Empirical Investigation of Engineering Change Order Percentages in Defense Contracts

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Abstract: Engineering Change Orders (ECO) are technical requirements changes to existing contracts. To account for the potential increase in contract costs stemming from ECOs, current acquisition practice is to estimate a dollar value to hold in management reserve (MR) in case of ECO occurrence. Estimators often rely on rules-of-thumb when developing these estimates. Specifically, many estimators use a 10% rule-of-thumb for estimating MR contract costs in the Development life cycle phase and a 5% rule-of-thumb for contracts in the Production life cycle phase. However, no empirical data appear to support or validate these 10% and 5% figures. Using a new data source, 1,216 contracts with ECOs were analyzed to determine the accuracy of the 10% and 5% rules-of-thumb as well as to determine if more accurate rules-of-thumb could be developed. Results suggest that if a contract is likely to have a positive ECO percentage, then 14% and 6% rules-of-thumb are more statistically appropriate for contracts in the Development and Production life cycle phases respectively. Lastly, Service, Contract Type, Commodity, Initial Program Size, and Schedule appear to impact ECO percentages.

Introduction

Since at least 1983, the Department of Defense (DoD) has instructed cost estimators to include in their contract estimates an additional percentage of the total costs to be held in reserve as a buffer against the possibility of an Engineering Change Order (ECO) (Gibson, 1983). An ECO is a tool used by management to direct a scope change to a contract (Engineering Change Proposals, 2021). This scope change is typically technical (e.g., correction of a design error that does not become evident until testing and modeling). Such scope changes amount to cost growth. Therefore, it would be beneficial to the government if accurate predictions could be made about the appropriate amount to hold in reserve. Reserving too much money limits the number of programs able to be funded. Reserving too little money puts a program at risk of being delayed or even cancelled.

The Government Accountability Office (GAO, 2008) determined that 63% of Major Defense Acquisition Programs (MDAPs) required contractual changes after system development. Such changes included administrative, engineering (also referred to as technical), and added non-technical work requirements changes. The same report showed that poorly defined requirements in acquisition programs can create significant cost growth. Major defense programs that had requirement changes after initial system development experienced mean cost growth of

72% from initial estimate, while those that did not have requirement changes experienced only 11%.

Per Gibson (1983) in a DoD ECO guidebook, a 10% estimate has provided reasonable coverage for the unanticipated requirements on many programs. The guidebook also provides suggestions for when to deviate from the 10%. However, no empirical data has been found that substantiates the validity of the 10% percentage. Some practitioners have continued to anchor estimates to that 10% rule-of-thumb (ROT) for Development contracts (DEV_{ROT}) in addition, to using a ROT for Production contracts ($PROD_{ROT}$). Specifically, the Air Force Life Cycle Management Center uses a 5% reserve for $PROD_{ROT}$ (S. Valentine, personal communications, 2021).

This article has three objectives. The first is to investigate whether DEV_{ROT} of 10% and $PROD_{ROT}$ of 5% provide a good estimate of the amount to be held in reserve for ECOs. If the first objective indicates that either ROT appears inaccurate, then the second objective is to develop a more accurate ROT to account for the percentage increase in cost due to ECOs. In conjunction with objective two, the third objective is to determine which factors, such as service, commodity type, contract type, or contract length, may drive differences in ECO percentages. These factors stem from previous research (Christensen & Templin, 2000; Arena et al., 2006; Bolten et al., 2008; Harmon & Arnold, 2013; Kozlak et al., 2017; Trudelle et al., 2017a, 2017b; D'Amico et al., 2018; Ellis et al., 2018) that indicate a possible association with program cost growth.

Methods

The data used for this article originated from the DoD contracting system known as Electronic Document Access (EDA). EDA is an online resource in which government contracting agencies upload scanned copies of actual contractual documents (EDA, 2017). The Defense Cost and Resource Center (DCaRC) commissioned a support contractor to establish a separate database from batches of contracts from EDA, which were identified of value by defense analysts. In October 2021, the support contractor provided the authors of this article the EDA data in the form of an Excel database.

To the best of our knowledge, the contracts in the current database were not chosen randomly. Each year, the DoD office of Cost Assessment Data Enterprise (CADE) sends out a data call to cost agencies DoD-wide requesting a list of contracts on which analysts would like information. Cost agencies then send their contract list to the support contractor, which in turn, then searches for them in EDA and transfers the data to the CADE database. The CADE database is updated on a quarterly basis.

Basic DoD contracts and their modifications comprise the database. The database includes a column of dollar amounts for each contract and modification, normalized for inflation to fiscal year (FY) 2020 using the 2020 OSD inflation table. Besides contract baseline cost, ECO cost, and ECO percentage (ECO cost / baseline cost), the database also contains contract number, service, commodity type, program, life cycle phase, contract type, contract start date, period of performance (PoP) end date, and schedule length in days (difference between PoP and contract start date).

Because only development and production contracts were germane to the analysis, we remove any Operating and Support (O&S) contracts in the database. To minimize the effect of error or unrealistic baselines, we omit any contract that exceeds 100% in absolute value for an ECO percentage. This exclusion is in-line with exclusion criteria from Ellis et al. (2018). Table 1 highlights the complete inclusion/exclusion criteria for the database we analyzed. The database contained 11,481 unique contracts with their respective modifications (if any) and reasons for modification. The Appendix lists the

INCLUSION CRITERIA	CONTRACTS ADDED	CONTRACTS REMOVED	CONTRACTS REMAINING
Original Dataset	11,481		11,481
Non-Technical Modifications		8,537	2,944
Blank Baseline or ECO Cost		12	2,932
Absolute Value of ECO % > 100%		498	2,434
O&S Contracts		1,218	1,216

Table 1: Inclusion/exclusion criteria describing the establishment of the final analyzed database.

programs which had contracts in the database. Due to the nature of the available data, the analysis in this research is solely at the contract level as opposed to the program level.

We analyze the finalized data using both descriptive measures and statistical inferential tests. The descriptive measures include means, standard deviations, coefficients of variation (CV), medians, interquartile ranges (IQR), and a quartile-based CV of IQR/medians. The inferential tests include *t*-tests, the nonparametric Kruskal-Wallis test (Wilcoxon Rank Sum when just comparing two populations) and Steel-Dwass multiple comparisons, Pearson's Chi-squared test for dependency between variables, associated odds ratios and confidence intervals for significant odds ratios. Given the large sample sizes for initially testing the current DEV_{ROT} and $PROD_{ROT}$ of 10% and 5%, assessment of normality is not needed. However, when conducting further tests comparing various services, commodities, and contract types (Table 2 lists those in our database), we chose the conservative nonparametric approach over the customary analysis of variance and subsequent Tukey analysis. For level of significance, we use an alpha of 0.05 for all the inferential tests. JMP Pro 15 was the software used to perform the statistical calculations.

SERVICES	COMMODITIES	CONTRACT TYPES
Air Force	AIS (Automated Information System)	Cost
Army	Decoys	Fixed
DoD (two or more services)	Electronics	Time and Materials (T&M)
Navy (includes Marines)	Engine	
	F-16	
	F/A-18	
	Ground Vehicle	
	Gun	
	Missiles	
	Non-lethal	
	Ordnance	
	Other Aircraft	
	Radar	
	Ship	
	Space	
	Targets/Drones	
	UAV (Unmanned Aerial Vehicle)	

Table 2: Breakdown of services, commodities, and contract types in the final analyzed database.

Results

From the 1,216 contracts in our final database, we first analyze the development ones. Table 3 reflects the summary statistics for these 448 contracts. With a *p*-value of less than 0.0001 for the accompanying *t*-test, empirical evidence suggests that DEV_{ROT} based on the mean value of 16.3% is statistically greater than 10%. But there is a high degree of variability present among the development contracts as reflected in both the standard deviation and IQR. This variability indicates that the median may also play a role in determining how much to estimate/reserve for ECO. A median value of 10.4% is very near the DEV_{ROT} value of 10% and is not statistically significant.

METRIC	DEVELOPMENT	PRODUCTION
Sample Size	448	768
Mean	0.163	0.088
Standard Deviation	0.279	0.286
Coefficient of Variation	1.711	3.253
Median	0.104	0.035
Interquartile Range (IQR)	0.265	0.141
IQR / Median	2.563	4.014

Table 3: Summary statistics for the 448 development and 768 production contracts. Numbers rounded to three decimal places.

Table 3 also reflects the summary statistics for the 768 production contracts. With a p-value of 0.0001 for the accompanying t-test, empirical evidence suggests that $\mathrm{PROD_{ROT}}$ based on the mean value of 8.8% is statistically greater than 5%. Like the development contracts, production contracts also display a high degree of variability with respect to ECO percentage as reflected in the standard deviation and IQR.

$\mathrm{DEV_{ROT}}$ and $\mathrm{PROD_{ROT}}$ are statistically different from one another with a p-value of less than 0.0001 for both the t-test and Wilcoxon Rank Sum test. This implies that development and production contracts statistically differ with respect to ECO percentages, with $\mathrm{DEV_{ROT}} > \mathrm{PROD_{ROT}}$. We present these results in separate subsections.

Development

Of the 448 development contracts, one contract had no ECO cost, 59 had negative ECO cost, while the remaining 388 (86.6%) had positive ECO cost. As stated previously in the Methods section, we conducted three Kruskal-Wallis (K-W) tests to determine any statistical difference among the services, commodity, and contract type with respect to ECO percentage. No statistical difference existed among services (p-value of 0.5387) or commodity type (p-value of .1022). For contract type, 65 contracts were identified as unknown (missing). Of the remaining 383, 251 (65.5%) were identified as cost, 85 as fixed, and 47 as T&M. A statistical difference appeared between cost and fixed (K-W p-value of 0.0385, with a subsequent p-value of 0.0277 for the Steel-Dwass (S-D) multiple comparisons). Table 4 highlights the metrics associated with cost, fixed, and T&M contracts, respectively. Note: both the mean ECO percentages for cost and T&M contracts were statistically (p-value < 0.0001) greater than $\mathrm{DEV_{ROT}}$ of 10%, while fixed type contracts were equivalent.

From studies noted in the Introduction section, we next address if dollar threshold and/or contract schedule length is associated with whether a contract is likely to exceed the $\mathrm{DEV_{ROT}}$ of 10%. The natural breaks are those set for DoD's classification. ACAT I is associated with Research, Development, Test and Evaluation (RDT&E) costs over $525M (in FY 2020 dollars); ACAT II with RDT&E programs between $200M and $525M (FY 2020); and ACAT III for all program less than $200M. The p-value for the Pearson's chi-squared test of independence was 0.4709. This finding suggests dollar thresholds associated with ACAT categories do not appear to affect the likelihood of exceeding the $\mathrm{DEV_{ROT}}$ of 10%.

Regarding contract length, only 346 (77.2%) of the contracts had complete schedule data (neither contract award date nor PoP end date

METRIC	COST	FIXED	T&M
Sample Size	251	85	47
Mean	0.172	0.102	0.211
Standard Deviation	0.264	0.271	0.399
Coefficient of Variation	1.531	2.654	1.89
Median	0.114	0.057	0.109
Interquartile Range (IQR)	0.269	0.215	0.421
IQR / Median	2.36	3.772	3.862

Table 4: Summary statistics for the 251 cost, 85 fixed, and 47 T&M development contracts. Numbers rounded to three decimal places.

were missing). We tested if contract length equal to or greater than five years had an increased chance of exceeding the DEV_{ROT} of 10%. This threshold is based on Trudelle et al., 2017a which showed that program length of five years or more appeared to be a statistically significant indicator of cost growth. The Pearson's chi-squared dependency test returned a *p*-value of 0.0007. The associated odds ratio of 3.99 (with an associated 95% confident interval of (1.71, 9.31)) suggests that development contracts that equal or exceed five years in length are four times more likely to exceed an ECO percentage of 10%.

Prior to preceding into a comparable analysis by narrowing to contracts with just net positive ECO cost (hereafter referred to as positive ECO cost), we investigate what factors (service, commodity, contract type) might indicate that a development contract is likely to experience positive ECO cost. The *p*-value for testing dependency between service and positive ECO cost was 0.9611, strongly suggesting no dependency whatsoever. Consistent to the previous finding regarding all ECO costs, development contracts, irrespective of commodity type, had a comparable chance of experiencing positive ECO with one exception, ground vehicles.

The ground vehicles in our database consisted of the Joint Light Tactical Vehicle (primarily Army/ Marine), the Joint Mine Resistant Ambush Protected (Army/Marine), the Logistic Vehicle System Replacement (Marine equivalent to the Army's Heavy Expanded Mobility Tactical Truck), and the Medium Tactical Vehicle Replacement (Marine equivalent of the US Army's Family of Medium Tactical Vehicles). These types of vehicles are approximately 3.81 times less likely to experience a positive ECO cost. The associated *p*-value for this Pearson chi-squared test was 0.0037 with a 95% confidence interval for the odds ratio of (1.45, 9.98). Table 5 contains the descriptive statistics for ground vehicles. As previously noted, high variability is present as shown by the standard deviation and IQR values.

METRIC	VALUE
Mean	0.125
Standard Deviation	0.389
Coefficient of Variation	3.112
Median	0.044
Interquartile Range (IQR)	0.559
IQR / Median	12.704

Table 5: Summary statistics for the 20 ground vehicle development contracts. Numbers rounded to three decimal places.

Regarding contract type, cost contracts appear to have a higher likelihood of experiencing a positive ECO cost compared to fixed and T&M. The *p*-value for the Pearson's chi-squared test was 0.0137 with an associated odds ratio of 2.05 and a 95% confidence interval of (1.15, 3.65). Overall, it appears that a cost development contract is more likely to experience positive ECO cost, while a ground vehicle like those in our database is less likely to experience positive ECO cost.

Next, we narrow to just those contracts with positive ECO cost, which represent 86.6% of all the development contracts in our database. Table 6 contains the descriptive measures of just the positive ECO contracts. As expected, both the mean and median are higher than those shown in Table 3. In addition, both the CV and IQR/Median are lower.

METRIC	VALUE
Mean	0.222
Standard Deviation	0.233
Coefficient of Variation	1.05
Median	0.14
Interquartile Range (IQR)	0.285
IQR / Median	2.045

Table 6: Summary statistics for the 388 development contracts with positive ECO cost. Numbers rounded to three decimal places.

Among just contracts that experienced positive ECO cost, neither service (K-W *p*-value of 0.2882) nor commodity (K-W *p*-value of 0.1371) appeared significant at the 0.05 level but contract type (K-W *p*-value of 0.0468) did. Given the *p*-value was very close to the 0.05 level, the subsequent S-D multiple comparisons lacked the statistical power to meet this significance threshold. S-D only indicated that fixed and T&M contracts might be different with a *p*-value of 0.0590. Table 7 highlights the metrics associated with cost, fixed, and T&M contracts for just those with positive ECO cost, respectively. Sixty contracts had missing information for contract type. Note: all contract types possessed a mean percentage statistically greater than DEV_{ROT} of 10% (*p*-value < 0.0001).

METRIC	COST	FIXED	T&M
Sample Size	223	68	37
Mean	0.224	0.182	0.337
Standard Deviation	0.218	0.208	0.326
Coefficient of Variation	0.973	1.138	0.967
Median	0.151	0.128	0.204
Interquartile Range (IQR)	0.286	0.227	0.617
IQR / Median	1.894	1.778	3.022

Table 7: Summary statistics for the ECO positive development contracts. Numbers rounded to three decimal places.

Next, we address if dollar threshold and/or contract schedule length might affect the chance a contract is likely to exceed the DEV_{ROT} of 10%. Using the same ACAT dollar thresholds as before, the *p*-value for the Pearson's chi-squared test of independence was 0.1382. This finding suggests dollar thresholds associated with ACAT categories may not affect the likelihood of exceeding the DEV_{ROT} of 10% when just examining contracts with positive ECO cost.

We did conduct *post hoc* analysis given this drop of *p*-value from 0.4709 (from the previous ACAT analysis) to 0.1382 with respect to investigating dollar threshold and exceeding DEV_{ROT} of 10%. We varied the dollar threshold incrementally between $10M to $100M and observed the spot whereby both the *p*-values and odd ratios change the most statistically. As shown in Table 8, that dollar amount appears to be around $30M. Table 9 highlights the metrics associated with contracts less than $30M and those equal to or greater than that value.

DOLLAR AMOUNT	ODDS RATIO	P-VALUE
<$10M	1.89	0.003
<$20M	1.94	0.0016
<$30M	2.17	0.0002
<$40M	1.75	0.0077
<$50M	1.62	0.0234
<$100M	1.57	0.0531

Table 8: Odds ratios and p-values for varying baseline contract amount from $10M to $100M in 2020 FY for ECO positive cost contracts.

METRIC	<$30M	$30M≥
Mean	0.268	0.17
Standard Deviation	0.255	0.194
Coefficient of Variation	0.949	1.144
Median	0.177	0.094
Interquartile Range (IQR)	0.318	0.216
IQR / Median	1.794	2.295

Table 9: Summary statistics for the ECO positive cost contracts less than $30M (in FY 2020 dollars) and those equal to or greater than $30M. Numbers rounded to three decimal places.

Regarding contract length, only 319 (82.2%) of the ECO positive contracts had complete schedule data (neither contract award date nor PoP end date were missing). We again tested if contract length equal to or greater than five years had an increased chance of exceeding the DEV_{ROT} of 10%. The Pearson's chi-squared test returned a *p*-value of 0.0009, suggesting dependency between them.

The odds ratio of 4.60 (with an associated 95% confident interval of (1.74, 12.17)) suggests that ECO positive development contracts that equal or exceed five years in length are more likely to exceed an ECO percentage of 10% than shorter contracts.

In summary, for development contracts it appears there is a high likelihood (86.6%) that these experience positive ECO cost. The median and mean ECO percentages are 14% and 22% respectively. Both are statistically greater than the DEV_{ROT} of 10%. Ground vehicles are less likely to experience positive ECO cost, while cost type contracts are more likely to experience positive ECO cost. Lastly, development contracts with a PoP equal to or exceeding five years and contracts less than $30M in FY 2020 dollars are likely to experience an ECO percentage greater than 10%. In the Discussion and Conclusion section, we quantify our ECO recommendations through a table utilizing the median values presented in this section due to the high variability reflected by the coefficient of variations and ratios of IQR/Median. We now turn to the results associated with the production contracts.

Production

For this subsection, we replicate the analysis and flow that we performed previously for development contracts but just for production contracts. Of the 768 production contracts, 148 had negative ECO cost, while the remaining 620 had positive ECO cost. These 620 contracts equate to approximately 80.7% of the production contracts. Such a relatively high percentage suggests that the analysis should also analyze the characteristics of just the positive ECO cost contracts to provide additional insight. Prior to this conditional analysis, we investigate inferential patterns among all the production contracts.

Testing ECO percentage differences among the services, the initial K-W produced a *p*-value of 0.0337, with Navy contracts being statistically lower than Air Force contracts (S-D *p*-value of 0.0276). However, it should be noted that a fair number of F/A-18 contracts (13 out of 71) had -100% ECO [Note: programs can have multiple contracts, thereby allowing this number to be plausible.], which drove the mean percentage of the F/A-18 to -7.2%. No other commodity had a negative ECO %. When excluding those 13 contracts, the K-W's *p*-value rose significantly to 0.1431, reflecting a truer picture among the services, suggesting that there appears to be no statistical difference among the services with respect to ECO %. Moving forward with any remaining inferential analysis in this part, we continue to exclude these 13 contracts.

For any K-W test, it is advisable to exclude any comparison group that has five or fewer observations because of low power issues (Kruskal & Wallis, 1952; Howell, 2002). Consequently, we removed the commodity groups Ship (3 contracts: DDG 51), Gun (2 contracts: CIWS and LW155), and AIS (2 contracts: GCSS-MC and DCGS-N). Therefore, we cannot make any inferential decisions regarding these commodities.

For the remaining commodities, we conducted a K-W test and found a statistical difference among the remaining commodities (*p*-value of 0.0160). The S-D multiple comparisons determined that Ground Vehicle and Other aircraft were statistically different from the other commodities (we separated the F-16 and F/A-18 from the Other Aircraft due to their relatively large number of contracts; Ellis et al. (2018) performed a similar measure for the F/A-18). The S-D multiple comparisons displayed a *p*-value of 0.0394 and noted that Ground Vehicle generally has lower ECO % compared to Other aircraft.

Investigating differences between contract types, we first needed to exclude production contracts labeled as unknown or missing. This number totaled 95. For the remaining, we had 75 cost, 569 fixed, and 16 T&M contracts. Unlike development contracts that primarily consisted of cost type contracts, most of the production contracts were fixed contracts (86.2%). When inferentially comparing among cost, fixed, and T&M contracts, the only statistical difference appeared between cost and fixed (K-W *p*-value of 0.0003, with a subsequent *p*-value of 0.0002 for the S-D for multiple comparisons). We saw similar results for development contracts. Table 10 highlights the metrics associated with cost, fixed, and T&M production contracts, respectively.

METRIC	COST	FIXED	T&M
Sample Size	75	569	16
Mean	0.236	0.094	0.091
Standard Deviation	0.306	0.245	0.431
Coefficient of Variation	1.295	2.614	4.726
Median	0.102	0.031	0.104
Interquartile Range (IQR)	0.347	0.139	0.565
IQR / Median	3.402	4.484	5.461

Table 10: Summary statistics for the 75 cost, 569 fixed, and 16 T&M production contracts. Numbers rounded to three decimal places.

As with development contracts, we next analyze if dollar threshold and/or contract schedule length might affect if a contract is likely to exceed the $PROD_{ROT}$ of 5%. We use dollar thresholds again with respect to ACAT level but adjust accordingly for production. Specifically, ACAT I is associated with Procurement costs greater than $3.065B (in FY 2020 dollars); ACAT II with Procurement dollar amounts less than ACAT I but greater than $920M (FY 2020); and ACAT III for anything less. The *p*-value for the Pearson's chi-squared test of independence was 0.7181. This finding suggests dollar thresholds associated with ACAT categories do not appear to affect the likelihood of exceeding the $PROD_{ROT}$ of 5%.

Regarding contract length, 624 (82.6%) of the contracts had complete schedule data (neither contract award date nor PoP end date were missing). We tested if contract length equal to or greater than five years (due to Trudelle et al. (2017a) findings) had an increased chance of exceeding the $PROD_{ROT}$ of 5%. The Pearson's chi-squared test returned a *p*-value of 0.0510, which just barely misses our level of significance of 0.05, suggesting perhaps borderline dependency at best that production contracts that equal or exceed five years in length are slightly more likely to exceed an ECO percentage of 5%.

Prior to proceeding into a comparable analysis by narrowing to production contracts with just a positive ECO cost, we investigate what factors might indicate a production contract is likely to experience positive ECO cost. The *p*-value for testing dependency between service and positive ECO cost was 0.0026, strongly suggesting dependency. Further investigation reveals that Air Force production contracts are statistically more likely than Navy (which includes Marines) and Army to experience positive ECO cost. The associated *p*-value for this Pearson's chi-squared test is 0.0002 with an odds ratio of 2.12 with a 95% confidence interval of (1.42, 3.18).

Because a strong dependency appears between service and likelihood of incurring positive ECO cost, we need to perform conditional analysis on service before comparing among commodities. This conditional analysis is required because there is a natural dependency between service and commodity. Due to small sample size for some commodities, we excluded AIS, Gun, and Ship contracts. When comparing among Air Force commodities, UAV and F-16 production contracts are less likely to experience positive ECO cost compared to the other commodities of Decoys, Electronics, Engines, Missiles, Ordnance, Other Aircraft, Space, and Targets/Drones. The *p*-value for this Pearson's chi-squared test was less than 0.0001 with an odds ratio of 5.71 and a 95% confidence interval of (2.84, 11.50).

For just Navy, we compare only the commodities F/A-18, Missiles, Other Aircraft, and Ground Vehicle contracts because of small sample issues (having five or fewer contracts) for the other commodities of Decoys, Engine, Space, Target/ Drones, and UAV. The commodity that is the least likely to experience positive ECO cost are Ground Vehicle production contracts compared to the other three commodities tested (comparable to what we found with development contracts). The *p*-value is less than 0.0001 with an odds ratio of 3.30 and a 95% confidence interval of (1.99, 5.47). The next commodity, the F/A-18, is less likely to experience positive ECO cost compared to Missiles and Other Aircraft. Its *p*-value is 0.0078 with an odds ratio of 2.93 and a 95% confidence interval of (1.30, 6.63). For Army only commodities, 0.3329 was the resultant *p*-value suggesting no commodity is more likely to experience positive ECO cost than another.

Regarding contract type, the *p*-value associated with testing the assumption if contract type (cost, fixed, and T&M) affects the likelihood of experiencing a positive ECO cost was 0.0762, suggesting a weak association since it isn't less than 0.05. Tentatively, it appears T&M is the least likely to experience positive ECO cost with cost type contracts being the most likely.

Next, we narrow to just those production contracts with positive ECO contracts, which represent 80.7% of all the production contracts in our database. Table 11 contains the descriptive measures of just the positive ECO contracts. As expected, both the mean and median are higher than those shown in Table 2. In addition, both the CV and IQR/Median are lower.

METRIC	VALUE
Mean	0.157
Standard Deviation	0.227
Coefficient of Variation	1.446
Median	0.055
Interquartile Range (IQR)	0.18
IQR / Median	3.264

Table 11: Summary statistics for the 620 production contracts with positive ECO cost. Numbers rounded to three decimal places.

Among just production contracts that experienced positive ECO cost, neither service (K-W *p*-value of 0.7242) nor commodity (K-W *p*-value of 0.3347 after excluding commodities with five or less contracts) appeared significant at the 0.05 level but contract type (K-W *p*-value of less 0.0001) strongly did (after excluding 88 contracts listed as unknown or missing information). The subsequent S-D analyses suggested strong statistical differences between cost and fixed type contracts (*p*-value of 0.0002) and between T&M and fixed contracts (*p*-value of 0.0055). Table 12 highlights the metrics associated with cost, fixed, and T&M production contracts for just those with positive ECO cost, respectively.

METRIC	COST	FIXED	T&M
Sample Size	65	457	10
Mean	0.281	0.148	0.34
Standard Deviation	0.305	0.216	0.282
Coefficient of Variation	1.085	1.458	0.831
Median	0.144	0.054	0.283
Interquartile Range (IQR)	0.399	0.177	0.398
IQR / Median	2.771	3.278	1.407

Table 12: Summary statistics for the ECO positive 65 cost, 457 fixed, and 10 T&M production contracts. Numbers rounded to three decimal places.

Next, we investigate if dollar threshold and/or contract schedule length might affect the chance that a positive cost production contract is likely to exceed the $PROD_{ROT}$ of 5%. Using the same ACAT dollar thresholds as before, the *p*-value for the Pearson's chi-squared test of independence was 0.8821. This finding suggests dollar thresholds associated with ACAT categories do not appear to affect the likelihood of exceeding the $PROD_{ROT}$ of 5% for just contracts with positive ECO cost.

Regarding contract length, only 550 (88.7%) of the ECO positive contracts had complete schedule data (neither contract award date nor PoP end date were missing). We again tested if contract length equal to or greater than 5 years had an increased chance of exceeding the $PROD_{ROT}$ of 5%. The Pearson's chi-squared test returned a *p*-value of 0.2817, suggesting lack of dependency between them.

In summary for production contracts, it appears there is a high likelihood (80.7%) that these experience positive ECO cost. Given that occurs, the median and mean ECO percentages are 5.5% and 15.7% respectively. Although the median is relatively close to the $PROD_{ROT}$ of 5%, the mean is much greater than 5%. Ground Vehicle production contracts experience less ECO % compared to Other Aircraft but no single commodity experienced uniformly lower ECO %. Cost production contracts statistically exceed fixed contracts with respect to ECO %, while borderline significance suggests contracts with schedule lengths of five or more years might exceed $PROD_{ROT}$ of 5%.

Regarding the likelihood of experiencing positive ECO cost, Air Force contracts have a higher chance than Navy. Among Air Force contracts, UAV and F-16 production contracts have lower positive ECO % chance compared to other commodities. Among Navy contracts (to include Marine), the least positive ECO % are Ground Vehicle commodities, followed by contracts for the F/A-18. The remaining commodities were comparable. There appeared no statistical difference among commodity with respect to Army production contracts. Lastly, for just positive ECO % production contracts, fixed contracts were statistically lower than both cost and T&M contracts. In the Discussion and Conclusion section, we quantify our ECO recommendations through a table utilizing the median values presented in this section because of the high variability reflected by the coefficient of variations and ratios of IQR/Median.

Discussion and Conclusion

Three key conclusions can be drawn from our findings. One, if a program manager wishes to use a rule-of-thumb, life-cycle phase matters. No single rule should be applied, and the traditional one is likely inappropriate regardless. Two, it appears that the variables of Service, Contract Type, Commodity, Program Size, and Schedule all have some degree of influence on the appropriate percentage to hold in reserve in case of ECO occurrence. Three, there are factors which correspond to increased likelihood of a contract incurring a positive ECO percentage, and those percentages will differ depending on those factors.

Table 13 summarizes the overall descriptive results for both the development and production contracts in our database. The mean ECO percentages for these contracts are compared to either DEV_{ROT} or $PROD_{ROT}$. Statistically, mean values are higher than both ROTs at the level of significance of 0.05 with *p*-values < 0.0001. The

LIFE CYCLE PHASE	CURRENT ROT	MEAN ECO% - ALL	MEDIAN ECO% - ALL	MEAN ECO% - ONLY POSITIVE VALUES	MEDIAN ECO % - ONLY POSITIVE VALUES	PERCENT OF CONTRACTS WITH POSITIVE ECO COST
Development	10%	16.30%	10.40%	22.20%	14.00%	86.60%
Production	5%	8.80%	3.50%	15.70%	5.50%	80.70%

Table 13: Summary statistics for the development and production contracts with ECO cost. Numbers rounded to three decimal places.

differences between the means and medians for both the development and production contracts indicate the relatively high variability associated with ECOs. This is supported by the earlier results with respect to relatively large standard deviations, IQRs, CVs, and ratios of IQRs to medians.

Given our overall findings, we suggest that if a ROT is to be used for ECO, a four-tiered approach should be taken. First, the life cycle phase of the contract should be considered. Second, characteristics of the contract should be reviewed to determine whether there is an increased likelihood of incurring a positive ECO percentage. Third, a baseline ROT percentage should be chosen as a starting point; we advocate the median percentage of the positive ECO contracts as an initial value. Lastly, characteristics of the contract that our analyses considered strongly statistically significant should be reviewed to determine whether to adjust this baseline ROT estimate upward or downward. If pressed to provide one single ECO percentage for each life cycle phase, we recommend revising DEV_{ROT} from 10% to 14% and $PROD_{ROT}$ from 5% to 6%.

With respect to tailoring suggested ROT % based on known program factors, we make the following recommendations with these caveats. One, we modified our level of significance threshold to 0.01 to minimize the chance of perhaps a spurious statistical finding affecting our conclusions and recommendations. Two, we use medians to arrive at these percentages in lieu of means to minimize the effect of outliers. Lastly, if a contract contains two or more significant factors that cause the new baseline ROT to change, then we recommend taking the higher adjustment among the significant factors to arrive at a single percentage recommendation. Tables 14 and 15 provide our suggested recommendations with respect to development and production contracts, respectively. Note: for any fractional percentages, we do round up to the nearest percentage for ease of convenience plus allowing for the realization that mean ECO % were always larger than median ECO %.

FACTOR	ADJUSTMENT	FINAL ECO/ MR%
Commodity = Ground Vehicle	-9%	5%
Baseline contract <$30M (FY 2020)	4%	18%
Contract schedule >= 5 years	13%	27%

Table 14: Suggested ECO percentages based on factors and adjustments from the new DEV_{ROT} of 14%.

FACTOR	ADJUSTMENT	FINAL ECO/MR%
Army or Navy contract	-2%	4%
Cost type contract	9%	15%
T&M type contract	23%	29%

Table 15: Suggested ECO percentages based on factors and adjustments from the new $PROD_{ROT}$ of 6%

We suggest that the ECO percentage estimates from Tables 14 and 15 should be used as an initial point estimate but should not be treated as an exact estimate. The means in all instances exceeded median estimates, and there is a great deal of variability associated with ECO costs. Cost estimators should use prior knowledge and other tools at their disposal to deviate from this point estimate when necessary. We again acknowledge that there is no one-size-fits-all ROT that should be used to estimate appropriate amounts to hold in MR in case of ECO. However, it does statistically appear that the original DEV_{ROT} and $PROD_{ROT}$ of 10% and 5% are generally lower than what we witnessed in our database.

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Appendix

3DELRR (Three-Dimensional Expeditionary Long -Range Radar)

ADM-141C (ITALD: Improved Tactical Air Launched Decoy)

ADM-160 (Miniature Air-Launched Decoy)

ADS (Active Denial System)

AEHF (Advanced Extremely High Frequency Satellite)

AGM-65 (Maverick)

AGM-84; RGM-84; UGM-84 (Harpoon SLAM-ER: Standoff Land Attack Missile-Expanded Response)

AGM-86A/B/C/D (ALCM: Air-Launched Cruise Missile)

AGM-88E (AARGM: Advanced Anti-Radiation Guided Missile)

AGM-142 (Have Nap)

AGM-154C (JSOW (Unitary): Joint Stand-Off Weapon Baseline Variant and Unitary Warhead Variant)

AGM-158 (JASSM/JASSM-ER: Joint Air-to-Surface Standoff Missile)

AGM-169 (JCM: Joint Common Missile)

AHLTA (Armed Forces Health Longitudinal Technology Application)

AIM-7; RIM-7 (Sparrow; Sea Sparrow)

AIM-9 (AIM-9X: Air-to-Air Missile Upgrade)

AIM-120 AMRAAM (Advanced Medium Range Air -to-Air Missile)

AQM-37 (Target Drone)

ASIP (Advanced Special Improvement Program models of Single Channel Ground and Airborne Radio System (SINCGARS))

AWACS (Airborne Warning and Control System)

AWS (AEGIS - MK 7 Advanced Shipboard Weapon System)

B-1 (Lancer)

B-2 (Spirit)

B-52 CONECT (B-52 Stratofortress Combat Network Communications Technology)

B-52H (Stratofortress)

B-61 Tail Kit (B61 Mod 12 Life Extension Program Tail Kit Assembly)

BGM-109 (Gryphon (Ground-Launched Cruise Missile))

BGM-178 (RATTLRS: Revolutionary Approach to Time-critical Long-Range Strike)

BQM-34 (Firebee)

BQM-74 (Chukar)

BQM-167 (Skeeter)

BTERM (Ballistic Trajectory Extended Range Munition)

C-5 (Galaxy)

C-17 (Globemaster III)

C-37A (Gulfstream V)

C-130 (Hercules)

CBU-97 (Sensor Fused Weapon (SFW))

CBU-105 (Sensor Fuzed Weapon)

CH-47 (Chinook)

CHAMP (Counter-electronics High Power Microwave Advanced Missile Project)

CIWS (Close in Weapons System)

CV-22 (Air Force variant Osprey)

DCAPES (Deliberate Crisis Action Planning and Execution Segments INC 2B)

DCGS Navy (Distributed Common Ground System Navy)

DDG 51 (Arleigh Burke Class Guided Missile Destroyer)

DEAMS (Defense Enterprise Accounting Management System)

E-2D (Advanced Hawkeye)

EA-18G (Growler)

EC-130H (Compass Call)

EELV (Evolved Expendable Launch Vehicle)

EPS (Enhanced Polar System)

EX-171 (ERM - Extended Range Munition)

F-15 (Eagle)

F-15 AN/ALQ-135 (Electronic Countermeasure)

F-15 ATP (Advanced Targeting Pod)

F-16 (Fighting Falcon)

F-22 (Raptor)

F-35 (Lightning II)

F-119 (F-22 Engine)

F-135 (F-35 Engine)

F-136 (F-35 Engine)

F/A-18 (Hornet)

FAB-T (Family of Beyond Line-of-Sight Terminals)

FMTV (Family of Medium Tactical Vehicles)

GBU-12 (Paveway II)

GBU-15 (Guided Bomb Unit 15)

GBU-24 (Paveway III)

GBU-39 (SDB I: Small Diameter Bomb Increment I)

GBU-53/B (SDB II: Small Diameter Bomb, Increment II)

GCSS-MC (Global Combat Support Systems - Marine Corps)

GPS III (Global Positioning System III)

GPS OCX (Global Positioning System Next Generation Operational Control System)

GQM-163 (Coyote)

GQM-173 (Multi-Stage Supersonic Target)

H-1 (Upgrade program)

HC/MC 130 (Recapitalization Aircraft)

HH-60 (Pave Hawk)

HMMWV (High Mobility Multi-Purpose Wheeled Vehicle)

IDECM (Integrated Defensive Electronic Countermeasures)

JAGM (Joint Air-to-Ground Missile)

JDAM (Joint Direct Attack Munition)

JLTV (Joint Lightweight Tactical Vehicle)

JPALS (JPALS - Joint Precision Approach and Landing System)

KC-46A (Pegasus)

LAIRCM (Department of the Navy Large Aircraft Infrared Countermeasure)

LRASM (Long Range Anti-Ship Missile)

LVSR (Logistics Vehicle System Replacement)

LW155 (Light Weight Howitzer 155 mm)

MC-130J (Commando II)

MGM-140 (ATACMS: Army Tactical Missile System)

MH-60R (Seahawk)

MH-139 (Grey Wolf)

MHS (Military Health System)

MIDS-LVT (Multi-Functional Information Distribution System - Low Volume Terminal (includes JTRS: Joint Tactical Radio System Terminals))

MIM-104A/B/C/D (Patriot)

MIM-104F (PAC-3: Patriot Advanced Capability 3)

MQ-1B (Predator)

MQ-4C (Triton)

MQ-9 (Reaper)

MRAP (Joint MRAP: Joint Mine Resistant Ambush Protected Vehicles)

MTVR (Medium Tactical Vehicle Replacement)

MUOS (Mobile User Objective System)

NAVSTAR GPS (Global Positioning System)

P-8A (Poseidon)

PIM (Paladin Integrated Management)

QF-4 (FSAT: Full Scale Aerial Target)

RIM-66 (Standard Missile 1 (SM-1MR))

RIM-116 (RAM BLK 2)

RIM-116A (RAM BLK 0)

RIM-116B (RAM BLK 1)

RIM-161 (SM-3: Standard Missile 3)

RIM-162 (ESSM: Evolved Sea Sparrow Missile)

RIM-174 (SM-6: Standard Missile-6)

RQ-4 (Global Hawk)

RUR-5 ASROC (Anti-Submarine Rocket (VLA: Vertical Launch))

SBIRS (Space-Based Infrared System)

SBSS B10 (Space-Based Space Surveillance Block 10)

SH-60/HH-60H/MH-60 (Sikorsky Seahawk)

SL-AMRAAM (Surface Launched - Advanced Medium-Range Air-to-Air Missile)

Space Fence (Space Fence Inc 1)

UH-60 (Black Hawk)

V-22 (Navy Osprey)

WCMD (Wind Corrected Munitions Dispenser)

WGS (Wideband Global SATCOM Program)

Weather Satellite Follow-on (WSF)

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