	57.000	103.500	19.0000	-1.378
MC	4	120.500	138.000	30.1250	-0.445
No Value	53	1991.00	1828.50	37.5660	2.404

1-Way Test, ChiSquare Approximation

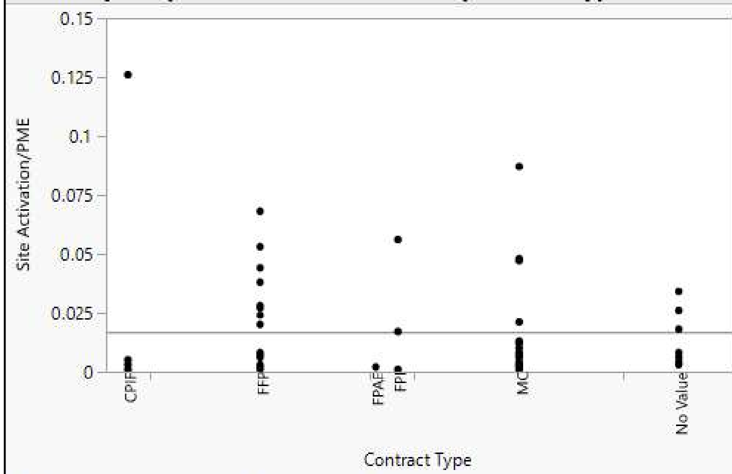
ChiSquare	DF	Prob>ChiSq
6.4868	4	0.1656

Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
2.72777	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
No Value	FPI	14.96855	9.65943	1.549632	0.5300	0.008000	-0.007000	0.2250000
No Value	FFP	13.63679	7.38116	1.847512	0.3462	0.008000	-0.004000	0.1360000
No Value	CPIF	10.37736	11.51811	0.900960	0.8966	0.008000	.	.
No Value	MC	6.58726	8.59164	0.766706	0.9401	0.004000	-0.029000	0.1520000
MC	FFP	1.66667	1.92450	0.866025	0.9093	0.005000	.	.
MC	FPI	1.16667	1.63512	0.713506	0.9535	0.005000	.	.
FFP	CPIF	0.00000	1.95180	0.000000	1.0000	0.000000	.	.
FPI	CPIF	0.00000	1.40683	0.000000	1.0000	-0.003500	.	.
FPI	FFP	0.00000	1.89572	0.000000	1.0000	0.000000	.	.
MC	CPIF	0.00000	1.59687	0.000000	1.0000	0.003000	.	.

Oneway Analysis of Site Activation/PME By Contract Type



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
CPIF	4	107.500	116.000	26.8750	-0.251
FFP	20	616.000	580.000	30.8000	0.596
FPAF	1	12.000	29.000	12.0000	-1.006
FPI	3	97.500	87.000	32.5000	0.359
MC	19	512.500	551.000	26.9737	-0.646
No Value	10	307.500	290.000	30.7500	0.358

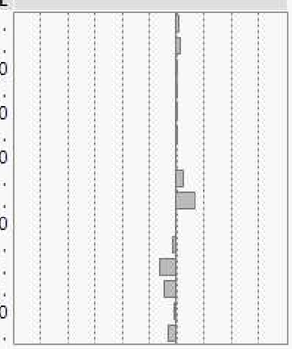
1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
1.8907	5	0.8640

Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

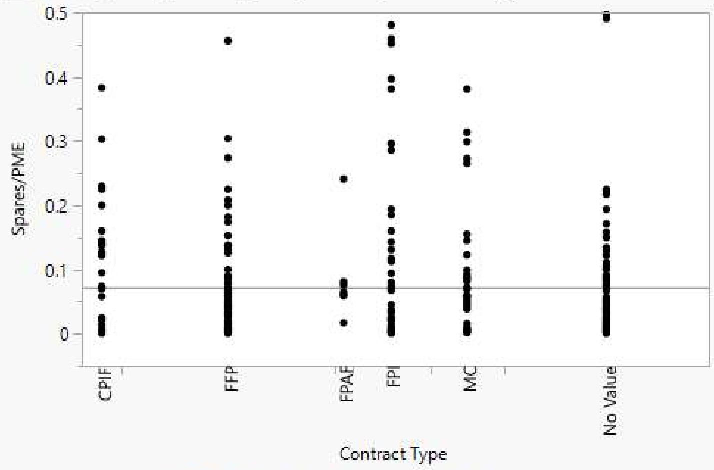
q*	Alpha
2.84970	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
No Value	FPAF	4.95000	3.438750	1.43948	0.7028	0.003000	.	.
MC	FPAF	4.21053	6.014756	0.70003	0.9820	0.004000	.	.
No Value	MC	1.98421	3.314215	0.59870	0.9912	0.001000	-0.017000	0.0160000
No Value	CPIF	1.22500	2.453020	0.49938	0.9962	0.001000	.	.
FFP	CPIF	1.05000	3.854416	0.27241	0.9998	0.001000	-0.125000	0.0650000
FPI	FFP	0.38333	4.182576	0.09165	1.0000	0.001500	.	.
MC	CPIF	0.15132	3.711686	0.04077	1.0000	0.000000	-0.125000	0.0840000
FPI	CPIF	0.00000	1.635118	0.00000	1.0000	0.006000	.	.
FPI	FPAF	0.00000	1.490712	0.00000	1.0000	0.015000	.	.
No Value	FFP	-0.37500	3.397387	-0.11038	1.0000	0.000000	-0.026000	0.0110000
FPAF	CPIF	-0.62500	1.767767	-0.35355	0.9993	-0.002000	.	.
No Value	FPI	-0.65000	2.545966	-0.25531	0.9999	-0.012000	.	.
MC	FPI	-2.12281	4.011366	-0.52920	0.9950	-0.009000	.	.
MC	FFP	-2.46316	3.637124	-0.67723	0.9845	-0.001000	-0.022000	0.0070000
FPAF	FFP	-5.77500	6.331173	-0.91215	0.9436	-0.005500	.	.



Excluded Rows 1

Oneway Analysis of Spares/PME By Contract Type



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
CPIF	20	4364.50	3160.00	218.225	3.056
FFP	107	13843.5	16906.0	129.379	-4.001
FPAF	9	1854.00	1422.00	206.000	1.603
FPI	39	7482.00	6162.00	191.846	2.479
MC	37	6014.00	5846.00	162.541	0.322
No Value	103	16212.0	16274.0	157.398	-0.081

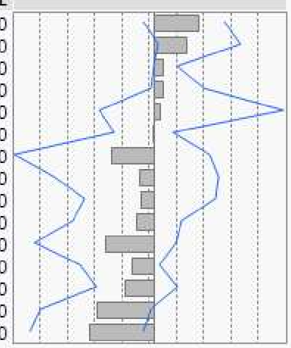
1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
27.3127	5	<.0001*

Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
2.84970	0.05

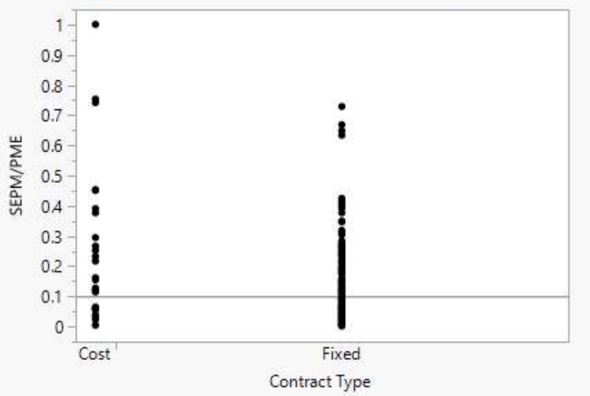
Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
FPAF	FFP	29.6926	11.64818	2.54912	0.1102	0.046000	-0.013000	0.073000
FPI	FFP	26.6425	7.89899	3.37289	0.0097*	0.033000	0.003000	0.090000
No Value	FFP	20.7694	8.38351	2.47742	0.1308	0.008000	-0.001000	0.023000
MC	FFP	14.8401	7.94381	1.86813	0.4220	0.009000	-0.005000	0.052000
FPI	FPAF	0.5470	5.17636	0.10567	1.0000	0.006000	-0.059000	0.135000
No Value	MC	-2.1674	7.77065	-0.27892	0.9998	-0.002000	-0.043000	0.019000
FPAF	CPIF	-3.3028	3.41684	-0.96662	0.9285	-0.046000	-0.149000	0.058000
FPI	CPIF	-3.8955	4.72281	-0.82483	0.9630	-0.017000	-0.108000	0.067000
MC	FPAF	-4.5586	4.97553	-0.91620	0.9425	-0.015000	-0.074000	0.064000
MC	FPI	-7.3735	5.06344	-1.45623	0.6923	-0.020000	-0.087000	0.028000
MC	CPIF	-9.6669	4.60005	-2.10148	0.2864	-0.053000	-0.128000	0.022000
No Value	FPI	-16.4200	7.73267	-2.12345	0.2750	-0.025000	-0.080000	0.005000
No Value	FPAF	-21.3247	11.28604	-1.88948	0.4086	-0.032000	-0.062000	0.024000
No Value	CPIF	-26.8988	8.71013	-3.08822	0.0246*	-0.062000	-0.122000	-0.004000
FFP	CPIF	-32.8776	8.95001	-3.67347	0.0033*	-0.070000	-0.132000	-0.012000



Excluded Rows 7

Kruskal-Wallis and Steel-Dwass Results (SEPM/Spares Descriptives) Fixed vs Cost Contracts

Oneway Analysis of SEPM/PME By Contract Type



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Cost	29	7629.00	5263.50	263.069	4.376
Fixed	333	58074.0	60439.5	174.396	-4.376

2-Sample Test, Normal Approximation

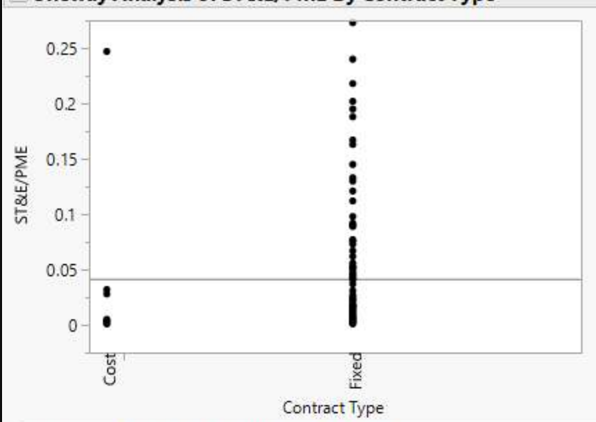
S	Z	Prob>|Z|
7629	4.37591	<.0001*

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
19.1567	1	<.0001*

Excluded Rows 387

Oneway Analysis of ST&E/PME By Contract Type



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Cost	8	358.000	452.000	44.7500	-1.058
Fixed	104	5970.00	5876.00	57.4038	1.058

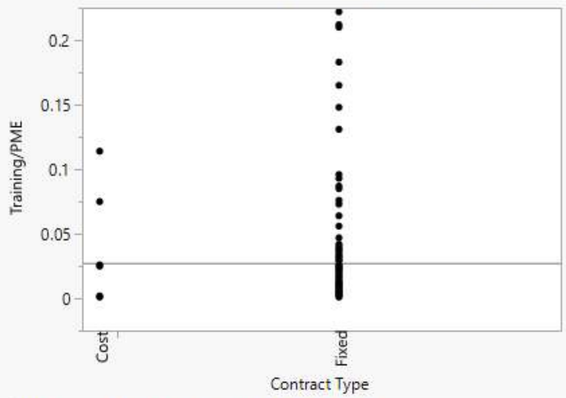
2-Sample Test, Normal Approximation

S	Z	Prob>|Z|
358	-1.05772	0.2902

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
1.1308	1	0.2876

Oneway Analysis of Training/PME By Contract Type



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Cost	9	502.000	562.500	55.7778	-0.581
Fixed	115	7248.00	7187.50	63.0261	0.581

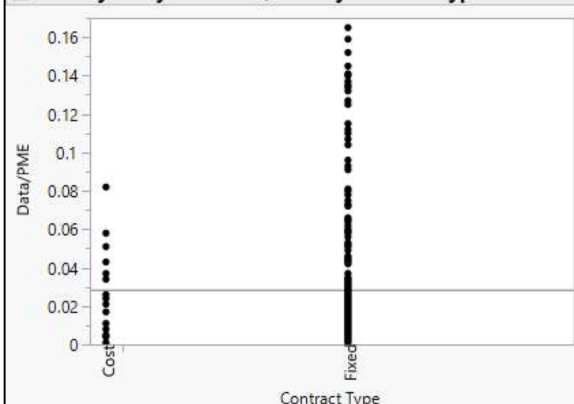
2-Sample Test, Normal Approximation

S	Z	Prob>|Z|
502	-0.58147	0.5609

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
0.3438	1	0.5577

Oneway Analysis of Data/PME By Contract Type



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Cost	18	2545.50	2448.00	141.417	0.302
Fixed	253	34310.5	34408.0	135.615	-0.302

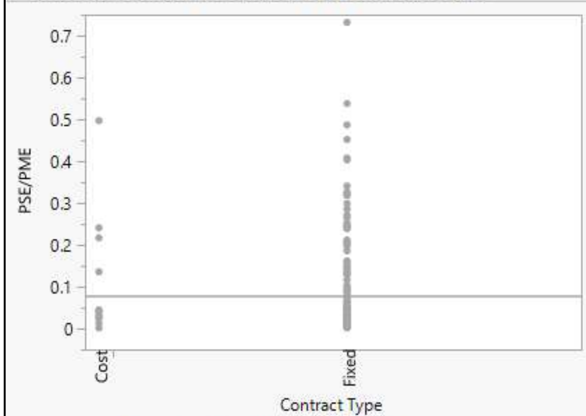
2-Sample Test, Normal Approximation

S	Z	Prob>|Z|
2545.5	0.30209	0.7626

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
0.0922	1	0.7614

Oneway Analysis of PSE/PME By Contract Type



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Cost	11	1315.50	1089.00	119.591	1.230
Fixed	186	18187.5	18414.0	97.782	-1.230

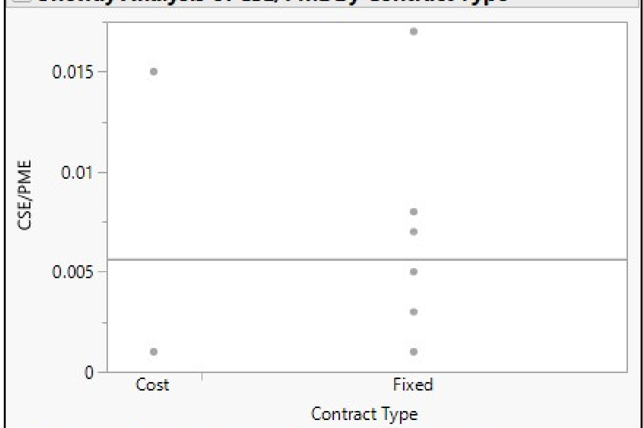
2-Sample Test, Normal Approximation

S	Z	Prob>|Z|
1315.5	1.23037	0.2186

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
1.5205	1	0.2175

Oneway Analysis of CSE/PME By Contract Type



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Cost	2	12.500	12.000	6.25000	0.000
Fixed	9	53.500	54.000	5.94444	0.000

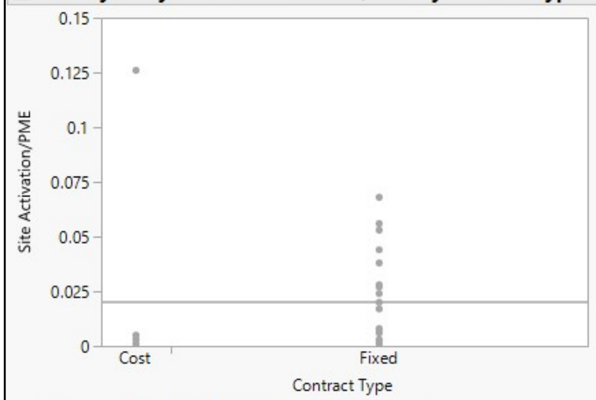
2-Sample Test, Normal Approximation

S	Z	Prob>|Z|
12.5	0.00000	1.0000

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
0.0146	1	0.9038

Oneway Analysis of Site Activation/PME By Contract Type



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Cost	4	54.500	58.000	13.6250	-0.198
Fixed	24	351.500	348.000	14.6458	0.198

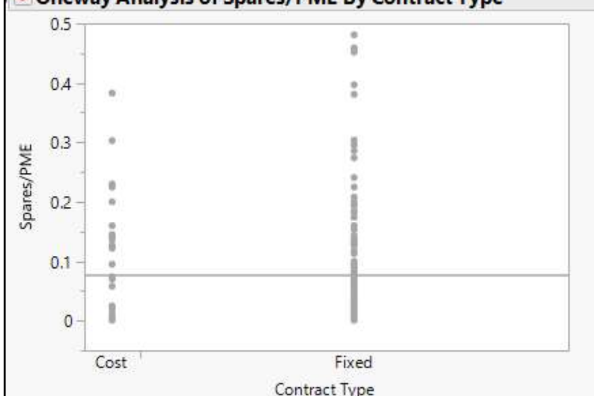
2-Sample Test, Normal Approximation

S	Z	Prob>|Z|
54.5	-0.19791	0.8431

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
0.0533	1	0.8174

Oneway Analysis of Spares/PME By Contract Type



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Cost	20	2387.50	1760.00	119.375	2.943
Fixed	155	13012.5	13640.0	83.952	-2.943

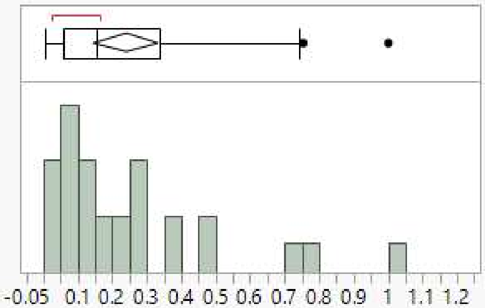
2-Sample Test, Normal Approximation

S	Z	Prob>|Z|
2387.5	2.94334	0.0032*

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
8.6771	1	0.0032*

SEPM/PME



Quantiles

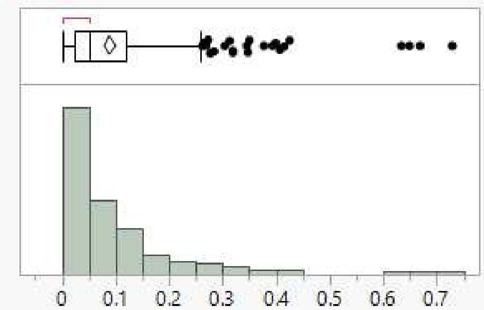
100.0%	maximum	1.001
99.5%		1.001
97.5%		1.001
90.0%		0.742
75.0%	quartile	0.336
50.0%	median	0.155
25.0%	quartile	0.0595
10.0%		0.033
2.5%		0.005
0.5%		0.005
0.0%	minimum	0.005

Summary Statistics

Mean	0.2401379
Std Dev	0.2450481
Std Err Mean	0.0455043
Upper 95% Mean	0.3333492
Lower 95% Mean	0.1469266
N	29

Distributions Contract Type=Fixed

SEPM/PME



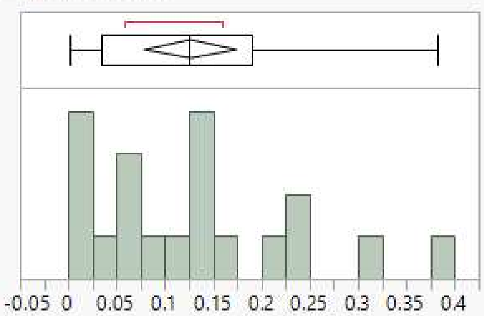
Quantiles

100.0%	maximum	0.729
99.5%		0.6888
97.5%		0.3969
90.0%		0.213
75.0%	quartile	0.1175
50.0%	median	0.051
25.0%	quartile	0.023
10.0%		0.009
2.5%		0.003
0.5%		0.001
0.0%	minimum	0.001

Summary Statistics

Mean	0.0890511
Std Dev	0.1070383
Std Err Mean	0.0058657
Upper 95% Mean	0.1005896
Lower 95% Mean	0.0775125
N	333

Spares/PME



Quantiles

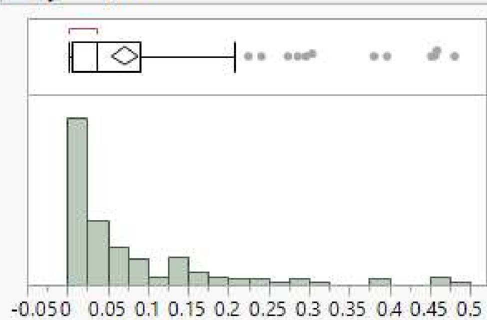
100.0%	maximum	0.383
99.5%		0.383
97.5%		0.383
90.0%		0.2957
75.0%	quartile	0.19
50.0%	median	0.1245
25.0%	quartile	0.03325
10.0%		0.0077
2.5%		0.001
0.5%		0.001
0.0%	minimum	0.001

Summary Statistics

Mean	0.1269
Std Dev	0.1026178
Std Err Mean	0.022946
Upper 95% Mean	0.1749266
Lower 95% Mean	0.0788734
N	20

Distributions Contract Type=Fixed

Spares/PME



Quantiles

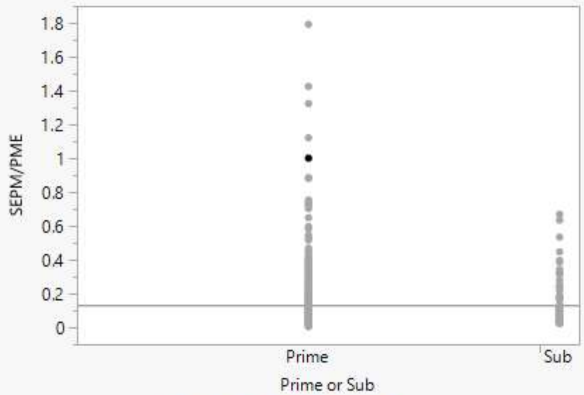
100.0%	maximum	0.481
99.5%		0.481
97.5%		0.4524
90.0%		0.1886
75.0%	quartile	0.09
50.0%	median	0.037
25.0%	quartile	0.006
10.0%		0.001
2.5%		0.001
0.5%		0.001
0.0%	minimum	0.001

Summary Statistics

Mean	0.0713419
Std Dev	0.0999216
Std Err Mean	0.0080259
Upper 95% Mean	0.087197
Lower 95% Mean	0.0554869
N	155

Kruskal-Wallis and Steel-Dwass Results by Contractor Type

Oneway Analysis of SEPM/PME By Prime or Sub



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Prime	686	251648	255535	366.834	-2.473
Sub	58	25492.0	21605.0	439.517	2.473

2-Sample Test, Normal Approximation

S	Z	Prob>|Z|
25492	2.47289	0.0134*

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
6.1167	1	0.0134*

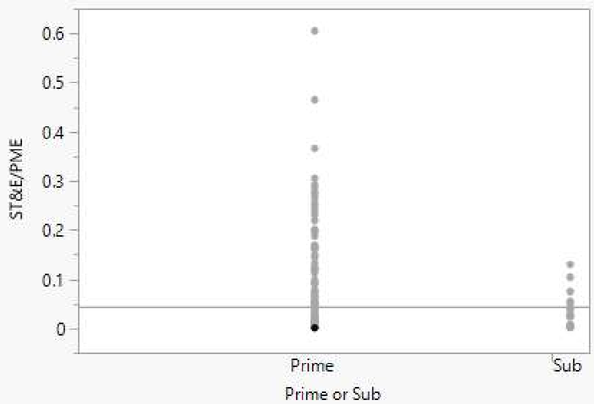
Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
1.95996	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Sub	Prime	72.67407	29.38837	2.472885	0.0134*	0.0250000	0.0060000	0.0480000

Excluded Rows 5

Oneway Analysis of ST&E/PME By Prime or Sub



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Prime	251	33518.5	34136.0	133.540	-1.832
Sub	20	3337.50	2720.00	166.875	1.832

2-Sample Test, Normal Approximation

S	Z	Prob>|Z|
3337.5	1.83156	0.0670

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
3.3601	1	0.0668

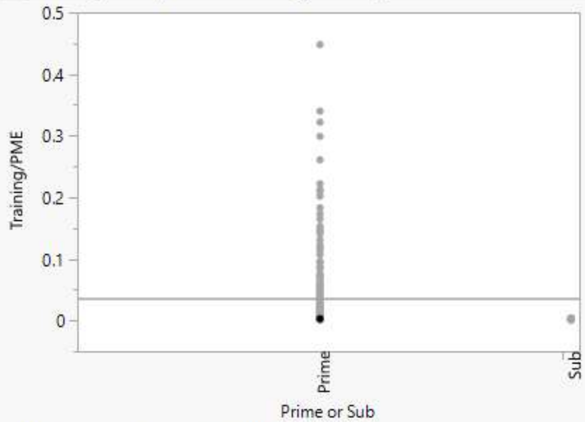
Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
1.95996	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Sub	Prime	33.30817	18.18568	1.831560	0.0670	0.0120000	0	0.0260000

Excluded Rows 4

Oneway Analysis of Training/PME By Prime or Sub



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Prime	231	28259.0	27720.0	122.333	2.808
Sub	8	421.000	960.000	52.625	-2.808

2-Sample Test, Normal Approximation

S	Z	Prob>|Z|
421	-2.80791	0.0050*

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
7.8990	1	0.0049*

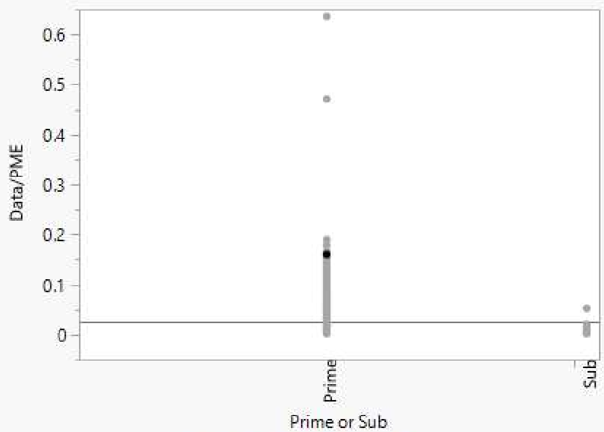
Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
1.95996	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Sub	Prime	-69.6437	24.80269	-2.80791	0.0050*	-0.008000	-0.027000	-0.001000

Excluded Rows 3

Oneway Analysis of Data/PME By Prime or Sub



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Prime	510	140323	136935	275.142	4.401
Sub	26	3593.50	6981.00	138.212	-4.401

2-Sample Test, Normal Approximation

S	Z	Prob>|Z|
3593.5	-4.40147	<.0001*

1-Way Test, ChiSquare Approximation

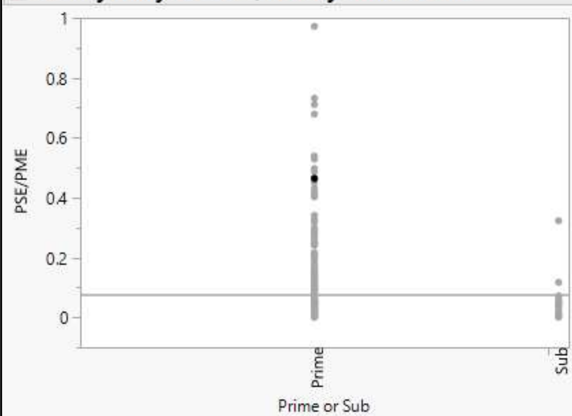
ChiSquare	DF	Prob>ChiSq
19.3787	1	<.0001*

Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
1.95996	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Sub	Prime	-136.910	31.10560	-4.40147	<.0001*	-0.008000	-0.014000	-0.003000

Oneway Analysis of PSE/PME By Prime or Sub



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Prime	345	62051.0	62272.5	179.858	-0.560
Sub	15	2929.00	2707.50	195.267	0.560

2-Sample Test, Normal Approximation

S	Z	Prob>|Z|
2929	0.56029	0.5753

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
0.3153	1	0.5744

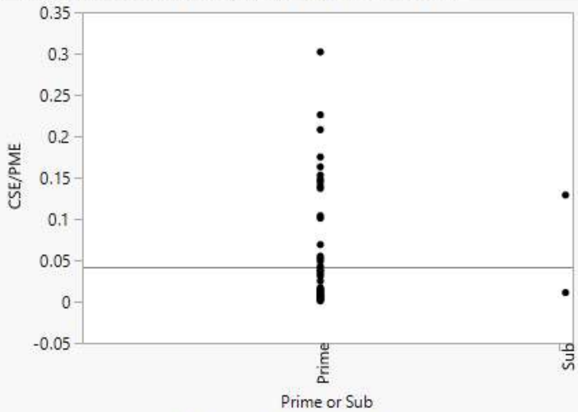
Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
1.95996	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Sub	Prime	15.37391	27.43910	0.5602921	0.5753	0.0050000	-0.014000	0.0260000

Excluded Rows 1

Oneway Analysis of CSE/PME By Prime or Sub



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Prime	66	2250.00	2277.00	34.0909	-0.965
Sub	2	96.000	69.000	48.0000	0.965

2-Sample Test, Normal Approximation

S	Z	Prob>|Z|
96	0.96506	0.3345

1-Way Test, ChiSquare Approximation

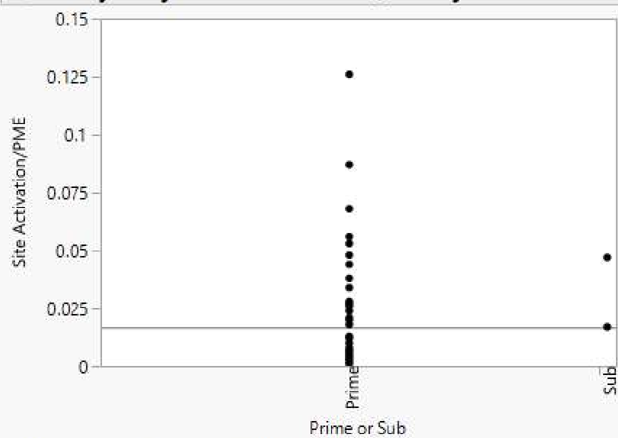
ChiSquare	DF	Prob>ChiSq
0.9668	1	0.3255

Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
1.95996	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Sub	Prime	13.65152	14.14573	0.9650624	0.3345	0.0100000	-0.126000	0.1280000

Oneway Analysis of Site Activation/PME By Prime or Sub



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Prime	55	1563.00	1595.00	28.4182	-1.371
Sub	2	90.000	58.000	45.0000	1.371

2-Sample Test, Normal Approximation

S	Z	Prob>|Z|
90	1.37093	0.1704

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
1.9396	1	0.1637

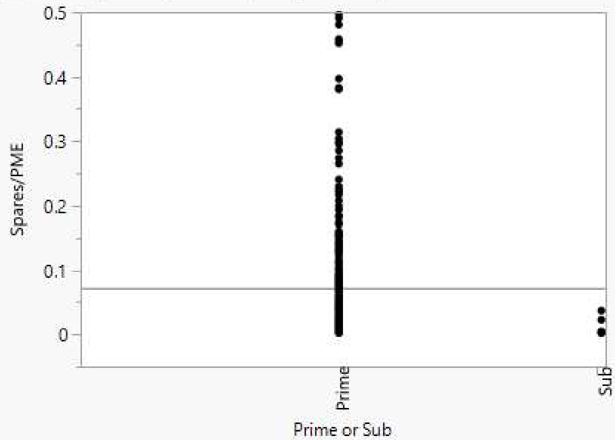
Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
1.95996	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Sub	Prime	16.32273	11.90629	1.370933	0.1704	0.0150000	-0.027000	0.0450000

Excluded Rows 1

Oneway Analysis of Spares/PME By Prime or Sub



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Prime	310	49361.0	48980.0	159.229	1.884
Sub	5	409.000	790.000	81.800	-1.884

2-Sample Test, Normal Approximation

S	Z	Prob>|Z|
409	-1.88400	0.0596

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
3.5588	1	0.0592

Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

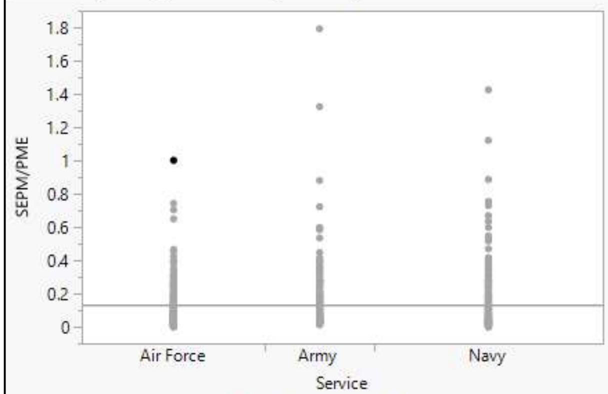
q*	Alpha
1.95996	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Sub	Prime	-77.3274	41.04428	-1.88400	0.0596	-0.028000	-0.086000	0.0010000

Excluded Rows 7

Kruskal-Wallis and Steel-Dwass Results by Service

Oneway Analysis of SEPM/PME By Service



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Air Force	262	88397.0	97595.0	337.393	-3.285
Army	155	71220.5	57737.5	459.487	5.663
Navy	327	117523	121808	359.396	-1.473

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
33.5998	2	<.0001*

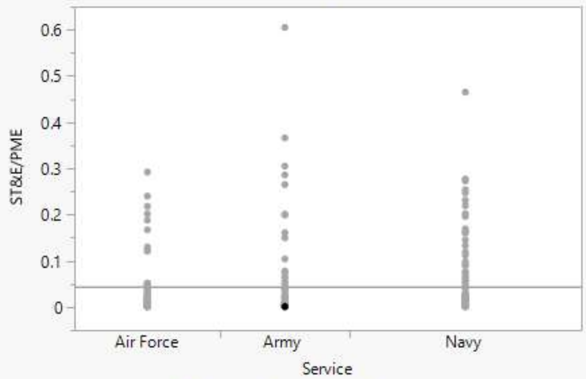
Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
2.34370	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Army	Air Force	68.0333	12.21255	5.57077	<.0001*	0.044000	0.025000	0.076000
Navy	Air Force	17.6788	14.10959	1.25296	0.4220	0.006000	-0.006000	0.019000
Navy	Army	-65.2034	13.58251	-4.80054	<.0001*	-0.038000	-0.067000	-0.019000

Excluded Rows 5

Oneway Analysis of ST&E/PME By Service



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Air Force	78	10402.0	10608.0	133.359	-0.352
Army	69	9193.50	9384.00	133.239	-0.338
Navy	124	17260.5	16864.0	139.198	0.617

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
0.3816	2	0.8263

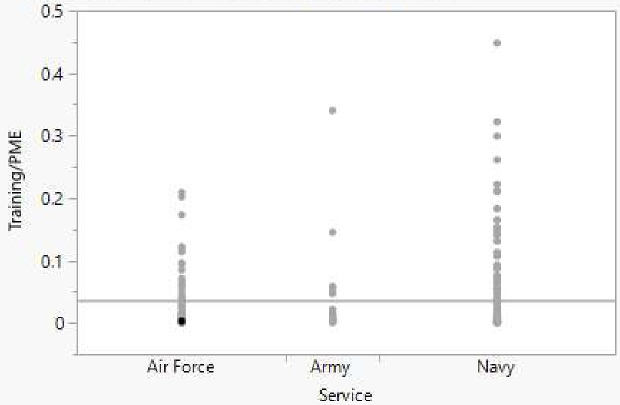
Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
2.34370	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Navy	Army	4.691912	8.379055	0.5599572	0.8413	0.0010000	-0.003000	0.0040000
Navy	Air Force	3.915943	8.437303	0.4641226	0.8881	0.0010000	-0.003000	0.0040000
Army	Air Force	0.477982	7.023818	0.0680516	0.9975	0.0000000	-0.004000	0.0050000

Excluded Rows 4

Oneway Analysis of Training/PME By Service



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Air Force	93	10959.5	11160.0	117.844	-0.385
Army	41	4593.50	4920.00	112.037	-0.811
Navy	105	13127.0	12600.0	125.019	0.995

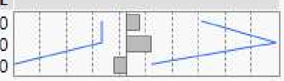
1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
1.1936	2	0.5506

Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

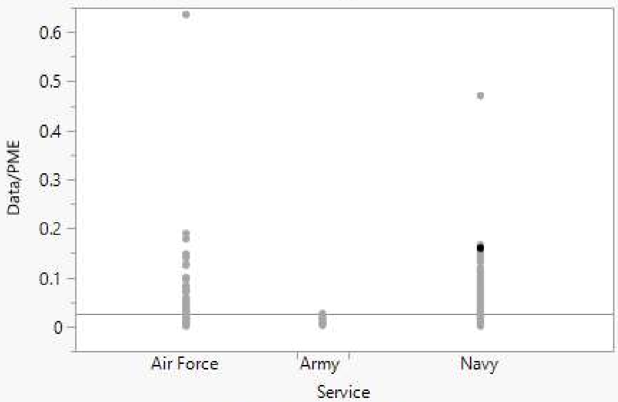
q*	Alpha
2.34370	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Navy	Air Force	6.79263	8.132899	0.835204	0.6811	0.001000	-0.002000	0.0060000
Navy	Army	6.47758	7.771736	0.833480	0.6822	0.002000	-0.002000	0.0120000
Army	Air Force	-4.72672	7.262360	-0.650852	0.7919	-0.001000	-0.009000	0.0020000



Excluded Rows 3

Oneway Analysis of Data/PME By Service



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Air Force	221	53474.5	59338.5	241.966	-3.326
Army	51	6387.50	13693.5	125.245	-6.951
Navy	264	84054.0	70884.0	318.386	7.354

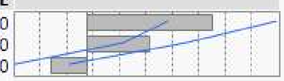
1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
77.6738	2	<.0001*

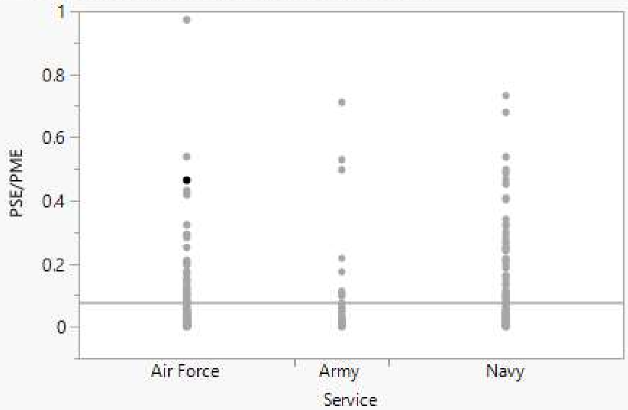
Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
2.34370	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Navy	Army	108.568	13.92053	7.79912	<.0001*	0.014000	0.009000	0.021000
Navy	Air Force	70.895	12.76878	5.55225	<.0001*	0.007000	0.004000	0.011000
Army	Air Force	-64.302	12.18682	-5.27633	<.0001*	-0.004000	-0.008000	-0.002000



Oneway Analysis of PSE/PME By Service



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Air Force	143	23915.5	25811.5	167.241	-1.962
Army	62	9227.50	11191.0	148.831	-2.634
Navy	155	31837.0	27977.5	205.400	3.948

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
16.9475	2	0.0002*

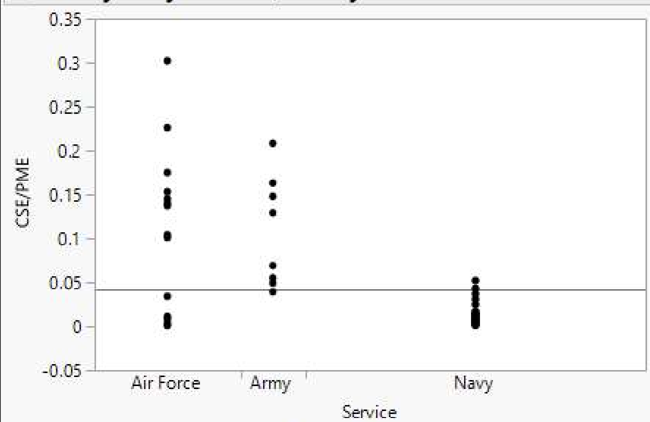
Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
2.34370	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Navy	Army	33.2839	9.431897	3.52886	0.0012*	0.016000	0.005000	0.0300000
Navy	Air Force	32.0587	9.988358	3.20961	0.0038*	0.012000	0.003000	0.0210000
Army	Air Force	-11.2951	9.016330	-1.25274	0.4221	-0.003000	-0.011000	0.0030000

Excluded Rows 1

Oneway Analysis of CSE/PME By Service



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Air Force	18	736.000	621.000	40.8889	1.597
Army	8	461.000	276.000	57.6250	3.523
Navy	42	1149.00	1449.00	27.3571	-3.792

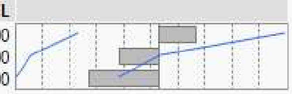
1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
18.4220	2	<.0001*

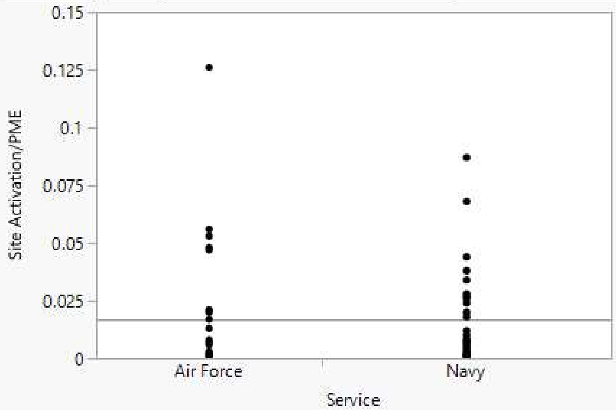
Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
2.34370	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Army	Air Force	3.5208	3.243883	1.08538	0.5231	0.038000	-0.084000	0.128000
Navy	Air Force	-10.6746	4.896425	-2.18008	0.0746	-0.041000	-0.133000	0.000000
Navy	Army	-24.4792	5.607934	-4.36510	<.0001*	-0.072500	-0.147000	-0.042000



Oneway Analysis of Site Activation/PME By Service



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Air Force	25	708.500	725.000	28.3400	-0.258
Navy	32	944.500	928.000	29.5156	0.258

2-Sample Test, Normal Approximation

S	Z	Prob>|Z|
708.5	-0.25821	0.7962

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
0.0709	1	0.7900

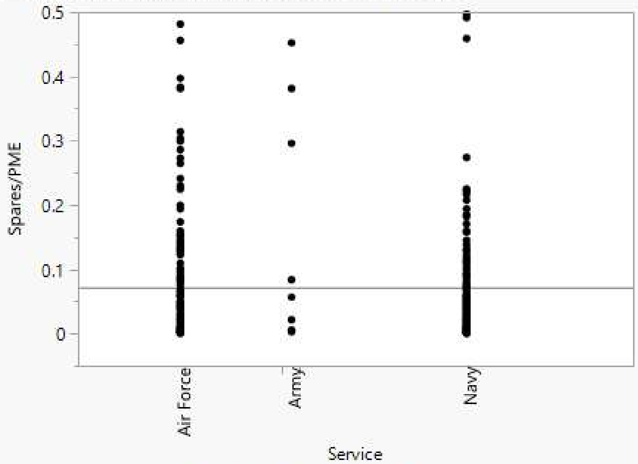
Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
1.95996	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Navy	Air Force	1.140000	4.414970	0.2582124	0.7962	0	-0.003000	0.0050000

Excluded Rows 1

Oneway Analysis of Spares/PME By Service



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Air Force	116	21607.0	18328.0	186.267	4.206
Army	10	1687.00	1580.00	168.700	0.376
Navy	189	26476.0	29862.0	140.085	-4.277

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
18.6375	2	<.0001*

Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

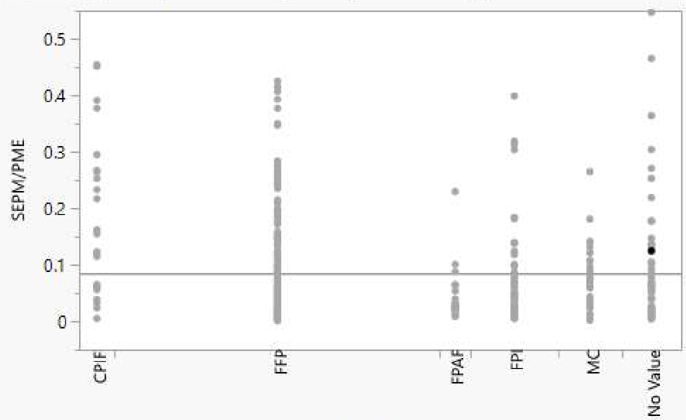
q*	Alpha
2.34370	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Army	Air Force	-4.0733	12.03338	-0.33850	0.9388	-0.003500	-0.066000	0.083000
Navy	Army	-15.2146	18.67532	-0.81469	0.6939	-0.005000	-0.185000	0.022000
Navy	Air Force	-45.0808	10.39811	-4.33549	<.0001*	-0.026000	-0.043000	-0.009000

Excluded Rows 7

Scenario Kruskal-Wallis and Steel-Dwass test results

Oneway Analysis of SEPM/PME By Contract Type



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
CPIF	25	7564.50	5287.50	302.580	3.849
FFP	228	46368.0	48222.0	203.368	-1.484
FPAF	21	3363.00	4441.50	160.143	-1.979
FPI	62	13155.0	13113.0	212.177	0.047
MC	44	8315.50	9306.00	188.989	-1.293
No Value	42	10487.0	8883.00	249.690	2.138

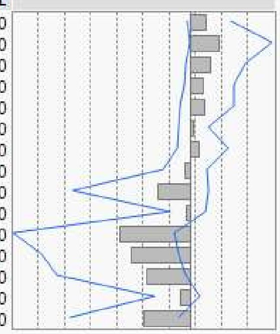
1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
24.2999	5	0.0002*

Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
2.84970	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
No Value	FFP	30.0987	13.11108	2.29567	0.1957	0.020000	-0.006000	0.052000
No Value	FPAF	13.6071	4.89822	2.77798	0.0610	0.036000	-0.001000	0.104000
No Value	MC	11.7738	5.38561	2.18616	0.2441	0.026000	-0.007000	0.070000
FPI	FPAF	10.4866	6.08461	1.72346	0.5161	0.016000	-0.009000	0.055000
No Value	FPI	9.1459	6.02819	1.51719	0.6531	0.018000	-0.014000	0.056000
FPI	FFP	5.8160	12.01048	0.48424	0.9967	0.003000	-0.017000	0.023000
MC	FPAF	5.1705	5.01261	1.03149	0.9075	0.010000	-0.019000	0.048000
MC	FPI	-5.9256	6.05894	-0.97799	0.9251	-0.007500	-0.037000	0.020000
No Value	CPIF	-8.7738	4.92139	-1.78279	0.4769	-0.042000	-0.154000	0.023000
MC	FFP	-10.0861	12.95186	-0.77874	0.9712	-0.005000	-0.028000	0.018000
FPAF	CPIF	-15.5962	3.97255	-3.92599	0.0012*	-0.093000	-0.230000	-0.022000
MC	CPIF	-17.8773	5.02209	-3.55972	0.0050*	-0.078500	-0.194000	-0.016000
FPI	CPIF	-18.5226	5.98365	-3.09553	0.0241*	-0.058000	-0.174000	-0.007000
FPAF	FFP	-24.4164	16.42361	-1.48666	0.6729	-0.014000	-0.047000	0.011000
FFP	CPIF	-59.6547	15.41632	-3.86958	0.0015*	-0.062000	-0.157000	-0.016000



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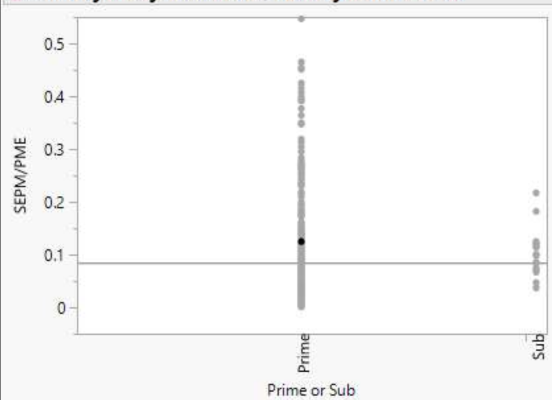
Oneway Analysis of SEPM/PME By Prime or Sub



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Prime	403	83580.5	85234.5	207.396	-3.183
Sub	19	5672.50	4018.50	298.553	3.183

2-Sample Test, Normal Approximation

S	Z	Prob>|Z|
5672.5	3.18285	0.0015*

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
10.1367	1	0.0015*

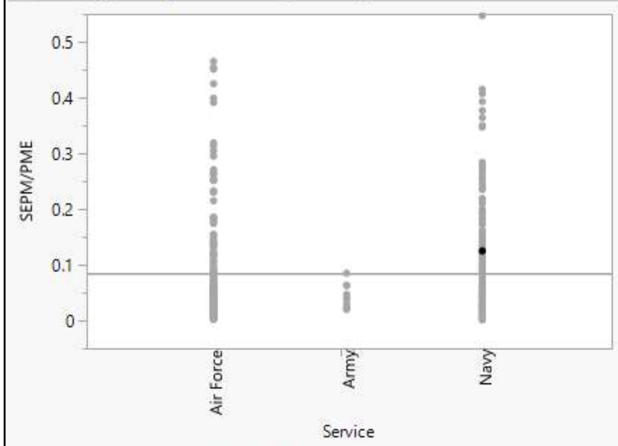
Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

q*	Alpha
1.95996	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
Sub	Prime	91.12929	28.63131	3.182854	0.0015*	0.0450000	0.0210000	0.0660000

Excluded Rows 5

Oneway Analysis of SEPM/PME By Service



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

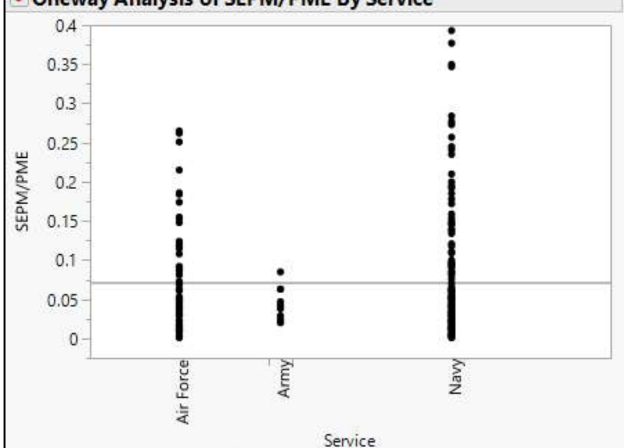
Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Air Force	204	41058.5	43146.0	201.267	-1.667
Army	10	1737.50	2115.00	173.750	-0.989
Navy	208	46457.0	43992.0	223.351	1.968

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
4.3582	2	0.1131

Excluded Rows 5

Oneway Analysis of SEPM/PME By Service



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
Air Force	74	7738.00	8029.00	104.568	-0.666
Army	10	993.500	1085.00	99.350	-0.472
Navy	132	14704.5	14322.0	111.398	0.853

1-Way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
0.7912	2	0.6733

Excluded Rows 533

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13. SUPPLEMENTARY NOTES

14. ABSTRACT
Cost estimators commonly use the analogy and factor method when developing Major Defense Acquisition Program (MDAP) estimates. Previous studies discussing and developing factors for the production lifecycle phase have been limited in scope and statistical analysis efforts. This research significantly expands the currently available toolkit for Department of Defense cost analysts by updating the current database of historical data and exploring potential relationships through statistical testing. Specifically, 3,462 unique factors were created across nine level II Work Breakdown Structure (WBS) elements broken down into four categories: commodity type, contract type, contractor type, and service. The production cost factors were created using data points from 145 MDAPs spanning from 1953 to 2018. Calculated factors were statistically tested for significant differences in their respective WBS element (by category) using non-parametric methods. The updated database and findings will aid analysts in quickly identifying categories that may impact their cost estimate. The practical and statistical analysis performed provide cost estimators with guidance and an improved production cost factor toolkit.

15. SUBJECT TERMS
Production, Cost Factors, Work Breakdown Structure (WBS), Cost Estimating, Major Defense Acquisition Program (MDAP)

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