The Relevance of Describability in the Performance of Defense Acquisition Contracts

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Abstract

The incomplete contracting approach is used to solve the hold-up problem in several prominent areas of public procurement. However, economists have questioned both the optimality of incomplete contracts and the relevance of a project's physical describability. This paper contributes to this discussion by providing empirical results related to the relevance of physical describability in defense contracts for military aircraft. Despite attempts by government officials to account for technological uncertainty, the underlying describability of the project appears to have adverse effects on adherence to contractual timelines, generating additional costs due to project delays.

1 Introduction

The possibility of contractual hold-up, in which parties risk the loss of relationship-specific investments in the event of a failed trade, has served as the motivating force behind the economic literature pertaining to incomplete contracting. In order to incentivize cost-minimizing investment by the contracted parties prior to the actual trade, several economists have argued that the buyer and seller can agree to an incomplete contract, which outlines contractual obligations but allows for risk-sharing due to indescribable aspects of the project in question. As in the case of many theoretical mechanisms, this incomplete contracting approach has its fair share of proponents and detractors. However, its prevalence in several prominent areas of procurement makes this debate particularly interesting. The primary purpose of this paper is to bring empirical results into the conversation.

The hold-up problem can take several forms. Bös (1996) derives a model of optimal incomplete contracts in which hold-up stems from the non-verifiability of the relationship-specific investments. Alternatively, Hart and Moore (1999) present a model of optimal incomplete contracting in which the hold-up problem is due to the parties' *ex ante* inability to describe all possible physical states of nature. In contrast, Bös (2001) provides a unique characterization of the hold-up problem, specific to projects in which the intermediate product has no value (e.g., "construction ruins," p. 105). In this situation, the buyer can be burdened with the bill for the sunk costs but receives no actual benefit in the event of project failure. As a result, the parties foresee this possibility and may underinvest, the classic manifestation of the hold-up problem.

Despite these theoretical foundations and the fact that describability clearly plays a role in real world contract design, evidenced by the use of a menu of different contract types in areas such as defense procurement, public service provision, and petroleum drilling, a debate emerged in the late 1990s regarding the optimality of incomplete contracts.

Maskin and Tirole (1999) posited their irrelevance theorems, claiming that the *ex ante* indescribability of the *physical* outcomes of a project were insufficient to prevent the implementation of a complete contract so long as the parties were able to describe the spectrum of possible *payoff* outcomes. The authors criticize previous work in the incomplete contracting literature, stating that the authors "do not attempt to derive complete contract foundations for the restricted class of contracts they study" and that the invocation of significant transaction costs is not sufficient to relegate contract design to an incomplete approach (pp. 83-84).

In response to this criticism, Hart and Moore (1999) provide a model of incomplete contracting, which they use to address Maskin and Tirole's irrelevance theorems. The authors' results indicate that an optimal contract may be incomplete in the presence of unachieved states of nature (indescribability). Additionally, Hart and Moore find that Maskin and Tirole's irrelevance results are heavily dependent on restrictive assumptions, and "describability *does* matter" when these assumptions are relaxed (p. 116). These two competing results have spawned further research, which attempts to closely examine the ability of contracts to solve the hold-up problem and/or to extend the discussion on the relevance of describability. This literature includes Schmitz (2008), Kunimoto (2008) and (2010), and Hoppe and Schmitz (2011), among others. To summarize, there seems to be a lack of consensus regarding the use of incomplete contracts to achieve an optimal outcome in the contracting literature. While certain economists have asserted that describability is an "irrelevant" consideration in achieving optimal allocations, a second group of economists maintain that describability is a critical factor in contract design and, thus, claim that incomplete contracts warrant a separate classification.

In this paper, my goal is to bring new information to the aforementioned discussion in the form of empirical results. The Federal Acquisition Regulation (FAR) provides guidelines for the acquisition of major weapons systems by the U.S. Department of Defense (DoD). This regulation includes a menu of contract types from which an acquisition official may choose, given the specific characteristics of the project and the winning firm. Given the description of these contract types from the FAR, one can then rank contracts in terms of the implied describability of the associated defense projects. Using this measure of describability, project characteristics, winning firm characteristics, and efficiency parameters from the DoD's Earned Value Management System, I can then create a model of contract performance and attempt to estimate the empirical effect of describability on cost and schedule performance. While a lack of counterfactual evidence in this study will not allow me to comment on the "optimality" of the use of incomplete contracting methods, I hope to shed light on the relevance of describability in determining contracting outcomes.

In order to empirically test theoretical predictions regarding describability, this paper uses contract data from Selected Acquisition Reports, which are required reports from the DoD to Congress for substantial weapons programs. The contract data includes time series observations of 89 different contracts for major weapons systems, including standardized measures of cost- and schedule-related inefficiencies. These alternate dependent variables provide the possibility to distinguish between the explanatory variables' effects on overall cost performance versus schedule-related cost performance, a distinction highlighted in previous studies of DoD acquisition. The analysis in this paper, while far from conclusive, suggests that the physical describability of these projects is relevant to the contracting process in two ways. First, the complexity and technological uncertainty of the project in question are primary considerations in the contract type decision by DoD officials. Second, this technological uncertainty, even after accommodation by the DoD via the contract type decision, appears to have an adverse effect on contract schedule performance in the form of costly production delays.

This paper proceeds as follows. Section 2 surveys the economic literature on contractual solutions to the hold-up problem, discusses the Maskin/Tirole and Hart/Moore debate in detail, and considers previous attempts to evaluate the determinants of contract efficiency. Section 3 discusses specific features of the DoD acquisition process that are relevant to the empirical portion of this paper:

Earned Value Management and contract types from the Federal Acquisition Regulation. Section 4 discusses the underlying model, Section 5 contains a detailed description of the data used for estimation, and Section 6 discusses estimation procedures. Section 7 presents the regression results and analysis, Section 8 presents robustness checks for the model, and Section 9 concludes.

2 Literature Review

2.1 Contractual Solutions to the Hold-Up Problem

The application of contracts to "solve" the hold-up problem is a well-documented subject in the contracting literature. Rogerson (1992) finds that first-best contractual solutions to the hold-up problem exist under extremely complex environmental conditions and in situations with a variety of assumptions regarding information asymmetries (p. 777). He provides a unique corollary of the hold-up problem: "the hold-up problem does not necessarily cause inefficiencies. Rather inefficiencies only occur if certain environmental properties are not satisfied or certain types of contracts cannot be written (p. 778)."

Fares (2006) surveys the literature pertaining to contractual solutions to the hold-up problem, specifically considering implementation of mechanisms that yield efficient investment even in the presence of contractual incompleteness. In particular the author's main goal is to demonstrate the importance of renegotiation design in achieving efficient investment outcomes. Summarizing conclusions from his survey, Fares claims that his paper mainly shows 1) that renegotiation design is a necessary component of solving the hold-up problem via contracts, and 2) this finding holds in cases of both selfish and cooperative investment (p. 753). These conclusions suggest that contracts seeking to implement efficient levels of investment must address the renegotiation process and must include a mechanism for monitoring the relative allocation of bargaining power between parties.

Hoppe and Schmitz (2011) seek to determine whether experimental data supports the theoretical ability of contracts to mitigate the hold-up problem. The results of their study suggest the following conclusions: 1) a fixed-price contract does not improve investment incentives compared to the no-contract benchmark, 2) a non-renegotiable option contract improves investment incentives compared to the benchmark, and 3) the ability to commit to the contract (prevent renegotiation) has a significant effect on a contract's ability to promote efficient investment (pp. 197-198).

Despite differences in the characterization of the hold-up problem itself and in underlying theoretical models, the above sample of papers from the contracting literature seem to agree that a solution to the problem exists in deliberate contractual design. Meanwhile, the existence of a hold-up problem during the Research and Development phase of DoD weapons projects is thoroughly described in Rogerson (1994), and the empirical work of Crocker and Reynolds (1993) analyzes the DoD's application of different contract types to accommodate varying levels of project risk. Therefore, one can conclude, at a minimum, that the DoD is attempting to contractually solve an incentive alignment problem with its contractors that originates from uncertainty regarding the technological feasibility of its weapons projects. This endeavor closely resembles the contractual situation at the heart of the Maskin/Tirole and Hart/Moore debate.

2.2 An Influential Debate

The stated goal of Maskin and Tirole (1999) is to "scrutinize" the concepts underlying the optimality of incomplete contracting (p. 83). The authors motivate this paper based on the lack of an accepted theoretical foundation for incomplete contracting, stating that many of the major contributions to the literature "do not attempt to derive complete contract foundations for the restricted class of contracts they study (p. 83)." They specifically take issue with the fact that the commonly assumed ability of dynamic programming for actors in the incomplete contracting literature should preclude the relevance of transaction costs in contract formulation (p. 84). In other words, even if the transaction costs prevent the ex ante description of physical outcomes, these costs should not affect the agents' abilities to forecast possible payoff outcomes. This assertion is the underlying foundation of the authors' irrelevance theorem: "If parties have trouble foreseeing the possible physical contingencies, they can write contracts that ex ante specify only the possibly payoff contingencies (p. 84)."

Maskin and Tirole seek to determine when the "indescribability" of a good or service affects the efficiency of the contracted outcome. Under the assumptions of their model, the authors demonstrate that a welfare-neutral, Pareto-optimal, payoff-based contract can be implemented under subgame perfect equilibrium in the event that states are indescribable (p. 104). Furthermore, they use their framework to show that their irrelevance result holds even in the presence of renegotiation, given risk averse participants (p. 102). Maskin and Tirole's findings suggest that concerns surrounding the indescribability of physical outcomes (incomplete contracts) may be unfounded, given the ability to describe payoff outcomes.

Hart and Moore (1999) respond to Maskin and Tirole's (hereafter MT) criticism of incomplete contracting theory. The authors seek to develop a "rigorous foundation" for the theory, based on the following idea of contractual incompleteness: a buyer seeks to purchase an item from a seller; the precise nature of the item is uncertain or is dependent on a heretofore unrealized state of nature; if the number of possible physical outcomes for the item is substantial, the cost of accounting for all contingencies in contractual form would be "prohibitively expensive (p. 115)." Therefore, the parties agree to an incomplete contract, allowing renegotiation of the terms of the contract at a stage when the nature of the item is defined or its physical characteristics become describable.

MT (1999) describe mechanisms that allow the parties to circumvent these prohibitively expensive transaction costs, by detailing the possible outcomes of trade ex ante and thus preventing the parties' need to describe the actual characteristics of the item itself. Hart and Moore evaluate this critique and MT's underlying "irrelevance theorems." They show that it is possible that an optimal contract may be incomplete, a notion clearly disputed by MT (1999).

Hart and Moore provide two possible definitions of an incomplete contract: 1) the contractual obligations of the parties involved may not be fully described, or 2) the parties are unable to describe possible contingencies because possible states of nature are prohibitively expensive to describe ex ante (p. 134). Hart and Moore conclude that the issues raised by type-1) contracts may be overcome by the actions described by Maskin and Tirole (1999). However, the authors assert that their model shows that an optimal contract in a type-2) situation may be incomplete. Furthermore, the authors suggest that both of these incomplete contract types are "qualitatively" different from comprehensive and complete contracts typically studied in the mechanism design literature, and thus merit a separate classification (p. 135).

Therefore, the literature presents two diametrically opposing views of the importance of describability in determining whether an incomplete contract can serve as an optimal solution to the hold-up problem. While my goal in this paper is not to evaluate the theoretical approaches of these opposing economists, I certainly believe that the existence of real world contracts intended to accommodate differing levels of project uncertainty and describability suggest that the MT (1999) mechanisms may not be feasible, particularly in defense acquisition. It seems that their assumption regarding welfare-neutrality between a contract's indescribable physical states and its describable payoff outcomes is overly optimistic. This idea becomes particularly problematic if one chooses to place a metric (e.g., a dollar amount) on the welfare impact of a specific contract.

For example, suppose the DoD wants to purchase a new anti-aircraft missile. If the DoD agrees to a contract that is based on a very specific set of technical specifications for this missile, one might expect an extremely different cost outcome than if the contract only specified "create an anti-aircraft missile." The first contract focuses research, development, and production in a detailed manner, while the second is much less defined and could lead defense firms in a variety of directions. If one measures welfare impact in terms of cost/benefit of the procurement program, these two methods could lead to significantly different welfare outcomes.

Frankly, incomplete contracts are frequently used in procurement, and it seems that the mere presence of a menu of different contracts with different levels of completeness solidifies the importance of "incomplete contracting." It seems that Maskin and Tirole's irrelevance theorem is relevant only in the context of environments where their mechanisms are feasible. However, this paper does yield at least one testable hypothesis: does the describability of a contract's physical characteristics influence its efficiency outcome?

2.3 Empirical Determinants of Contract Performance

Perhaps unsurprisingly, the efficient performance of defense acquisition programs is a politically-charged and contentious issue. Due to the United States' singular role in the international security environment, DoD expenditure on major weapons systems has largely dwarfed that of both its adversaries and allies, particularly following the end of the Cold War. The magnitude of this defense expenditure naturally attracts the attention of the US public, and the procurement of the nation's most ambitious projects typically receives a preponderance of this public scrutiny. As one might expect, economists have also shown interest in the efficient conduct of defense acquisition programs.

Peck and Scherer (1962) evaluate the outcomes of twelve military acquisition programs in terms of deviation from time, cost, and quantity baselines. These deviations are expressed using the final parameter value as a percentage of its original planned value. In their sample, the authors find that technological uncertainty plays a role in development cost overruns but has "little if any effect" on time overruns (p. 436). In contrast, urgency had more explanatory power for time overruns than did program costs, leading the authors to refute a common opinion (e.g., "unavailability of funds is a major villain in causing schedule slippages") (p. 447). The authors also discuss service demands; lack of clarity in program decisions and objectives; delayed decisions (particularly in lower priority programs); contractor technical and managerial capability; and conflicting objectives between the contractor and the Government as possible determinants of cost, time, and quality variance in weapons procurement.

Marshall and Meckling (1962) focus on cost estimation during operational development, which they define as "the effort to take ideas or components that have been tested experimentally and embody them in useful equipment (p. 462-463)." The authors offer four separate categories which collectively describe the success or failure of a weapons program: cost, performance, time, and utility (p. 464-465). In a manner similar to Peck and Scherer (1962), the authors use percent deviations of the final program costs and timelines from the original estimates as measures of efficiency. Additionally, Marshall and Meckling present adjusted measures of the program cost deviations, which take into account quantity changes and inflation.

Using survey classifications of the different projects in their data sample, the authors demonstrate that the nature of technological advance (small, medium, or large) plays a significant role in the magnitude of total factor increases in costs (p. 472). In terms of schedule deviation, or "time slippages," their results indicate that the accuracy of baseline schedules is inversely related to technological advancement and program maturity (p. 473). Marshall and Meckling attribute the majority of the large deviations in program costs and schedules to overly optimistic initial estimates for the program parameters. In their summary, the authors discuss the incentive to be overly optimistic in cost estimation at the beginning of a weapons program: contractors want the DoD to accept their plan, and the DoD wants Congress to support their development goals. However, they also admit that contractor penalties for poor estimation were relatively weak in 1962 (p. 475).

Economists have also explored the determinants of contract performance in the provision of other public services, specifically considering the effect of contract type in addition to other pertinent factors. For example, Piacenza (2006) estimates X-inefficiency for public transportation firms in Italy using a stochastic frontier variable cost function. He models X-inefficiency as a function of regulatory scheme (cost-plus vs. fixed-price) and environmental factors (aggregating to the delivery speed), among other variables. Using this approach, the author finds that the incentive-maximizing regulatory structure provided by the fixed-price (FP) regime indeed results in X-inefficiency reduction for the firms that use fixed-price contracts (p. 268). Additionally, Piacenza finds a differential effect of the regulatory scheme based on the existing environmental factors affecting the transportation company's delivery speed (p. 274). His results indicate that high speed rail lines subject to FP contracts decreased X-inefficiency to a greater degree than average speed rail lines with FP contracts. Therefore, Piacenza suggests that a full evaluation of a company's existing infrastructure must accompany any regulatory scheme decision, as the company's ultimate performance may depend on both.

Similarly, Jensen and Stonecash (2009) use a difference-in-difference estimation approach to analyze the effects of a natural experiment involving the use of two different contract types in the provision of water services: cost-plus and fixed-price. This experiment results from a change in contract type by one provider while the other remains the same. In contrast to previous studies, the authors find that the change to cost-plus contracts by one of the firms led to significant additional savings, using three different measures of maintenance costs (p. 290). However, their results are confounded by the fact that they are unable to control for both unbalanced bidding on the cost-plus contracts and differences in work quality, which could affect the interpretation of their results.

These entries in the empirical literature suggest that technological uncertainty, project urgency, production/managerial capacity, and contract type play a critical role in the eventual performance outcomes of public sector contracts. Therefore, these elements must be considered in any model of contract performance for the DoD.

This paper will contribute to the aforementioned literature in the following manner. First, I will demonstrate the link between the physical describability of projects and contract types administered for those projects, utilizing application instructions for contract types from the Federal Acquisition Regulation. Second, I will attempt to model the efficiency outcome for an array of modern DoD aircraft programs as a function of project, firm, and contract characteristics. Finally, I will use this link to determine the empirical significance of describability in the cost outcome of DoD aircraft contracts, perhaps indicating relevance or irrelevance of describability in the DoD contracting environment. My main goal for this paper is to contribute empirical evidence to the incomplete contracting literature in support of a discussion that has been largely theoretical to this point.

3 Institutional Background: Earned Value Management (EVM) and Describability in DoD Contracts

The specialized technological nature of major weapons systems requires that the DoD employ distinctive approaches to both R&D and procurement. In order to simultaneously serve as good stewards of taxpayer money and advance the frontier of defense technology, the DoD uses both a stringent monitoring process to ensure compliance with contract guidelines and an extensive menu of contract types to accommodate varying levels of project uncertainty. Both of these features of the defense acquisition process are unique to the DoD and warrant further explanation, as they will serve prominent roles in the empirical portion of this paper.

3.1 EVM Background and Terminology

In order to synchronize management of defense acquisition programs across all military services, the US Department of Defense pioneered the Earned Value Management (EVM) System as a project management technique in the 1960s. EVM serves as the DoD's required standard for project management today, and the data from the EVM process is used to prescribe corrective actions and even cancellation of contracts for US weapons projects. The backbone of the EVM process is a set of 32 system guidelines, which are intended to guide contractors and acquisition officials in creating systems to monitor weapons contracts. These guidelines are quite general, allowing involved parties to tailor the EVM system to the project in question. A particular strength of the EVM process is its ability to simultaneously incorporate measures of project scope, cost, and schedule. According to the DoD EVM Guide, "EVM encompasses both performance measurement (i.e., what is the project status) and performance management (i.e., what can we do about it?)."[1]

While this system involves monitoring of multiple parameters related to contract performance, this paper will specifically focus on two variables from the EVM process: cost variance (CV) and schedule variance (SV). These are not, as one might reasonably expect, traditional second moments and require further explanation. In order to define these measures, I must also define several additional EVM terms. First, a project's planned value (PV) is defined as "the value to be earned as a function of project work accomplishments up to a given point of time" (Anbari, p. 13). Second, a program's actual cost (AC) is the cumulative total cost of work performed as of a specific point in time (Anbari, p. 13). Finally, the earned value (EV) of the contract is "the amount budgeted for performing the work that was accomplished by a given point in time" (Anbari, p. 13). Using these terms, we define the cost variance of a project as the difference between the program's earned value and actual cost at a given point

[1]DoD EVM Guide, p.11

in the project timeline (CV = EV-AC). Similarly, a project's schedule variance is determined by finding the difference between the project's earned value and planned value (SV = EV-PV).[2]

In examining these formulae, it is apparent that positive values of CV and SV signify a project that is performing above expectations, zero values indicate a strictly efficient program, and negative values indicate adverse and inefficient performance outcomes. To illustrate these concepts, Figure 1 depicts the hypothetical EVM parameter curves for a project with negative CV and SV.[3] Alternatively, consider the following example of EVM in the administration of a hypothetical contract. A defense contract has an overall price of $10 million. Suppose the software development package and engineering design package for the contract consist of 30% and 20% of the total contract price, respectively. According to the contract's milestones, the firm should complete both the software package and the engineering design package before the first annual review. At the annual review, the firm reveals that it has completed only the software package at a cost of $4 million. This means that the cost variance for the project is (EV-AC) = ($3M - $4M) = -$1M. Meanwhile, the schedule variance is (EV-PV) = ($3M - $5) = -$2M. Therefore, one can assess that a project is over - budget and behind schedule at a given point in time merely by observing negative values of cost and schedule variance.

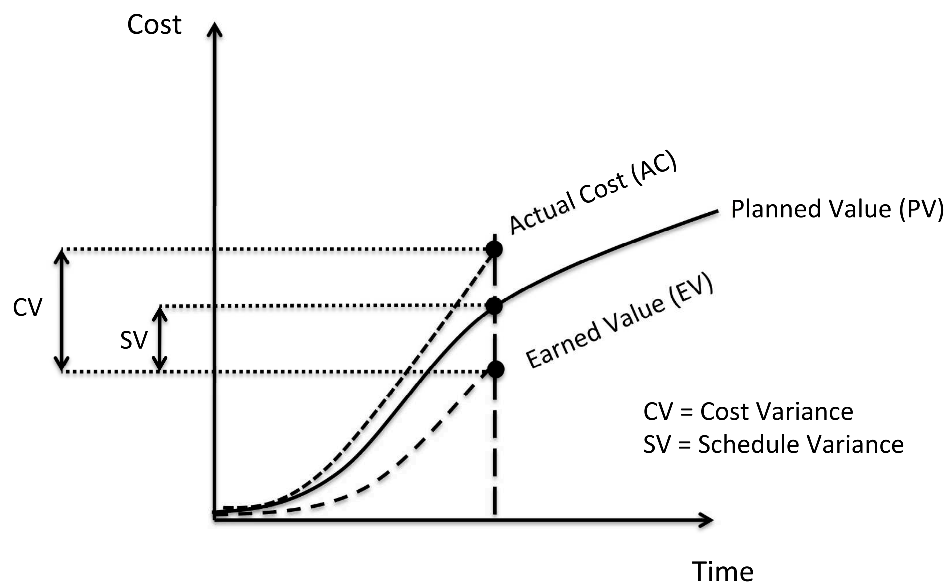

Figure 1: Earned Value Management (EVM) Parameters

[2]The formulas for these parameters can be found in both the DoD EVM Guide and Anbari, 2003.

[3]I constructed this figure using Figure 4 from Anbari, 2003, as an example

For each of the Major Defense Acquisition Programs (MDAPs) included in the data sample for this paper, I have annual measurements of both cost and schedule variance at the contract level. While previous studies have utilized empirical estimates of contract efficiency in testing theoretical hypotheses, these measures of CV and SV provide me with standardized measurements of efficiency, which I can use to test hypotheses regarding the determinants of contract performance.

3.2 Hierarchy of Describability in DoD Contracts

Among other factors, the US Government Federal Acquisition Regulation (FAR) directs that contracting officers should consider the "type and complexity" of contracted projects in negotiating contract types with winning defense firms. The FAR concedes that "complex requirements, particularly those unique to the government, usually result in greater risk assumption by the Government (16.104d)." This phrasing indicates that the DoD acquisition process is capable of accommodating projects with varying levels of technological uncertainty and complexity through the use of contract types that differ in terms of the amount of risk shouldered by the DoD. If one concedes that it is primarily internal uncertainty that the contracting officer is capable of evaluating during the initiation of a contract, the contracting officer's major focus in accommodating complexity should be selecting a contract type that reflects the level of physical describability of the project in question. This physical describability of the project could feasibly include aspects of design, scope, scale of production, and input materials.

In fact, the application instructions for various contract types in the FAR reflects this suggested relationship between describability and contract type. Given these directions from the FAR, one can then establish an implied ranking of the physical describability of the projects that different contracts are able to accommodate. For example, the data sample for this paper includes the following contract types: Cost-Plus-Incentive-Fee (CPIF), Cost-Plus-Award-Fee (CPAF), Cost-Plus-Fixed-Fee (CPFF), and Fixed-Price-Incentive-Fee (FPIF). Using the application instructions for these contract types from the FAR, I can then infer the relative describability of the contracted projects.

- **FPIF > CPIF**: Contracting officials are only able to use cost-reimbursement contracts when uncertainty does not allow for a sufficiently accurate cost estimation (16.301-2). Therefore, projects covered by fixed-price contracts should be relatively more describable than all cost-reimbursement contracts.[4]

[4] According to FAR section 16.301-2, acquisition officials are able to use cost-reimbursement contracts only in the event that "(1) Circumstances do not allow the agency to define its requirements sufficiently to allow for a fixed-price type contract; or (2) Uncertainties involved in contract performance do not permit costs to be estimated with sufficient accuracy to use any type of fixed-price contract."

- **CPIF > CPAF**: Award-fee contracts are to be used when the creation of incentive targets is not feasible. This indicates that the physical describability of projects covered by an incentive fee contract should be more conducive to establishing cost and performance targets than one covered by an award fee contract.[5]

- **CPAF > CPFF**: Cost-plus-fixed-fee contracts provide the least incentive for cost minimization and the most secure profits for the defense firm. The FAR's description of this contract type suggests that it should be used as a last resort, when incentive fees aren't practical and "the level of effort" is unknown (16.306b).[6]

Using these relationships, I can order the contract types in terms of describability from most to least: FPIF, CPIF, CPAF, CPFF. These relative describability "rankings" serve as a variable that I can test as a determinant of contract efficiency, which is indicated by contract EVM parameters. The empirical results from this procedure would then allow me to comment on the overall impact of describability on contract performance and the relevance of describability in contract theory. Given that the FAR's contract menu is intended to afford flexibility to the acquisition official in acquiring complex projects at the best value to the government, this empirical approach will also serve as a test of the efficacy of acquisition officials' application of the FAR in controlling cost growth in defense projects.

4 Model

In order to test for the impact of a project's relative level of physical describability on eventual contract efficiency via the contract type decision, I will use a reduced form model of contract performance. While previous evaluations of contract type (e.g., Piacenza, 2006) have estimated efficiency measures using structural equations, the availability of EVM performance statistics ensures that I am not imposing any additional restrictions on my analysis due to structural assumptions. This approach is certainly acceptable, according to the contract evaluation literature surveyed in this paper.

One can speculate that multiple different project characteristics could have a significant impact on the corresponding contract's ability to adhere to price

[5] Section 16.401e directs that acquisition officials should employ an award fee contract when "The work to be performed is such that it is neither feasible nor effective to devise predetermined objective incentive targets applicable to cost, schedule, and technical performance."

[6] Section 16.306b indicates that contracting officers should employ cost-plus-fixed-fee contracts when "(i) The contract is for the performance of research or preliminary exploration or study, and the level of effort required is unknown; or (ii) The contract is for development and test, and using a cost-plus-incentive-fee contract is not practical." Due to the fact that the fixed fee does not vary with the performance costs of the contract and is determined at the award date of the contract, the FAR indicates that this type of contract provides little incentive for the contractor to minimize costs and should be used only to facilitate "contracting for efforts that might otherwise present too great a risk to contractors (16.306a)."

and schedule guidelines. For example, contract type may influence the government's level of involvement in administration of the contract, corresponding to the relative amount of risk that the government shares for cost growth. As previously mentioned, the contract type may also serve as an indicator of the relative physical describability of the project in question. Therefore, it is possible that a project requiring a low-powered contract (CPFF for instance) may be relatively more prone to production difficulties, which could ultimately result in a relatively lower level of performance efficiency. Along the same line of reasoning, a research and development contract may naturally be more prone to technological obstacles than a production contract in which proof of concept and system validation have already occurred.

Other identifying features of the project/contract in question could potentially have a significant impact on the contractor's ability to adhere to contractual guidelines. In the case of a dual source project (e.g., the DoD often procures aircraft engines for a single platform from two different manufacturers), the defense firms may have additional motivation to adhere strictly to contract requirements due to the presumed ability of the government to terminate one of the contracts in the case of poor relative performance. The length of the contract may also affect its performance outcome. In one sense, the government may not engage in lengthier contracts for projects with high levels of technological uncertainty to limit its exposure to unexpected cost growth. However, longer contracts may also enable the contractor to exercise greater flexibility in the application of corrective action and eventually result in desirable efficiency outcomes. These two competing theories suggest that the effect of contract length could be different if measured at the end of a contract versus in the interim.

Learning curve effects are also well documented for various manufacturing process and, specifically, for the aircraft industry. (See, for example, Benkard, 2000.) In repeat iterations of an identical contract, one therefore might expect contracting efficiency measures to improve relative to past versions of the same contracts. Similarly, a firm's familiarity with defense manufacturing and the DoD procurement process may have an impact on their ability to provide reliable cost estimates and projected timelines, thereby directly influencing the firm's performance in adhering to contractual requirements. As a result, a firm's previous contracting history with the DoD may affect its ability to adhere to cost and schedule milestones.

To test these hypotheses regarding the effect of specific contract characteristics on the efficiency outcome of the contract in question, I can use the following reduced form model for contract performance:

$$P_i = F(d_i, x) + \epsilon_i, \tag{1}$$

where P is the contract performance in EVM terminology (cost or schedule variance), $F(\cdot)$ is a contract-invariant efficiency function, d is the physical describability of the contract indicated by its contract type, x is a set of identifying contract characteristics, and ϵ is a contract specific error term.

One possible confounding feature of this empirical approach is the possibility that, as I have briefly alluded to above, the physical describability of a project may affect contract performance other than through the selected contract type. For example, a more complex, next generation technology may warrant a less complete contract type (e.g., CPFF) during its research and development phase. Clearly, the selection of this type of contract indicates that the possible outcomes for this project will be numerous and difficult to foresee, but the additional oversight from the DoD that accompanies this contract type should serve to control or impede cost growth. However, it remains a possibility that the contract will not fully accommodate ALL complications due to the indescribable nature of the project. Therefore, it is possible that describability can affect both the contract type decision and the contract performance simultaneously, creating an endogeneity issue. In order to account for this possibility, I will use an instrumental variable for contract type, which I will further discuss in the estimation section of this paper.

5 Data

This paper uses data collected directly from Selected Acquisition Reports (SARs), which are submitted to Congress annually by the US Department of Defense. Congress uses SARs to guide funding decisions for major defense projects. In order to qualify for SAR submission, a project must either a) exceed \$365 million in total research, development, training, and evaluation (RDT&E) or b) exceed \$2.19 billion in total procurement costs (FY 2000 constant \$).[7] The data sample used for estimation in this paper consists of contracts from active military aircraft programs with SARs submitted from December 1997 to December 2011. These programs include multiple aircraft procured by each branch of service (Army, Navy, Air Force) and one managed by the DoD as a whole (F-35 Lightning). Due to differences in program start dates and duration of procurement, the data has an unbalanced panel structure.[8]

Due to the contractor's sole responsibility for cost performance and resulting profits in firm-fixed-price (FFP) and fixed-price-with-economic-price-adjustment (FPEPA) contracts, the US government does not apply EVM in the administration of these contracts. As a result, program managers do not collect and report cost and schedule variances for these contracts as part of the SAR process. As an additional restriction, the database includes "combination" contracts, indicating that one contract type could not accommodate the work performed under the contract. In these contracts, it is impossible to align the contract type with the physical describability rankings previously discussed in this paper. Table 1 depicts the distribution of contracts in the entire sample and their translation into contract-year observations. Note the exclusion of

[7] Defense Acquisition University, www.acc.dau.mil.

[8] There is no indication in the available SARs that the DoD terminated any of the projects contained in my data sample due to poor contract performance. All of the projects include a natural progression of R&D and procurement phases.

FFP, FPEPA, and Combination contracts from the "relevant" sample leads to a reduction of 93 contracts and 310 contract-year observations. Additionally, the distribution of contract types in the relevant sample (FPIF, CPIF, CPAF, CPFF) is indicative of the government's increasing responsibility for cost growth as the contract becomes less complete. FPIF contracts appear most frequently, followed by approximately equivalent amounts of CPIF and CPAF contracts, and CPFF contracts are issued almost half as often as FPIF. This distribution belies the government's efforts to incentivize cost minimization to the maximum possible degree in each contract.

Table 2 details the available cost variance and schedule variance observations for the contracts in the data sample. Of the 367 relevant contract-year observations, 331 include cost variation observations and 322 include schedule variance observations. Nine total contracts experienced cost variance without schedule variance, but no contract demonstrated schedule variance without simultaneous cost variance. The ratio of positive to negative observations is similar across the two types of performance measures: a 45/55 split in cost variance and a 40/60 split in schedule variance. Table 3 lists summary statistics for different expressions of cost and schedule variances from the estimation sample. Note the change in sign when cost variance is expressed as a percentage of the initial contract price. This is due to the common occurrence of major changes to contract price between the award date and a contract's first appearance in a SAR. As a result, the initial price is typically not representative of the eventual price of the contract. With this exception, the mean values of the other statistics are all negative, perhaps indicating a tendency for contracts to perform over budget and behind schedule in major aircraft programs.

Table 1: Distribution of Contracts by Type

	Contract Observations	**Contract-Year Observations**
FFP	62	205
FPEPA	6	30
FPIF	33	92
CPIF	26	88
CPAF	25	127
CPFF	18	60
Combination	25	75
Total	195	677
Relevant Sample	102	367

In addition to the previously described information, the contract section of each SAR provides each contract's managing military branch; initial price and quantity; current price and quantity; funding category (R&D vs. Procurement); award date; basic contractor information; contractor and military program manager estimates of price at completion; and brief explanations of

Table 2: Observations of Cost and Schedule Variance

	Cost Variance	**Schedule Variance**
Total Observations	331	322
Relevant Observations	298	290
Positive Obs. (Raw)	135	118
Positive Obs. (Percentage)	45.30	40.69
Negative Obs. (Raw)	163	172
Negative Obs. (Percentage)	54.70	59.31

Table 3: Summary Statistics for Cost Variance and Schedule Variance

Variable	Observations	Mean	Std. Dev.	Min	Max
Cost Variance (CV)	305	-4.282	67.524	-376.5	779.1
CV/Current Price	305	-0.002	0.028	-0.171	0.097
CV/Initial Price	305	0.002	0.176	-1.347	1.812
Cumulative CV	89	-15.236	58.508	-315	130.6
Average (CV/Current Price)	85	-0.002	0.019	-0.076	0.043
Average (CV/Initial Price)	85	0.003	0.064	-0.28	0.269
Schedule Variance (SV)	305	-3.125	51.751	-457.2	581.6
SV/Current Price	305	-0.003	0.024	-0.161	0.114
SV/Initial Price	305	-0.018	0.267	-2.488	2.382
Cumulative SV	89	-12.02	26.867	-130.6	7.4
Average (SV/Current Price)	85	-0.007	0.02	-0.125	0.04
Average (SV/Initial Price)	85	-0.027	0.085	-0.591	0.04

factors contributing to the current levels of cost variance and schedule variance. I will describe and analyze these explanations in greater detail in the estimation section of this paper.

While the database that produces each SAR relies on the Federal Procurement Database System (FPDS) to provide contractor characteristics, many of these entries are incomplete, missing, or recorded in a non-uniform manner. Therefore, I collected firm employment, revenue, and other financial figures from annual investor reports and Securities and Exchange Commission filings (form 10-K) for each of the contractors in the data sample. Additionally, while the FPDS information on firm characteristics was less than desirable, I was still able to use this system to collect detailed information regarding contract length, as it contains the actual completion date for each contract. Due to my need to use outside sources to collect additional data, I was unable to find all pertinent information for each contract, and data availability ultimately reduced the estimation sample to 89 contracts with 305 contract-year observations. Tables 4 and 5 list the distributions of contract types and contracting firms in the estimation sample, respectively.[9]

Table 4: Contract Type Distribution (Estimation Sample)

	Total	% of Sample
FPIF	30	35.29%
CPIF	21	24.71%
CPAF	24	28.24%
CPFF	14	16.47%

[9]Due to business confidentiality concerns, I am unable to provide actual firm names for the contractors in my data sample.

Table 5: Distribution of Contracts by Firm (Estimation Sample)

Firm	Total Contracts	% of Sample
A	5	5.62%
B	1	1.12%
C	15	16.85%
D	16	17.98%
E	1	1.12%
F	1	1.12%
G	14	15.73%
H	23	25.84%
I	13	14.61%

6 Estimation

The main goal of this paper is to comment on the relevance of physical describability in contract performance outcomes, using defense contracts to provide empirical information for the debate regarding the use of incomplete contracting. My main variable of interest is, therefore, the physical describability of the underlying project as indicated by the contract type chosen by the acquisition official. Due to the fact that this variable, along with many of a contract's other identifying characteristics, is time-invariant, I cannot use the within transformation and achieve my intended purpose. As a result, I will conduct cross-sectional analysis of my data sample and supplement this with panel analysis using the pooled OLS and between effects panel estimators. More concretely, I will estimate the following contract performance equations, using a) a cross-sectional structure and b) an unbalanced panel structure:

$$a)P_i = \beta_0 + \beta_1 DRNK_i + \beta_2 CUMDQ_i + \sum_{j=3}^{4} \beta_j SUMEXPL_{ji} + \sum_{l=5}^{m} \beta_l x_{li} + \epsilon_i, \tag{2}$$

and

$$b)P_{it} = \beta_0 + \beta_1 DRNK_i + \beta_2 DQ_{it} + \sum_{j=3}^{14} \beta_j EXPL_{jit} + \sum_{l=15}^{m} \beta_l x_{lit} + \epsilon_{it}. \tag{3}$$

In equation (2), P_i is either the contract's cumulative cost variance or schedule variance for the duration of the contract, $DRNK_i$ represents the describability ranking of the contract's type in accordance with the previous discussion, $CUMDQ_i$ is the cumulative change in quantity over the duration of the contract, the $SUMEXPL_i$s are the sum of the positive and sum of the negative variance explanations offered by the program manager over the duration of the contract, and the x_{li}s are control variables, which account for identifying characteristics of the contract in question.

For equation (3), I have a similar set of explanatory variables, consisting of disaggregated versions of the variables used in equation (2). P_{it} is the cost or schedule variance for contract i in time period t, $DRNK_i$ is the same time-invariant describability ranking used in equation (2), DQ_{it} is the change in quantity for contract i in time period t, the $EXPL_{jit}$s are the categorized variance explanations for the contract in period t, and the x_{lit}s are time variant and invariant characteristics of contract i. The primary importance of the panel analysis is the inclusion of the more robust set of variance explanations, which cannot be included in the cross-sectional analysis due to more limited degrees of freedom.

6.1 Dependent Variables

The cost variance and schedule variance figures for each contract are expressed in dollar amounts as of the date of the Selected Acquisition Report in which they appear. For sake of comparison across contracts, it is necessary to adjust these figures for inflation. Additionally, it is reasonable to expect that higher-priced projects may result in relatively higher cost and schedule variance dollar amounts relative to less expensive projects. Therefore, it may also be worthwhile to normalize cost and schedule variance figures by contract price at the time of the recorded cost or schedule variance.[10] Table 6 lists the names and definitions of the dependent variables used in both cross-sectional and panel analysis.

6.2 Instrumental Variable for Describability Ranking

Given the previous discussion of the link between the physical describability of a project and the resulting contract type chosen by acquisition officials, I can rank projects covered by FPIF, CPIF, CPAF, and CPFF contracts in terms of implied describability as in Table 7. However, for estimation purposes, I must account for the possibility that the describability of the project affects the subsequent performance of the contract via a separate channel other than the contract type decision. In other words, the inclusion of the ordered describability ranking in Table 7 may create an endogeneity issue in estimating equations (2) and (3). In order to address this problem, I will use an instrumental variable approach in my regression analysis.

In a previous paper, I demonstrated the ability to model the acquisition official's contract type decision for these same aircraft programs as a function of both project and firm characteristics. To create the instrumental variable

[10] Note that cost variance observations always occur with respect to the current contract price. In other words, the current price will not also include previously accumulated cost variance. In scenarios when acquisition officials adjust the contract price due to performance issues, the cumulative cost variance is reset to zero. In this sense, there should be no concern that the current price of the contract is moving with the cumulative cost variance.

Table 6: List of Dependent Variables

Cost Variance (CV)	Definition
cumcv	Cumulative Cost Variance over duration of contract, adjusted for inflation
avcvpercurp	Average ratio of Cost Variance to Current Price over duration of contract
cv	Inflation-adjusted Cost Variance
cvpercurp	Cost Variance/Current Contract Price
Schedule Variance (SV)	
cumsv	Cumulative Schedule Variance over the duration of contract, adjusted for inflation
avsvpercurp	Average ratio of Schedule Variance to Current Price over duration of contract
sv	Inflation-adjusted Schedule Variance
svpercurp	Schedule Variance/Current Contract Price

Table 7: Describability Rank of Contract Types

DRNK (Describability Rank) =	1 if type =	CPFF
	2 if type =	CPAF
	3 if type =	CPIF
	4 if type =	FPIF

for describability ranking, I will utilize this same contract type selection model to predict the expected contract type, $EDRNK_i$, for each contract, given its associated project and firm characteristics.[11] Due to the fact that the contract selection model uses many of the same explanatory variables that I will use as control variables for this paper, I will not discuss this estimation process at length here. For transparency, the regression results for this procedure are presented in Appendix B.

Using this method, the regression model accounts for 61% of the variation in the $DRNK$ variable. Table 8 presents a comparison of $DRNK$ and the instrumental variable produced via the contract choice model, $EDRNK$. The contract choice model provides me with a variable that is highly correlated with the $DRNK$ variable but is plausibly exogenous to the actual performance outcome of the project at hand. The lack of a controlling variable for technological uncertainty or complexity in the contract choice model is likely a) responsible for the imprecision of the contract type predictions and b) cause to believe it will be not be highly correlated with the contract's cost and schedule variances.[12] Additionally, the predicted describability ranking from OLS estimation is a continuous variable, which should further diminish problematic correlation between the predicted contract type and the contract's performance outcome.

Table 8: Summary Statistics for DRNK and EDRNK

	Obs.	Mean	Std. Dev.	Min	Max
drnk	149	4.020	1.772	1	6
edrnk	149	4.020	1.388	0.441	6.153

6.3 Control Variables

Despite the fact that all of the contracts in my estimation sample are part of large-scale military aircraft programs, the details of each contract are quite diverse. In order to isolate the effect of the project's physical describability on the subsequent performance outcome for the associated project, it is essential to account for these potentially confounding factors. In addition, it may be informative to uncover the independent statistical effect of these variables on contract performance, as empirical evidence from the defense industry is quite sparse and outdated. Table 9 provides a list of the explanatory variables used in

[11] The previous paper mentioned here used a ranking of contractual "completeness," which measured actual portions of the contract that were left open to subsequent renegotiation. The "describability" ranking for this same set of contracts is very similar, as only the ranking of the CPIF and CPFF contracts differ. As one of the robustness checks for my previous paper, I estimated the model using the describability scale. This distinction between "completeness" and "describability" mirrors the two possible definitions of incomplete contracts provided by Hart and Moore.

[12] This inability to control for technological heterogeneity in a precise manner is due to the lack of any uniform measure of this variable across contracts.

estimation of equations (2) and (3). Note that in some cases I have listed both the individual and aggregated variables, which I then use in the appropriate data setting (e.g., *cumdq* is used for equation (2) and *dq* is used in equation (3)).

Several of these variables may be of particular interest in comparing the contracting environment for military aircraft to other industrial settings. For example, the *iteration* variable could provide further evidence on the effects of learning on defense manufacturing. One might expect the cost and schedule performance of a military contractor to improve for the tenth lot (*iteration*=10) of aircraft produced relative to the first lot (*iteration*=1). Additionally, a contractor's ability to implement and follow EVM procedures may improve as they become more experienced with military contracting. The variable *prevcont* is intended to capture this administrative learning effect. As the theoretical foundations for this paper rely heavily on the power of incentives in contracting, I have also included a control for the use of a passive incentive mechanism, dual source contracting. Although dual source contracts make up only a small portion of the overall estimation sample, the effect of competitive pressure could be substantial for these select contracts.

To further account for heterogeneity between projects, I have also included controls for military branch, source of funding (*rd* versus *proc*), firm size (*employment* and *revenue*), and firm risk level (*cratio* and *lev*). Tables 10 and 11 provide summary statistics for the continuous and binary control variables, respectively.

Table 9: Control Variables

Variable	Definition
dq	Change in quantity over the current period
cumdq	Cumulative quantity change over duration of contract
prevcont	Number of Existing Contracts for Firm Prior to Award Date
duals	Indicator Variable for Presence of Multiple Sources (=1 if Multiple)
length	Number of Months between Contract Award Date and Scheduled Completion
iteration	Control for repeat procurement of same item (i.e., Lot 9 = 9)
winage	Within Program Age (in Years): Contract Award Date - Initial Award Date for Program
wincage	Within Contract Age (in Years): Observation Date - Initial Award Date for Contract
rd,proc	Separate Intercepts for RDT&E and Procurement (O&M excluded)
army, navy, af	Separate Intercepts for Army, Navy, AF (DoD excluded)
Firm Controls	
lemp	Log of Annual Employment
lrev	Log of Inflation- and Exchange Rate- Adjusted Annual Revenue (Segment Level)
cratio	Firm's Current Ratio (Current Liabilities/Current Assets)
lev	Firm's Leverage Ratio (Long-Term Debt/Total Assets)

Table 10: Summary Statistics for Continuous Control Variables

	Obs.	Mean	Std. Dev.	Min	Max
dq	305	0.256	1.876	-7	21
cumdq	89	0.976	4.189	-12	30
prevcont	89	13.011	11.012	0	46
length	89	43.461	29.125	2	138
iteration	89	2.843	3.118	1	15
winage	89	6.854	6.728	0	23
wincage	305	1.803	1.916	0	9
emp	305	142081.4	59656.11	32000	293000
rev	305	11962.4	8879.696	2275.759	20894.2
cratio	305	0.87	0.216	0.422	1.38
lev	305	0.163	0.054	0.064	0.381

Table 11: Summary Statistics for Binary Control Variables

	Obs.	Mean
duals	7	0.079
rd	45	0.506
proc	43	0.483
army	12	0.135
navy	45	0.506
af	17	0.191

6.4 Program Manager Variance Explanations

In addition to the hypothetical effects of the explanatory variables mentioned above, I must also account for the fact that the SAR format provides other concrete, yet imprecise, information regarding the performance of each contract. For example, this will prevent the model from falsely attributing poor performance to project describability that is actually due to contractor labor disputes. For each contract subject to EVM monitoring listed in the SAR, the program manager must provide explanatory comments regarding the net change in cost (CV) and schedule variation (SV). These comments provide brief explanations of the underlying causes leading to changes in the contract's performance measures. Unfortunately, the program manager does not attach dollar amounts or even percentages of the total contract value attributable to these factors, which would allow me to fully account for their impact on the CV and SV. Alternatively, I have created six general categories and recorded the program manager's explanation of net changes in CV and SV in terms of these categories for each contract-year observation. Due to the fact that acquisition officials report separate effects of these underlying problems on CV and SV, I record the effects separately and also record whether the issue has a positive (improvement) or negative (degradation) effect on contract performance. This leads to a total of 24 indicator variables that capture the underlying causes of contract performance in accordance with the program manager's explanatory comments.[13] These categories and corresponding indicator variables are listed below. Appendix A provides actual explanations from the subject SARs, categorized in accordance with the following framework.

1. **Change in Manufacturing Inputs**: This category includes changes in material costs or changes in the amount of materials required. In addition, this category includes external changes in the price of labor. Examples of positive changes include the use of less material than originally budgeted and decreased wage costs due to a manufacturer's decision to hire locally. Examples of negative changes include an increase in material prices and underestimation of required amounts of materials. (CV: *poscdpc(+), negcdpc(-)*; SV: *possdpc(+), negsdpc(-)*)

2. **Supply Chain Management**: The execution of a MDAP contract often includes multiple outside vendors and subcontractors, who supply components and parts to the prime contractor for integration and assembly. Negative examples from this category include delinquent deliveries of parts from subcontractors, parts shortages, chain reaction production delays, and delays in the awarding of subcontracted efforts by the prime contractor. Positive effects from this category are typically due to early delivery of parts and components. (CV: *poscsuppman(+), negcsuppman(-)*; SV: *posssuppman(+), negssuppman(-)*)

[13] There are six total categories, which are further divided into positive and negative effects. Additionally, there are separate explanations of the categories' effects on CV and SV: $6 \times 2 \times 2 = 24$.

3. **Corrective Actions in Production**: The Earned Value Management System (EVMS) requires the use of process monitoring and periodic reviews to assist the defense contractor in preemptively identifying issues in the manufacturing process that will cause cost or schedule overruns. The resulting prescribed actions from this review process can have positive or negative short run effects on both cost and schedule variation, depending on the magnitude of the change to the production process. Examples in this category include accelerated timelines that may incur greater short run costs to mitigate future schedule delays,[14] additional product testing mandated by the review team, correction of deficiencies identified during product testing, and staffing adjustments to address problem areas. (CV: *posccorract(+), negccorract(-)*; SV: *posscorract(+), negscorract(-)*)

4. **Fundamental Change to Contract Details**: Due to the challenging level of technological complexity of the typical MDAP, program managers and defense contractors are often forced to make fundamental changes to the design or scope of the MDAP, which in turn has an effect on the contract costs and schedule performance. Additionally, an MDAP's priority level may result in its relegation to a standby status or a loss of resources in the event of a national defense emergency, leading to adverse cost and schedule outcomes. Examples from this category include design changes to major components, contract amendments to incorporate additional capabilities, loss of resources due to other operational requirements, incorporation of funds spent before contract definitization, and other major contract revisions (e.g., restructures and re-designs). Additionally, this category includes "over-target-baseline" revisions, which reset the cost and schedule variances to zero as the contractor and Government essentially agree that the original baseline contract was inadequate or overly ambitious. (CV: *poscdbase(+), negcdbase(-)*; SV: *possdbase(+), negsdbase(-)*)

5. **Administrative Factors**: As with any production contract, administrative parameters can have a significant effect on contract outcomes for MDAPs, despite the fact that these parameters may be insignificant to the physical execution of the contract. Administrative errors and the correction of these errors can, thus, have a significant effect on the cost and schedule variance outcomes for MDAPs. Examples from this category include accounting errors, EVMS reporting errors, changes in General and Administrative (G&A) and overhead rates, expenditure of funds prior to contract definitization, and invoicing problems. (CV:*poscadmin(+), negcadmin(-)*; SV: *possadmin(+), negsadmin(-)*)

6. **Changes to Required Effort**: The final category includes changes in the amount of "effort" or billed hours of work. Program managers often report that a particular component or work package requires "more

[14]In this situation, the manufacturer implements an internal timeline that is more demanding than the basline contract schedule

effort than originally planned" or "more hours than originally planned." Alternatively, the execution of the contract can require less effort/fewer hours than specified in the project. These explanations indicate that the contractor's employees completed the contractual task in question in a greater or shorter amount of billable time than estimated in the original contract, or the contractor adjusted the amount or skill level of the labor assigned to the contract. (CV: *posceffort(+), negceffort(-)*; SV: *posseffort(+), negseffort(-)*)

The inclusion of these factors in an estimation equation results in an additional twelve explanatory variables, which the 305 observations of the unbalanced panel supports with ease. However, the aggregation of these variables over the duration of the contract, which would be necessary to use all of the categories in a cross-sectional setting, seems to be a very imprecise treatment. It is impossible to attribute exact portions of the cost and schedule variance within a single contract-year observation to these factors, and the aggregation of these variables would require that I assign relative impacts over the entire duration of the contract. Rather than make an inevitably poor assumption, I will sum the positive variance explanations and negative variance explanations over the life of the contract and use this generic result in the cross-sectional model. While this is still not an ideal method of accounting for these factors, it prevents me from assigning potentially misleading importance to the individual variance categories. (CV: *sumposcv(+), sumnegcv(-)*; SV: *sumpossv(+), sumnegsv(-)*)

Tables 12 and 13 provide summary statistics and distribution for the variance explanations, respectively. Note from Table 12 that it is quite common for the program manager to provide no explanation for observed cost and schedule variance (approximately 35% in both cases). It is even more common that only one explanation is provided (approximately 45% for instances of cost variance and 43% for schedule variance). Anecdotally, these trends are likely due to the prevalence of singular "problem areas," which continue to cause problems over the life of a contract, and to the imprecise method by which program managers are required to account for cost and schedule variances for SAR purposes. Meanwhile, in Table 13, the tendency to provide explanatory comments in the case of negative cost or schedule variance outcomes is much greater than for positive outcomes. This is particularly striking given the overall ratio of positive to negative observations in the case of both performance measures (45:55 for CV and 40:60 for SV).

Table 12: Collected Explanation Data

	Cost Variance	**Schedule Variance**
Total Observations	298	290
Number of Explanations		
$\geq$ **1 (Raw)**	193	184
$\geq$ **1 (% of Total)**	64.77	63.45
$>$ **1 (Raw)**	57	29
$>$ **1 (% of Total)**	19.13	10.00
None (Raw)	105	106
None (% of Total)	35.23	36.55

Table 13: Distribution of Explanations by Type and Effect

	1A	**1B**	**2A**	**2B**	**3A**	**3B**	**4A**	**4B**	**5A**	**5B**	**6A**	**6B**	**Total**
CV Explanations	18	24	10	27	9	19	19	33	21	36	19	33	268
SV Explanations	0	2	16	66	30	13	19	28	4	37	0	3	218

Enumeration is based on listing order from Section 6.4.

A = Positive Effect. B = Negative Effect.

7 Results and Analysis

7.1 Cross Sectional Model

Tables 14 and 15 present the 2SLS estimation results for equation (2) with cost variance and schedule variance as the dependent variable, respectively. Each table presents the results of four regressions, including two sets of results for each version of the contract's cumulative variance (adjusted for inflation and expressed as a percentage of current price). Within these sets, one regression includes only the baseline regression, while the second column includes controls for military branch.[15] In order to assist the reader in understanding these regression results, it may be prudent to again mention the EVM definitions of the cost and schedule variances. A positive cost or schedule variance is a desirable outcome, indicating that the contract is under-budget or on-schedule. Conversely, a negative cost or schedule variance is an adverse outcome, suggesting that the contract is over-budget or behind-schedule.

In Table 14, column (1) shows that the coefficient for a contract's describability ranking has, on average, a marginally significant positive effect on the adjusted cumulative cost variance. This indicates that the cost variance improves as the describability ranking of the contract increases, suggesting that increased describability of the underlying project improves the chances of keeping the contract under budget. The program manager cost variance explanations, sumposcv and sumnegcv, enter with the expected sign and significance. In column (2), the addition of the controls for military branch results in the insignificance of the describability ranking, while the coefficient on the indicator variable for Army contracts is positive and significant. This is likely due to the fact that the excluded military category, DoD projects, includes only the F-35, which is the most expensive acquisition program in the history of the DoD.

As previously mentioned, it is reasonable to expect that more expensive projects would be naturally prone to larger dollar amounts of cost and schedule variance. Therefore, expressing the variance as a percentage of the contract price may provide a more reasonable comparison across contracts. In columns (3) and (4), I see the effects of this transformation. The contract describability ranking no longer has a significant effect on the cost variance outcome when cost variance is expressed as a percentage of the contract's current price, and the contract's parent branch no longer has a significant effect on cost performance. This finding is supportive of my assertion that the significance of the branch control in column (2) was due to the magnitude of the cost variance in the excluded category, which only includes contracts from the F-35 project.

[15] The bottom row of each regression table reports the P-Value of the Durbin-Wu-Hausman Chi-Squared test for exogenous regressors. The null hypothesis for this test is that the regressors are exogenous. Also, several of the specifications do not report an R-Squared value for the regression. This is due to the fact that, in a 2SLS regression, there is no constraint forcing the residual sum of squares to be less than the total sum of squares, potentially leading to negative R-squared values. In specifications where this occurs, I have chosen to suppress the R-squared value rather than report a negative value. For a more thorough explanation, see Sribney, et al. (1999).

In Table 15, I use the same progression of analysis as in Table 14 with versions of schedule variance as the dependent variable. In column (1), I again see a marginally significant, positive effect of the describability ranking. In contrast to Table 14, however, I see additional significant effects, some of which are counterintuitive. For example, I observe negative and significant effects from the procurement indicator and iteration variable. These findings suggest that contracts in more advanced stages of acquisition and repeat iterations of the same contract will perform poorly in terms of schedule adherence relative to contracts in early phases of production. However, when the branch controls are added in column (2), these coefficients become insignificant and the iteration coefficient becomes positive. A possible explanation for the negative impact of the procurement indicator is linked to the use of procurement funds during full rate production. At this stage, engineering changes and additional equipment added to aircraft impact a much larger number of units than in the RDT&E-phase contracts. As a result, the schedule impact of these changes may be greater in procurement contracts even though changes should occur with less frequency. Meanwhile, the branch coefficients and the indicator for dual source contracts become positive. The positive effect of the the dual source contracting environment is intuitive, as one might expect contractors in pseudo competition to adhere more closely to contract guidelines.

When I use the normalized dependent variable in columns (3) and (4), none of the coefficients for describability ranking are significant and both are positive. Comparing the results for the iteration coefficient in Table 15 to those in Table 14, it appears that there is a differential effect of repeat iterations on CV and SV. Specifically, it appears that production lots procured later in the acquisition process are more likely to fall behind schedule than to exceed budgeted costs. Upon inspection of the data sample, this is likely due to the fact that production lots tend to increase in quantity as contractors perform a repeat contract. Alternatively, there appears to be no significant effect of repeat iteration on the cost performance (CV) of a contract. Summarizing the results of my cross-sectional analysis, the evidence for the effect of describability via the selected contract type on subsequent performance outcomes remains unclear. However, additional information from the panel model may allow me to use the results of both approaches to draw conclusions about the relevance of describability in the defense acquisition process.[16]

[16]Note that I have also estimated each model without including the program manager explanations. In the cross-sectional model, the results are robust only when I include the program manager explanations. Specifically, the coefficient on *drnk* only achieves significance when I include program manager explanations. However, in the panel model, the results presented here are robust with and without the program manager explanations, exhibiting classic signs of omitted variable bias when the program manager explanations are not included in the specification. I attribute the difference between the two models to the relatively imprecise nature of the control variables in the cross-sectional setting. I am unable to finely capture the effects of standard complications in the cross-sectional model due to the smaller data sample and the resulting smaller number of degrees of freedom.

Table 14: IV Regressions for Cost Variance

	(1)	(2)	(3)	(4)
	cumcv	cumcv	avcvpercurp	avcvpercurp
drnk	43.554*	47.957	-0.005	-0.030
	(25.649)	(69.080)	(0.009)	(0.023)
cumdq	-0.672	-0.732	-0.000	0.000
	(0.726)	(0.853)	(0.000)	(0.000)
prevcont	-1.145	-1.390	0.000	0.000
	(0.697)	(1.024)	(0.000)	(0.000)
duals	4.369	17.389	0.007	0.016
	(20.403)	(26.752)	(0.005)	(0.011)
length	-0.230	-0.259	-0.000*	-0.000
	(0.291)	(0.262)	(0.000)	(0.000)
winage	0.536	1.205	-0.000	-0.000
	(0.932)	(1.562)	(0.000)	(0.001)
iteration	-3.100	-2.859	0.001	0.003
	(2.988)	(6.014)	(0.001)	(0.002)
proc	12.596	13.777	0.005	0.010
	(21.753)	(23.099)	(0.007)	(0.011)
rd	62.416	78.213	-0.000	-0.026
	(39.998)	(85.361)	(0.012)	(0.029)
sumposcv	10.169*	12.138**	0.006***	0.005*
	(6.113)	(6.005)	(0.001)	(0.003)
sumnegcv	-12.290**	-12.856**	-0.003***	-0.003**
	(5.031)	(5.039)	(0.001)	(0.001)
army		60.191**		0.014
		(27.953)		(0.013)
navy		8.928		0.020
		(47.828)		(0.014)
af		7.938		0.027
		(49.750)		(0.017)
Constant	-130.089	-167.663	0.012	0.066
	(83.024)	(179.658)	(0.029)	(0.065)
N	89	89	85	85
R-Squared	.	.	0.244	.
Wald	20.34**	27.82**	44.16**	22.57*
DWH P-Value	0.063	0.423	0.985	0.039

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: IV Regressions for Schedule Variance

	(1)	(2)	(3)	(4)
	cumsv	cumsv	avsvpercurp	avsvpercurp
drnk	26.789*	-18.443	0.026	0.012
	(14.649)	(24.687)	(0.018)	(0.016)
cumdq	0.391	0.701***	0.000	0.000
	(0.284)	(0.192)	(0.000)	(0.000)
prevcont	-0.403	-0.112	-0.000	-0.000
	(0.437)	(0.323)	(0.000)	(0.000)
duals	0.316	20.452**	-0.001	0.005
	(8.642)	(9.642)	(0.007)	(0.008)
length	-0.173	-0.097	0.000	0.000
	(0.126)	(0.089)	(0.000)	(0.000)
winage	-0.626	-0.665	-0.000	-0.000
	(0.627)	(0.480)	(0.001)	(0.001)
iteration	-3.051*	0.361	-0.002	-0.001
	(1.838)	(2.326)	(0.002)	(0.002)
proc	-34.806**	-18.584	-0.016	-0.012
	(13.697)	(11.471)	(0.011)	(0.011)
rd	1.489	-36.763	0.011	-0.000
	(16.636)	(25.202)	(0.020)	(0.020)
sumpossv	-0.343	1.628	0.004*	0.005**
	(3.060)	(2.974)	(0.002)	(0.002)
sumnegsv	-4.687**	-3.877**	-0.002	-0.002*
	(2.159)	(1.760)	(0.001)	(0.001)
army		36.099***		0.014
		(10.741)		(0.013)
navy		38.402**		0.008
		(16.295)		(0.012)
af		49.586***		0.018
		(18.823)		(0.013)
Constant	-35.898	45.612	-0.071	-0.045
	(39.265)	(57.105)	(0.056)	(0.051)
N	89	89	85	85
R-Squared	.	0.269	.	0.088
Wald	23.28**	74.92***	13.69	24.25**
DWH P-Value	0.019	0.393	0.127	0.443

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2 Panel Model

As an alternative method, I will now estimate equation (3) using both a pooled OLS estimator and the between panel estimator. Columns (1) and (2) of Table 16 present the results of panel IV estimation for cost variance, using a pooled OLS estimator. I again present two different versions of the dependent variable: inflation-adjusted cost variance and cost variance expressed as a percentage of the contract's current price.[17] In columns (1) and (2) of Table 16, I again see inconclusive evidence of the direction of the effect of the underlying physical describability of the project. Neither of the coefficients for the describability ranking variable are significant, but the sign of the coefficient is uniform across both specifications. Of the additional regressors, only the program manager variance explanations are significant, and I observe that the relative magnitudes of the coefficients on the variance explanations suggest that the design change indicator (poscdbase) produces the largest effect. This is supported by the fact that this category includes over-target-baseline adjustments of a contract's budget. In most cases, this type of adjustment occurs in projects that are performing extremely poorly, and a large positive cost variance is used to reset the cumulative cost variance to zero.

In columns (3) and (4) of Table 16, I use the between effects panel estimator to estimate equation (3).[18] The reported p-values for the Hausman test statistic suggest that either a) the IV estimator is inefficient in these specifications, or b) I have chosen a weak instrument. This finding must be taken into consideration while interpreting the following results. The dependent variables are identical to those used in columns (1) and (2), but the results are quite different. In column (3), the coefficient on describability ranking is positive and marginally significant. However, the coefficient is insignificant once the variance is normalized by current price in column (4). In contrast to columns (1) and (2), much fewer of the cost variance explanations are significant when estimated using the between estimator, which one might expect as this method identifies the effect of variation in the averages of these values across contracts.[19]

Columns (1) and (2) of Table 17 present the results of pooled OLS estimation of equation (3). In both specifications, the variation in the dependent variable is primarily accounted for by the program manager variables. Generally speaking, the pooled OLS estimator performs poorly for the schedule variance specifications. In column (2), the coefficient on describability ranking is positive and marginally significant, but the F-statistic for this regression suggests that this model does not predict a significant amount of variation in the dependent variable. However, the results of using the between estimator in columns (3) and (4) of Table 17 support the pooled OLS results, as the coefficient for de-

[17] In the panel setting, the underlying data are individual contract-year observations rather than the cumulative figures used in the previous section.

[18] For columns (3) and (4) of Tables 16 and 17, I include the P-value of the Hausman specification test statistic. The null of this test is that there is no systematic difference between the two estimators (OLS vs. IV). Therefore, a failure to reject the null in this case suggests that the IV estimator does not offer an improvement in terms of consistency.

[19] The branch controls were insignificant in all of the panel specifications for CV and SV.

scribability ranking is again positive and significant.[20] I again observe decreased significance for many of the variance explanation categories in comparing the pooled OLS and between estimates of the regression coefficients.

Interestingly, it appears that there is an observable difference in the categories affecting cost variance compared to those in the schedule variance. In Table 16, I observe that cost variance is consistently affected by corrective actions. Meanwhile, schedule variance is consistently affected by supply management issues and administrative issues in Table 17. Unsurprisingly, both types of variance are affected by baseline changes, which is likely due to the use of over-target-baseline corrections that set both CV and SV to zero.

Although it is difficult to draw any firm conclusions given the precision of my models, it is possible to observe several trends when one considers both the cross-sectional and panel results from the preceding sections. First, in the case of cost variance, the sign of the coefficient on the cost variance is inconsistent in the cross-sectional model. Specifically, the effect is negative when I use cost variance as a percentage of current contract price as the dependent variable. In speaking with DoD EVM officials, this is likely due to differential administrative procedures across different contract types.[21] For example, in a CPFF contract, the government will likely require more frequent cost monitoring and will quickly demand corrective action in response to deficiencies, primarily due to the fact that it bears the entire cost burden for this type of contract. As a result, annual reports of cost variance for a CPFF could be reflecting active government management of the contract. Conversely, in a FPIF contract, the contractor bears the majority of the cost-growth burden, and the government's administration of the contract will be relatively more passive. Given this discussion, it might then be possible to see, on average, a tendency for more describable projects and contract types to report poorer annual contract performance measures, reflective of the government's willingness to let the contractor address the situation on its own. Second, although the significance of the coefficient on the describability ranking in the schedule variance regressions is inconsistent, the coefficient itself is positive in every specification save one. Third, combining the two previous observations, it appears that the effect of the describability ranking of the underlying project on contract performance occurs in the expected direction. In six of eight cost variance specifications, describability ranking has a positive effect. Additionally, the negative coefficient for describability ranking in the cross-sectional model, using *avcvpercurp*, seems to be explainable given the government's approach to administering less complete contract types. Meanwhile, contracts using contract types that are generally more "complete," presumably stemming from the subject parties' ability to accurately describe the work at hand, seem to perform better in terms of adherence to production schedule than those covering less describable projects.

[20] Again, note the p-values of the Hausman test statistic. It is likely that the IV estimator does not provide an improvement in consistency over the OLS estimator in this case.

[21] My explanation of this phenomenon is attributable to a personal interview with an official in the DoD's Earned Value Management Division on 14 December 2012.

Table 16: Panel IV Estimation: Cost Variance

	(1) cv	(2) cvpercurp	(3) cv	(4) cvpercurp
drnk	13.661	0.008	19.836*	0.011
	(25.659)	(0.011)	(11.675)	(0.012)
dq	0.104	0.000	-1.421	0.000
	(1.863)	(0.001)	(2.512)	(0.003)
prevcont	-0.497	-0.000	-0.455	-0.000
	(0.440)	(0.000)	(0.302)	(0.000)
duals	-2.114	0.005	-5.893	0.003
	(12.051)	(0.005)	(10.040)	(0.010)
length	0.044	-0.000	0.051	-0.000
	(0.127)	(0.000)	(0.092)	(0.000)
iteration	0.093	0.000	-1.186	0.000
	(2.301)	(0.001)	(1.473)	(0.001)
wincage	0.510	0.000	-0.110	-0.001
	(2.026)	(0.001)	(3.276)	(0.003)
proc	-9.298	-0.018	-11.878	-0.042
	(41.899)	(0.019)	(32.473)	(0.033)
rd	1.376	-0.004	11.828	-0.024
	(41.246)	(0.018)	(26.020)	(0.026)
poscdpc	6.017	0.008	0.234	-0.012
	(17.941)	(0.008)	(24.051)	(0.024)
negcdpc	-4.533	-0.000	10.960	0.016
	(15.825)	(0.007)	(19.117)	(0.019)
poscsuppman	-9.742	0.003	-14.327	-0.008
	(25.653)	(0.011)	(21.678)	(0.022)
negcsuppman	-52.103***	-0.006	-34.918	0.010
	(13.694)	(0.006)	(21.305)	(0.022)
posccorract	26.218	0.012	47.636**	0.031
	(20.725)	(0.009)	(21.209)	(0.021)
negccorract	-43.944***	-0.016**	-48.619*	-0.044*
	(16.083)	(0.007)	(25.808)	(0.026)
poscdbase	90.642***	0.034***	18.486	0.026
	(14.604)	(0.007)	(22.230)	(0.023)
negcdbase	-5.257	-0.016***	-9.730	-0.033
	(13.188)	(0.006)	(20.405)	(0.021)
poscadmin	13.730	0.010	-2.340	0.003
	(14.900)	(0.007)	(22.014)	(0.022)
negcadmin	-13.837	-0.016**	-36.682	-0.038
	(17.035)	(0.008)	(26.589)	(0.027)
posceffort	8.198	0.026***	8.803	0.022
	(18.984)	(0.008)	(16.146)	(0.016)
negceffort	-8.544	-0.011*	4.534	0.003
	(12.848)	(0.006)	(22.397)	(0.023)
Constant	-43.788	-0.033	-62.497*	-0.034
	(88.598)	(0.039)	(36.739)	(0.037)
Firm Controls	Yes	Yes	Yes	Yes
N	305	305	305	305
R-Squared	0.250	0.261	0.001	0.218
F-Statistic	4.011	4.994	N/A	N/A
DWH P-Value	0.269	0.269	N/A	N/A
Wald	N/A	N/A	45.84***	38.53**
Hausman P-Value	N/A	N/A	1.000	1.000

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Panel IV Estimation: Schedule Variance

	(1)	(2)	(3)	(4)
	sv	svpercurp	sv	svpercurp
drnk	14.449	0.022**	16.538*	0.020**
	(21.018)	(0.011)	(8.925)	(0.010)
dq	-0.158	0.000	-0.054	0.003
	(1.651)	(0.001)	(2.335)	(0.003)
prevcont	-0.537	-0.000*	-0.509**	-0.000
	(0.369)	(0.000)	(0.252)	(0.000)
duals	-1.629	-0.005	-1.443	-0.002
	(10.473)	(0.005)	(8.934)	(0.010)
length	-0.018	0.000	-0.038	0.000
	(0.108)	(0.000)	(0.093)	(0.000)
wincage	-0.205	0.001	1.035	0.004
	(1.873)	(0.001)	(3.059)	(0.003)
iteration	-1.118	-0.001	-1.242	-0.000
	(1.839)	(0.001)	(1.074)	(0.001)
proc	-16.677	-0.027	-36.744	-0.036
	(34.099)	(0.017)	(24.055)	(0.027)
rd	-0.129	0.002	-16.369	-0.015
	(34.336)	(0.017)	(22.116)	(0.025)
negsdpc	-9.719	-0.016	-35.236	-0.038
	(35.976)	(0.018)	(52.859)	(0.059)
posssuppman	3.486	0.013	-5.913	0.012
	(17.924)	(0.009)	(17.042)	(0.019)
negssuppman	-15.036	-0.016***	-13.080	-0.031***
	(9.551)	(0.005)	(9.743)	(0.011)
posscorract	13.624	0.012**	3.518	0.012
	(11.644)	(0.006)	(17.318)	(0.019)
negscorract	0.174	-0.019*	-3.996	-0.027
	(19.073)	(0.010)	(21.860)	(0.024)
possdbase	65.554***	0.017***	7.698	0.019
	(13.132)	(0.007)	(22.631)	(0.025)
negsdbase	-20.716*	-0.006	-10.814	-0.010
	(11.088)	(0.006)	(16.678)	(0.019)
possadmin	5.152	-0.001	-39.945	-0.012
	(26.604)	(0.013)	(53.129)	(0.059)
negsadmin	-8.565	-0.026***	-33.199***	-0.040***
	(10.374)	(0.005)	(11.321)	(0.013)
negseffort	27.587	0.006	60.430	0.063
	(31.331)	(0.016)	(39.850)	(0.045)
Constant	-24.416	-0.059	-22.054	-0.060
	(72.339)	(0.036)	(33.423)	(0.037)
Firm Controls	Yes	Yes	Yes	Yes
N	305	305	305	305
R-Squared	0.105	.	.	0.153
F-Statistic	2.006	3.729	N/A	N/A
DWH P-Value	0.451	0.020	N/A	N/A
Wald	N/A	N/A	18.42	32.42*
Hausman P-Value	N/A	N/A	1.000	1.000

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

8 Robustness Checks

8.1 Split Sample Results

In the previous chapter, I demonstrated the outlier effect of the F-35 program on my estimation results. Additionally, the cross-sectional results from this chapter indicate that the identity of the controlling branch of the US military may have a differential effect on a contract's performance in terms of cost and schedule adherence. Any effect of this nature likely stems from differing technological requirements of the military branches and resulting technological heterogeneity in the projects controlled by each branch. For example, the programs controlled by the Army in the data sample include several modernization programs for existing airframes, whereas the Navy's projects include procurement of new fixed-wing and rotary aircraft. As a result of the differing levels of technological complexity associated with these programs, one might expect the contract performance outcomes to also vary. In order to further examine this possibility, I now present split-sample regression results, divided by controlling military branch, for both the cross-sectional and panel models.

Tables 18, 19, and 20 provide estimation results of the cross-sectional model for Army, Navy, and Air Force contracts, respectively. Note that the binary control variables do not apply to each sample. For example, none of the Army contracts in the data sample were dual source projects. Columns (1) and (2) of each table list the results for cost variance, while columns (3) and (4) list results for schedule variance. The model performs particularly well for the Army and Air Force contracts in the schedule variance specifications. Comparing these results to the cross-sectional estimation for the entire data sample, several trends are preserved. I continue to observe a negative and significant effect of the procurement indicator variable on schedule performance, which is present for all three military branches. The effect of the describability ranking on schedule performance is positive for all three branches and significant in both specifications for the the Air Force contracts. However, the effect of describability on cost performance is negative in four of six specifications and is never significant.

In moving to the panel model, sample size becomes a primary issue when I attempt to use the between estimator. Due to the limited number of contracts for the Army and Air Force, I am unable to use the between transformation in those samples due to the resulting restriction on degrees of freedom. However, I will present pooled OLS estimation results for all three branches and additionally include between estimation results for the Navy sample. Note that in these regression tables, I have elected to only display the program manager variance explanations that produce a significant effect on the dependent variable, despite the fact that I have included all of the explanations in each specification.

In Table 21, there is evidence of a positive effect of moving into the procurement phase of a program on contract cost performance, while repeat iterations appear to have a negative effect on cost performance for both versions of the dependent variable. Alternatively, only the re-baseline program variance explanation has a significant effect on schedule performance. In contrast to the cross-sectional results, contract describability ranking has a positive effect on cost performance but a negative effect on schedule performance in the pooled OLS model.

Table 22 presents the estimation results of the panel model for the sample of Navy contracts, using cost variance measures as the dependent variables. Columns (1) and (2) are the results from the pooled OLS estimator, while columns (3) and (4) use the between transformation. In these specifications, only the program manager variance explanations exhibit any significant effect on cost variance. The describability ranking coefficient is never significant and is negative in three of four specifications. Table 23 presents pooled OLS and between effects estimates of the panel model with schedule variance as the dependent variable. Again, I observe that only the coefficients for select program manager explanations are significant, and the effect of the describability ranking is again negative in three of four specifications.

In Table 24, the only variables exhibiting a high degree of significance are program manager explanations of the effects of negative corrective actions and positive re-baseline changes on the contract's cost performance. However, these findings are not robust to normalization of the cost variance by the contract price. The coefficient estimates for describability ranking reveal a negative but insignificant effect on cost variance and an insignificant and non-uniform effect on schedule variance.

A clear concern in conducting this type of split-sample analysis would be the effects of small-sample bias. While I see evidence of a significant effect of describability on schedule performance in the cross-sectional results for the Air Force sample, this result is based on a sample of seventeen contracts. Alternatively, I see no clear evidence of any significant effect of describability from the split-sample analysis of the panel model estimates, and only the program manager variance explanations appear to have any significant effect across the different branches. In summary, it appears that the differential effects on contract performance of management by each military branch, which one observes in the estimation results for the full sample, are likely due to unobserved technological heterogeneity that is indicative of branch-specific projects. The significant positive effects of the branch controls in the full sample are likely due to the presence of the F-35, as split-sample analysis does not reveal any information suggesting that the branch-controlled contracts are administered in a unique manner.

Table 18: Cross-Sectional IV Regressions: Army Contracts

	(1)	(2)	(3)	(4)
	cumcv	avcvpercurp	cumsv	avsvpercurp
drnk	-13.748	-0.015	0.980	0.004
	(12.708)	(0.022)	(2.589)	(0.004)
cumdq	11.696	0.018	1.044	0.003**
	(13.765)	(0.021)	(0.798)	(0.001)
prevcont	1.319	-0.003	-2.800**	0.000
	(4.161)	(0.010)	(1.426)	(0.003)
length	0.182	0.000	-0.202	-0.001***
	(0.211)	(0.000)	(0.131)	(0.000)
winage	-2.647	0.010	9.938***	0.010*
	(12.004)	(0.028)	(3.813)	(0.006)
iteration	-2.313	-0.012*	-2.317	-0.016*
	(3.101)	(0.006)	(5.207)	(0.009)
proc	52.690	0.094	-22.288*	-0.056***
	(51.435)	(0.099)	(12.225)	(0.021)
sumposcv	-22.762	-0.017		
	(28.178)	(0.049)		
sumnegcv	5.770	0.007		
	(9.316)	(0.014)		
sumpossv			6.666***	0.018***
			(2.031)	(0.004)
sumnegsv			-1.059	-0.008*
			(2.314)	(0.004)
Constant	-12.259	-0.015	20.075**	0.033**
	(22.189)	(0.048)	(9.944)	(0.014)
N	12	12	12	12
R-Squared	0.517	0.839	0.699	0.688
Wald	1177.78***	3272.93***	787.96***	684.25***
DWH P-Value	0.035	0.332	0.412	0.068

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Cross-Sectional IV Regressions: Navy Contracts

	(1) cumcv	(2) avcvpercurp	(3) cumsv	(4) avsvpercurp
drnk	84.669	-0.031	14.006	0.010
	(105.210)	(0.036)	(16.957)	(0.018)
cumdq	-0.311	-0.000	0.640***	0.000
	(0.598)	(0.000)	(0.110)	(0.000)
prevcont	-1.019	0.000	0.068	-0.000
	(1.178)	(0.000)	(0.204)	(0.000)
duals	0.365	0.005	-0.303	0.005
	(40.891)	(0.017)	(5.854)	(0.007)
length	-0.265	-0.000	-0.057	0.000
	(0.678)	(0.000)	(0.140)	(0.000)
winage	1.968	-0.000	0.003	0.000
	(2.380)	(0.001)	(0.463)	(0.001)
iteration	-6.356	0.002	-3.204*	-0.001
	(7.461)	(0.002)	(1.669)	(0.002)
proc	21.436	0.018	-14.401	-0.003
	(45.985)	(0.016)	(12.068)	(0.016)
rd	117.731	-0.012	3.389	0.001
	(122.895)	(0.042)	(18.304)	(0.025)
sumposcv	9.778	0.006*		
	(8.367)	(0.003)		
sumnegcv	-14.471*	-0.003		
	(8.683)	(0.002)		
sumpossv			-1.222	0.005
			(2.445)	(0.003)
sumnegsv			-5.011	-0.001
			(3.049)	(0.002)
Constant	-282.192	0.073	-25.556	-0.041
	(319.757)	(0.108)	(48.660)	(0.067)
N	45	45	45	45
R-Squared	.	.	0.250	0.266
Wald	25.12***	16.39	153.47***	19.88**
DWH P-Value	0.186	0.063	0.171	0.949

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: Cross-Sectional IV Regressions: Air Force Contracts

	(1)	(2)	(3)	(4)
	cumcv	avcvpercurp	cumsv	avsvpercurp
drnk	-15.582	0.009	2.993**	0.021***
	(14.461)	(0.013)	(1.295)	(0.008)
cumdq	0.547	-0.001	0.911***	0.001*
	(1.844)	(0.001)	(0.317)	(0.001)
prevcont	-0.838	0.000	0.214**	0.001**
	(1.012)	(0.001)	(0.088)	(0.000)
length	-0.288**	-0.000	0.136***	0.000
	(0.133)	(0.000)	(0.036)	(0.000)
winage	2.024	-0.002	-0.505**	-0.003***
	(2.467)	(0.002)	(0.202)	(0.001)
iteration	0.822	0.001	0.016	0.001
	(1.240)	(0.001)	(0.118)	(0.001)
proc	24.646	-0.015	-6.250***	-0.045***
	(25.921)	(0.026)	(2.214)	(0.011)
sumposcv	-8.159	0.004		
	(6.528)	(0.004)		
sumnegcv	1.959	-0.002		
	(3.098)	(0.002)		
sumpossv			0.049	0.002
			(1.457)	(0.005)
sumnegsv			-1.152***	-0.001
			(0.282)	(0.001)
Constant	43.423	-0.017	-10.867***	-0.049*
	(33.918)	(0.039)	(3.958)	(0.025)
N	17	17	17	17
R-Squared	0.184	.	0.915	0.687
Wald	41.49***	24.32***	804.93***	85.73***
DWH P-Value	0.083	0.363	0.970	0.136

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Panel IV Estimation: Army Contracts

	(1)	(2)	(3)	(4)
	cv	cvpercurp	sv	svpercurp
drnk	1.994	0.033	-0.463	-0.010
	(3.753)	(0.032)	(1.669)	(0.013)
dq	0.894	0.006	-0.160	0.001
	(0.961)	(0.008)	(0.542)	(0.004)
prevcont	0.109	0.000	0.067	-0.001
	(0.343)	(0.003)	(0.252)	(0.002)
length	0.133	0.001	-0.095	-0.001
	(0.171)	(0.001)	(0.105)	(0.001)
iteration	-6.974	-0.080*	-1.041	0.006
	(5.092)	(0.044)	(2.795)	(0.021)
wincage	0.355	-0.000	0.910	0.005
	(1.384)	(0.012)	(0.967)	(0.007)
proc	14.996*	0.187**	-0.816	-0.005
	(8.040)	(0.069)	(4.504)	(0.034)
possdbase			17.500***	0.118***
			(5.121)	(0.039)
negsdbase			-3.660	-0.047*
			(3.447)	(0.026)
Constant	-5.396	0.058	17.170	0.213
	(26.252)	(0.225)	(18.918)	(0.145)
Firm Controls	Yes	Yes	Yes	Yes
PM Explanations	Yes	Yes	Yes	Yes
N	34	34	34	34
R-Squared	0.659	0.609	0.734	0.636
F-Statistic	1.217	1.069	2.057	1.382
DWH P-Value	0.091	0.053	0.305	0.112

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22: Panel IV Estimation for Cost Variance: Navy Contracts

	(1)	(2)	(3)	(4)
	cv	cvpercurp	cv	cvpercurp
drnk	-24.799	-0.083	7.114	-0.005
	(101.364)	(0.213)	(9.568)	(0.013)
dq	-1.504	-0.002	-1.407	-0.003
	(2.637)	(0.006)	(2.095)	(0.003)
prevcont	0.065	0.001	0.120	0.001
	(0.366)	(0.001)	(0.360)	(0.000)
duals	6.244	0.014	-3.997	-0.001
	(26.379)	(0.056)	(12.647)	(0.017)
length	0.113	0.000	-0.036	-0.000
	(0.237)	(0.000)	(0.091)	(0.000)
iteration	1.765	0.004	-0.002	0.000
	(4.486)	(0.009)	(1.018)	(0.001)
wincage	-0.810	-0.003	-1.314	-0.001
	(4.891)	(0.010)	(3.040)	(0.004)
proc	30.953	0.066	-8.798	0.011
	(90.369)	(0.190)	(23.886)	(0.032)
rd	-7.461	-0.036	-2.076	0.015
	(48.837)	(0.103)	(17.595)	(0.023)
negcdpc	-16.899*	-0.001	-13.230	0.019
	(8.750)	(0.018)	(10.205)	(0.014)
negcsuppman	-34.777**	-0.014	8.185	-0.009
	(14.214)	(0.030)	(23.387)	(0.031)
posccorract	47.516**	0.008	70.626***	0.004
	(20.487)	(0.043)	(19.598)	(0.026)
poscdbase	36.722***	0.031	4.049	0.022
	(11.954)	(0.025)	(19.923)	(0.027)
posceffort	5.246	0.027	-5.162	0.050**
	(14.320)	(0.030)	(17.058)	(0.023)
negceffort	-23.177**	-0.017	-18.951	-0.030
	(11.030)	(0.023)	(16.299)	(0.022)
Constant	51.789	0.212	-17.245	-0.006
	(277.527)	(0.585)	(23.971)	(0.032)
Firm Controls	Yes	Yes	Yes	Yes
PM Explanations	Yes	Yes	Yes	Yes
N	160	160	160	160
R-Squared	0.190	.	0.794	0.721
F-Statistic	3.624***	0.607	N/A	N/A
DWH P-Value	0.688	0.290	N/A	N/A
Wald	N/A	N/A	75.94***	46.42***
Hausman P-Value	N/A	N/A	1.000	1.000

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23: Panel IV Estimation for Schedule Variance: Navy Contracts

	(1)	(2)	(3)	(4)
	sv	svpercurp	sv	svpercurp
drnk	-4.331	0.065	-1.913	-0.001
	(47.535)	(0.174)	(7.449)	(0.024)
dq	0.167	0.002	-0.522	0.004
	(1.391)	(0.005)	(1.317)	(0.004)
prevcont	0.018	-0.000	0.004	-0.000
	(0.142)	(0.001)	(0.187)	(0.001)
duals	2.401	-0.015	2.288	0.014
	(11.476)	(0.042)	(7.841)	(0.026)
length	-0.003	-0.000	-0.011	0.000
	(0.090)	(0.000)	(0.068)	(0.000)
wincage	0.000	0.005	1.328	0.003
	(2.948)	(0.011)	(2.654)	(0.009)
iteration	-0.670	-0.003	-0.984	0.001
	(2.006)	(0.007)	(0.809)	(0.003)
proc	-1.081	-0.034	1.855	0.009
	(26.936)	(0.098)	(10.463)	(0.034)
rd	-8.688	0.047	-2.080	0.003
	(37.173)	(0.136)	(10.300)	(0.034)
negssuppman	-9.892	-0.024	-2.481	-0.041*
	(7.373)	(0.027)	(7.173)	(0.023)
negsdbase	-10.442	0.013	-19.963**	0.000
	(13.792)	(0.050)	(9.449)	(0.031)
Constant	19.995	-0.217	9.937	-0.036
	(151.422)	(0.553)	(19.780)	(0.064)
Firm Controls	Yes	Yes	Yes	Yes
PM Explanations	Yes	Yes	Yes	Yes
N	160	160	160	160
R-Squared	0.347	.	0.544	0.495
F-Statistic	3.744***	0.428	N/A	N/A
DWH P-Value	0.909	0.325	N/A	N/A
Wald	N/A	N/A	28.28	22.40
Hausman P-Value	N/A	N/A	1.000	1.000

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 24: Panel IV Estimation: Air Force Contracts

	(1) cv	(2) cvpercurp	(3) sv	(4) svpercurp
drnk	-10.170	-0.096	94.307	-0.004
	(54.983)	(0.230)	(2608.284)	(1.287)
dq	0.793	0.001	1.064	-0.004
	(1.182)	(0.005)	(33.694)	(0.017)
prevcont	0.092	0.001	-2.133	0.000
	(1.400)	(0.006)	(58.698)	(0.029)
length	-0.179	-0.001	0.867	0.000
	(0.449)	(0.002)	(23.112)	(0.011)
iteration	-0.163	0.001	2.966	0.001
	(0.903)	(0.004)	(81.448)	(0.040)
wincage	-0.931	-0.001	-0.102	0.002
	(1.138)	(0.005)	(11.160)	(0.006)
proc	13.560	0.160	-180.886	0.013
	(98.179)	(0.410)	(5022.863)	(2.479)
negccorract	-47.336***	-0.054		
	(15.857)	(0.066)		
poscdbase	32.990***	0.039		
	(8.822)	(0.037)		
Constant	59.693	0.305	-284.248	-0.059
	(191.203)	(0.799)	(7516.958)	(3.710)
Firm Controls	Yes	Yes	Yes	Yes
PM Explanations	Yes	Yes	Yes	Yes
N	52	52	52	52
R-Squared	0.709	.	.	0.628
F-Statistic	3.803***	0.563	0.062	2.919***
DWH P-Value	0.739	0.080	0.787	0.988

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

8.2 Effect of Describability on Contract Administration

It is possible that the physical describability of a project and the resulting contract type may affect the dynamics of the administration of the contract in addition to the performance outcome. For example, in conversations with DoD officials, it is apparent that contracts in which the government shoulders a larger share of the cost burden often require more frequent cost reporting from the contractor.[22] Additionally, the describability of a contract may affect the ability of the government and the contractor to determine an accurate price for the contract or to estimate future costs. It is quite common in my data sample to observe changes to the baseline contract, which drastically alter the contractual details. This, in turn, often resets the cost and schedule variances to zero by incorporating over-target costs into the contract. While the panel analysis conducted in this paper takes this possibility into account, the cross-sectional analysis is unable to account for this type of effect. A poorly performing contract that is re-baselined could have a cumulative positive variance upon completion. Therefore, it may be appropriate to consider whether a contract's describability rank has a distinct effect on the intermediate dynamics of the contract in addition to looking at the performance outcomes. Given this discussion, I will now estimate equation (2) with a set of variability measures as dependent variables, using a reduced form approach to model the effect of describability on contract administration via the contract type decision.

Table 25 lists the additional dependent variables and a definition of each. A brief explanation of each type of statistic is perhaps warranted at this point.

- **Sharpe Ratio**: The Sharpe Ratio is a statistic used in the finance literature to measure the ratio of return to risk for a financial portfolio. It is calculated by dividing the mean of the excess return of an asset by the standard deviation of the excess return (Schuster and Auer, 2012). This excess is relative to a benchmark asset, often a risk-free investment. Clearly, if one compares two assets to an identical benchmark, a higher Sharpe ratio indicates more return per unit of risk. Due to the fact that cost and schedule variances can take positive and negative values, this seems to be an appropriate way to measure the government's return per unit of risk for a contract. Underperformance would result in a verifiable loss (negative cost or schedule variance), while over-performance would result in a gain (positive cost or schedule variance). Additionally, the DoD contracting environment has its own risk-free benchmark: the firm fixed price contract. Due to the fact that the contractor bears full responsibility for all cost growth in an FFP contract, EVM is not applied, and the variances are always zero from the government's point of view. Therefore, I can calculate the Sharpe Ratio for either cost or schedule variance for a particular contract using the following formula (using cost variance as an

[22] This information is attributable to a personal interview with DoD EVM officials, 14 December 2012.

example):

$$SR_{CV} = \frac{\mu_{CV}}{\sigma_{CV}} \tag{4}$$

- **Coefficient of Variation**: In contrast to the Sharpe Ratio, the coefficient of variation is purely a measure of variability and is appropriate in comparing variables with widely differing mean values (Scheel, 1978). In this case, a comparison of coefficients of variation for two different measures allows one to determine which of the two measures is more variable. I have calculated the coefficient of variation for several different measures in my data sample: contract price, unit price (with initial price), unit price (without initial price), difference in the contractor's estimate at completion and the program manager's estimate at completion, difference in the contractor's estimate and the current price, and difference in the program manager's estimate and the current price. The formula for the coefficient of variation is (for a generic variable x):

$$CoefV_x = \frac{\sigma_x}{\mu_x} \tag{5}$$

- **Mean Squared Forecasting Error**: In each SAR, both the contractor and program manager provide estimates for the cost of the contract at completion(EAC). In the next annual SAR, I observe an update to the contract's price and a new estimate from each party. Presumably, the estimate from the previous SAR should serve as a forecast of the contract price in the current SAR. Therefore, I can calculate the forecasting error for each party for every contract-year in which there is a preceding estimate and use these forecast errors to calculate a mean square forecasting error for each contract. The formula for this statistic is (using the PM as an example):

$$MSFE_{PM} = \frac{\sum_{t=2}^{N}(EAC_{t-1} - CP_t)^2}{N} \tag{6}$$

Table 25: Variability Measures

Cost Variance (CV)	Definition
cvsr	Cost Variance Sharpe Ratio
svsr	Schedule Variance Sharpe Ratio
pcoefv	Contract Price Coefficient of Variation
upcoefvi	Unit Price Coefficient of Variation (including initial price)
upcoefv	Unit Price Coefficient of Variation (without initial price)
diffcoefv	Coefficient of Variation of Difference in PM and Contractor Estimates
diffcoefvc	Coefficient of Variation of Difference in Contractor Estimate and Current Price
diffcoefvp	Coefficient of Variation of Difference in PM Estimate and Current Price
lcmsfe	Log of Contractor's Mean Squared Forecasting Error
lpmsfe	Log of PM's Mean Squared Forecasting Error

Table 26: Summary Statistics for Variability Measures

Variable	Observations	Mean	Std. Dev.	Min	Max
cvsr	69	0.053	1.107	-4.699	4.142
svsr	69	-0.231	0.523	-2.67	1
pcoefv	89	0.331	0.47	0	2
upcoefvi	54	0.198	0.236	0	0.956
upcoefv	55	0.13	0.177	2.78E-16	0.814
diffcoefv	50	1.373	0.639	0.073	3.068
diffcoefvc	58	0.176	0.533	0.146	2.236
diffcoefvp	56	1.178	0.463	0.146	2.236
cmsfe	70	963069.5	6839603	0.00E+00	5.68E+07
pmsfe	71	987887.8	6769086	0	5.68E+07

Tables 27 and 28 display the estimation results for equation (2) using the Sharpe ratios for cost variance and schedule variance, respectively. In each table, I list three specifications, including a baseline regression, baseline with variance explanations, and baseline with variance explanations and branch controls. In the case of the cost variance Sharpe ratio, columns (1) and (2) show a significant and negative effect from the length of the contract. This indicates that the government is more likely to receive a poor "return" for a longer duration contract, on average. However, this effect becomes insignificant when military branch controls are added. For the schedule variance Sharpe ratio in Table 28, I observe a positive and significant effect from cumulative quantity change and a negative and significant effect from repeat iteration. Meanwhile, column (2) suggests a positive and marginally significant effect from describability ranking, which becomes insignificant upon the addition of the branch controls. From these results, it does not appear that the describability of the project via the contract type has a consistently significant effect on the DoD's "return" per unit of risk for a contract.

Tables 29, 30, and 31 present the results of IV estimation of equation (2) using coefficients of variation for different measurements of the contract's price. I have specific reasons for considering each of these. Due to the fact that quantity changes often account for substantial increases in contract price, particularly for full-scale production contracts, I wanted to compare the effects on overall contract price to effects on the unit price. Additionally, I have previously mentioned that the initial price of a contract is often not representative of the eventual price of the contracts, and the largest changes in price often occur between the award date and the first SAR (the dates at which the parties record initial and current prices). Therefore, I am presenting results for the coefficient of variation of the unit price both with and without the initial price.

In Table 29, the analysis proceeds as follows. Columns (1) and (3) include schedule variance explanations and explanations with branch controls, respectively. Columns (2) and (4) use cost variance explanations and cost variance explanations with branch controls, respectively. The results show a consistently negative and significant effect on the variability of the overall price due to the contractor's previous number of in-sample aircraft contracts. This perhaps indicates that firms develop an aptitude for estimating prices as they become more experienced in DoD contracting. In addition, I observe a positive and significant effect from the iteration variable in columns (1) and (2), but this becomes insignificant and even changes sign as military branch controls are introduced. There is no consistent sign or effect of the describability ranking on the coefficient of variability for the overall contract price. The model performs particularly poorly in Tables 30 and 31, and the model fails to predict a statistically significant amount of variation in either the upcoefvi or upcoefv variables.

Tables 32, 33, and 34 present results related to the variability of the contractor and program manager estimates of the contract price at completion. Table 32 suggests that the variability in the difference between the two parties' estimates is significantly decreased in repeat iterations of the same contract. However, this effect becomes insignificant when I control for firm attributes. In Table 33, columns (5) and (6) show that the coefficient on the describability ranking has a positive and significant effect on the variability between the current contract price and the contractor's estimate at completion. Table 34 shows a negative and significant effect for the coefficient on the procurement indicator variable, indicating that the program manager's estimates follow the current price of the contract more closely for the later stages of an acquisition project, on average. While the results in Table 34 do not show a significant effect for the describability ranking on the dependent variable, the sign of the coefficient is consistent with the estimates from Table 33. Perhaps it is possible that the DoD is more willing to accept variable cost estimates from the contractor in cases where the contractor bears a larger share of the cost burden. Conversely, it may be the case that the government is more active or willing in implementing corrective actions or incorporating unforeseen costs in contracts in which it bears a greater share of the cost burden.

Tables 35 and 36 use the mean squared forecasting error of the contractor and program manager estimates at completion in comparison to the next period's price of the contract. The effect of describability ranking is positive but insignificant in eleven of twelve specifications. Both tables report a positive and significant coefficient for the length variable in every specification. This indicates that longer contract periods will complicate each party's ability to accurately estimate the contract's price at completion. Also, I observe in both tables that the firm employment has a significant and negative effect, whereas the firm revenue has a significant, positive effect. This is an interesting result, considering that both of these variables are being considered as a proxy for firm size. Due to the fact that I'm using total employment but segment revenue, this may be an indication of a difference in the estimation capabilities of defense firms versus defense divisions of larger corporations.[23] For example, a large corporation with a defense segment may employ a much larger number of people than a stand-alone defense firm. Conversely, the defense firm's revenues may be much greater than the revenues of the defense segment of a larger corporation. The results of Tables 35 and 36 suggest that the overall effect may be more accurate price estimation results from the defense segments of larger corporations. However, this may be due to a tendency for these segments to contract for less complex projects than the specialized defense firms.

In summary, the regression results from this section of the paper do not suggest a definitive role for the describability ranking of the contract on the ability of the contractor and program manager to administer the contract. Almost all of the results indicate a positive relationship with these measures of variability, but the relationship is rarely significant and marginal at best. However, this relationship supports the cost-sharing structure of the different contract types. As project describability increases, the contract type will become more complete, and the contractor will bear a greater share of the cost burden. As a result, one might expect the cost estimates of the two sides to increase in variability as the contractor becomes more invested in tying the contract price to its own estimates, while the government will likely be less actively involved in the contractor's estimation and administration processes.

[23] I'm forced to use these differing measures due to the unavailability of sector employment data for large firms

Table 27: IV Regressions for Cost Variance Sharpe Ratio

	(1)	(2)	(3)
	cvsr	cvsr	cvsr
drnk	0.647	0.609	-0.561
	(0.632)	(0.558)	(0.612)
cumdq	0.003	-0.006	-0.000
	(0.009)	(0.011)	(0.010)
prevcont	-0.007	-0.002	0.002
	(0.012)	(0.009)	(0.010)
duals	-0.176	0.037	0.685
	(0.250)	(0.308)	(0.520)
winage	-0.011	-0.000	0.017
	(0.036)	(0.028)	(0.027)
length	-0.006*	-0.006*	-0.005
	(0.004)	(0.003)	(0.005)
iteration	0.031	0.007	0.051
	(0.086)	(0.071)	(0.072)
proc	-0.870	0.177	0.895
	(0.820)	(0.700)	(0.591)
rd	0.079	1.143	0.344
	(0.983)	(0.810)	(0.894)
sumposcv		0.263***	0.249**
		(0.096)	(0.111)
sumnegcv		-0.160***	-0.149***
		(0.060)	(0.053)
army			1.003
			(0.630)
navy			1.072
			(0.678)
af			1.739**
			(0.789)
Constant	-0.986	-2.008	-0.090
	(2.114)	(1.842)	(1.923)
N	69	69	69
R-Squared	.	0.123	0.210
Wald	18.24**	22.32**	35.27***
DWH P-Value	0.342	0.289	0.210

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 28: IV Regressions for Schedule Variance Sharpe Ratio

	(1)	(2)	(3)
	svsr	svsr	svsr
drnk	0.209	0.310^{*}	0.536
	(0.151)	(0.182)	(0.384)
cumdq	0.012^{***}	0.012^{***}	0.011^{***}
	(0.004)	(0.003)	(0.004)
prevcont	0.008	0.009	0.007
	(0.006)	(0.006)	(0.007)
duals	-0.252	-0.316	-0.451^{*}
	(0.175)	(0.192)	(0.241)
winage	0.002	-0.001	0.002
	(0.010)	(0.010)	(0.012)
length	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)
iteration	-0.094^{*}	-0.092^{*}	-0.111^{*}
	(0.052)	(0.051)	(0.058)
proc	-0.027	-0.130	-0.238
	(0.211)	(0.200)	(0.253)
rd	0.172	0.236	0.424
	(0.267)	(0.305)	(0.474)
sumpossv		0.115^{**}	0.123^{*}
		(0.050)	(0.071)
sumnegsv		-0.078^{**}	-0.086^{*}
		(0.039)	(0.047)
army			-0.200
			(0.270)
navy			-0.327
			(0.237)
af			-0.190
			(0.315)
Constant	-0.750	-0.981	-1.331
	(0.517)	(0.642)	(1.078)
N	69	69	69
R-Squared	0.164	0.162	.
Wald	38.71***	52.89***	53.22***
DWH P-Value	0.217	0.065	0.047

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 29: IV Estimation: Coeff. of Variation in Contract Price

	(1)	(2)	(3)	(4)
	pcoefv	pcoefv	pcoefv	pcoefv
drnk	-0.125	-0.113	0.551	0.738
	(0.232)	(0.222)	(0.671)	(0.683)
cumdq	0.005	0.004	0.000	-0.004
	(0.005)	(0.005)	(0.008)	(0.008)
prevcont	-0.012***	-0.011***	-0.018*	-0.019**
	(0.003)	(0.004)	(0.009)	(0.010)
duals	0.382	0.386	0.083	0.083
	(0.286)	(0.288)	(0.398)	(0.412)
winage	-0.004	-0.004	0.001	0.006
	(0.008)	(0.008)	(0.014)	(0.017)
length	-0.001	-0.001	-0.002	-0.003
	(0.001)	(0.001)	(0.002)	(0.003)
iteration	0.058**	0.058**	0.003	-0.010
	(0.029)	(0.028)	(0.056)	(0.061)
proc	-0.076	0.040	-0.316	-0.097
	(0.147)	(0.185)	(0.385)	(0.414)
rd	-0.136	0.011	0.433	0.919
	(0.299)	(0.295)	(0.646)	(0.825)
sumpossv	-0.070*		-0.083	
	(0.036)		(0.067)	
sumnegsv	0.012		-0.004	
	(0.022)		(0.052)	
sumposcv		0.022		0.079
		(0.038)		(0.082)
sumnegcv		-0.035*		-0.051
		(0.020)		(0.045)
army			-0.457	-0.458
			(0.324)	(0.379)
navy			-0.660	-0.875
			(0.461)	(0.548)
af			-0.659	-0.868
			(0.549)	(0.643)
Constant	0.849	0.683	-0.354	-1.069
	(0.799)	(0.779)	(1.482)	(1.620)
N	89	89	89	89
R-Squared	0.226	0.236	.	.
Wald	67.29***	62.67***	35.00***	25.47**
DWH P-Value	0.780	0.844	0.127	0.038

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 30: IV Estimation: Coeff. of Variation in Unit Price (including initial price)

	(1)	(2)	(3)	(4)
	upcoefvi	upcoefvi	upcoefvi	upcoefvi
drnk	1.017	0.672	-1.162	0.624
	(4.789)	(1.835)	(45.232)	(19.051)
cumdq	-0.004	-0.004	0.007	-0.006
	(0.021)	(0.013)	(0.272)	(0.201)
prevcont	-0.014	-0.010	0.006	-0.012
	(0.038)	(0.012)	(0.438)	(0.194)
duals	-0.541	-0.259	0.484	-0.179
	(2.342)	(0.539)	(19.781)	(4.759)
winage	0.043	0.033	-0.053	0.042
	(0.199)	(0.092)	(2.251)	(1.100)
length	0.003	0.001	-0.003	0.001
	(0.012)	(0.003)	(0.126)	(0.005)
iteration	-0.115	-0.069	0.190	-0.073
	(0.680)	(0.274)	(6.603)	(2.850)
proc	-1.090	-0.673	1.481	-0.587
	(5.597)	(2.128)	(53.412)	(21.745)
sumpossv	0.032		-0.107	
	(0.269)		(3.721)	
sumnegsv	-0.055		0.083	
	(0.265)		(2.998)	
sumposcv		0.088		0.098
		(0.314)		(3.552)
sumnegcv		-0.014		0.008
		(0.063)		(0.305)
army			-0.450	0.202
			(17.850)	(4.179)
navy			0.013	-0.039
			(1.131)	(3.792)
af			-0.021	0.252
			(7.233)	(0.684)
Constant	-1.965	-1.352	2.564	-1.381
	(9.796)	(4.018)	(98.920)	(40.506)
N	54	54	54	54
R-Squared	.	.	.	.
Wald	4.31	6.95	12.23	9.96
DWH P-Value	0.387	0.333	0.921	0.918

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 31: IV Estimation: Coeff. of Variation in Unit Price (excluding initial price)

	(1)	(2)	(3)	(4)
	upcoefv	upcoefv	upcoefv	upcoefv
drnk	0.338	0.309	0.214	0.143
	(0.641)	(0.522)	(0.448)	(0.330)
cumdq	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.003)	(0.002)	(0.003)
prevcont	-0.002	-0.003	-0.002	-0.002
	(0.006)	(0.005)	(0.005)	(0.004)
duals	-0.195	-0.156	-0.116	-0.045
	(0.337)	(0.226)	(0.249)	(0.159)
winage	0.017	0.016	0.016	0.014
	(0.032)	(0.028)	(0.027)	(0.023)
length	0.000	-0.000	-0.000	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)
iteration	-0.036	-0.034	-0.029	-0.024
	(0.074)	(0.064)	(0.058)	(0.047)
proc	-0.434	-0.377	-0.261	-0.136
	(0.876)	(0.694)	(0.610)	(0.445)
sumpossv	0.027		0.027	
	(0.077)		(0.066)	
sumnegsv	-0.021		-0.013	
	(0.034)		(0.028)	
sumposcv		-0.003		-0.004
		(0.048)		(0.047)
sumnegcv		0.009		0.017
		(0.021)		(0.016)
army			0.068	0.089
			(0.148)	(0.130)
navy			0.007	0.055
			(0.112)	(0.140)
af			0.155	0.206
			(0.153)	(0.157)
Constant	-0.579	-0.537	-0.379	-0.306
	(1.400)	(1.174)	(0.953)	(0.695)
N	55	55	55	55
R-Squared	.	.	.	.
Wald	2.17	1.91	3.72	5.01
DWH P-Value	0.264	0.235	0.316	0.356

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 32: IV Estimation: Coeff. of Variation in PM/CTR Estimation Difference

	(1) diffcoefv	(2) diffcoefv	(3) diffcoefv	(4) diffcoefv	(5) diffcoefv	(6) diffcoefv
drnk	0.405	0.431	0.071	0.069	1.195	1.252
	(0.483)	(0.459)	(0.503)	(0.450)	(1.210)	(1.183)
cumdq	-0.008	-0.009	-0.007	-0.007	-0.017	-0.018
	(0.008)	(0.009)	(0.007)	(0.007)	(0.013)	(0.014)
prevcont	0.006	0.007	0.006	0.007	-0.033	-0.033
	(0.008)	(0.010)	(0.010)	(0.010)	(0.038)	(0.039)
duals	-0.692	-0.632	-0.529	-0.464	-0.770	-0.759
	(0.507)	(0.424)	(0.469)	(0.385)	(0.768)	(0.730)
winage	-0.019	-0.019	-0.008	-0.008	0.102	0.108
	(0.012)	(0.012)	(0.019)	(0.018)	(0.105)	(0.107)
length	0.006	0.006	0.006	0.006*	0.010	0.010
	(0.004)	(0.004)	(0.004)	(0.004)	(0.008)	(0.008)
iteration	-0.102*	-0.111*	-0.094*	-0.099*	-0.170	-0.181
	(0.060)	(0.058)	(0.057)	(0.055)	(0.134)	(0.133)
proc	-0.161	-0.173	0.212	0.235	-1.222	-1.287
	(0.561)	(0.530)	(0.645)	(0.536)	(1.503)	(1.460)
sumpossv	0.044		0.058		0.022	
	(0.073)		(0.094)		(0.156)	
sumnegsv	0.016		0.016		0.033	
	(0.064)		(0.052)		(0.089)	
sumposcv		0.040		0.017		0.056
		(0.109)		(0.090)		(0.181)
sumnegcv		0.000		0.016		0.002
		(0.047)		(0.034)		(0.085)
army			0.250	0.238		
			(0.458)	(0.396)		
navy			0.171	0.191		
			(0.331)	(0.326)		
af			0.557	0.580		
			(0.394)	(0.387)		
lavgemp					0.815	0.855
					(0.699)	(0.708)
lavgdrev					0.298	0.299
					(0.530)	(0.533)
avgcrat					0.701	0.756
					(1.471)	(1.537)
avglev					4.480	4.409
					(5.510)	(5.586)
Constant	0.433	0.389	0.783	0.782	-15.017	-15.657
	(0.961)	(0.926)	(1.060)	(0.990)	(14.058)	(14.152)
N	50	50	50	50	50	50
R-Squared	0.052	0.016	0.345	0.339	.	.
Wald	19.33**	18.46**	26.90**	26.53**	13.61	10.94
DWH P-Value	0.728	0.897	0.819	0.799	0.218	0.195

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 33: Coeff. of Variation of Difference in CTR Estimate & Current Price

	(1) diffcoefvc	(2) diffcoefvc	(3) diffcoefvc	(4) diffcoefvc	(5) diffcoefvc	(6) diffcoefvc
drnk	0.242	0.253	0.416	0.442	0.434*	0.475*
	(0.270)	(0.286)	(0.351)	(0.338)	(0.238)	(0.283)
cumdq	-0.000	0.000	-0.003	-0.003	-0.002	-0.002
	(0.004)	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)
prevcont	0.008	0.007	0.004	0.003	-0.008	-0.011
	(0.006)	(0.007)	(0.009)	(0.009)	(0.012)	(0.014)
duals	0.628**	0.530	0.413	0.329	0.578**	0.395
	(0.285)	(0.343)	(0.436)	(0.436)	(0.235)	(0.273)
winage	-0.018	-0.019	-0.014	-0.016	0.022	0.024
	(0.012)	(0.012)	(0.013)	(0.013)	(0.031)	(0.034)
length	0.000	-0.000	-0.000	-0.001	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
iteration	-0.033	-0.023	-0.032	-0.024	-0.034	-0.024
	(0.031)	(0.030)	(0.030)	(0.029)	(0.028)	(0.029)
proc	-0.411	-0.482	-0.696	-0.783	-0.724**	-0.849**
	(0.368)	(0.404)	(0.518)	(0.497)	(0.333)	(0.424)
sumpossv	-0.150**		-0.105		-0.167**	
	(0.060)		(0.074)		(0.075)	
sumnegsv	0.005		-0.012		0.028	
	(0.030)		(0.038)		(0.026)	
sumposcv		-0.042		-0.002		-0.076
		(0.067)		(0.070)		(0.080)
sumnegcv		-0.034		-0.046		-0.019
		(0.031)		(0.031)		(0.028)
army			0.215	0.205		
			(0.405)	(0.384)		
navy			-0.273	-0.375		
			(0.343)	(0.351)		
af			-0.214	-0.314		
			(0.337)	(0.348)		
lavgemp					0.137	0.239
					(0.290)	(0.304)
lavgdrev					0.191	0.115
					(0.233)	(0.245)
avgcrat					0.461	0.452
					(0.971)	(1.072)
avglev					3.165	3.810*
					(2.243)	(2.309)
Constant	0.905	0.917	0.759	0.814	-3.927	-4.554
	(0.559)	(0.572)	(0.614)	(0.572)	(3.359)	(3.536)
N	58	58	58	58	58	58
R-Squared	0.093	0.046	.	.	0.042	.
Wald	23.80***	19.55**	27.41***	22.28**	41.52***	30.23***
DWH P-Value	0.348	0.343	0.240	0.222	0.129	0.128

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 34: Coeff. of Variation of Difference in PM Estimate & Current Price

	(1) diffcoefvp	(2) diffcoefvp	(3) diffcoefvp	(4) diffcoefvp	(5) diffcoefvp	(6) diffcoefvp
drnk	0.252	0.267	0.194	0.208	0.302	0.354
	(0.226)	(0.249)	(0.214)	(0.198)	(0.221)	(0.266)
cumdq	0.003	0.003	0.002	0.001	0.001	-0.000
	(0.005)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)
prevcont	0.010	0.009	0.009	0.008	0.002	-0.002
	(0.006)	(0.006)	(0.006)	(0.006)	(0.010)	(0.012)
duals	0.510	0.412	0.605	0.548	0.601**	0.434
	(0.326)	(0.360)	(0.407)	(0.401)	(0.288)	(0.302)
winage	0.006	0.005	0.015	0.015	0.036	0.044
	(0.012)	(0.012)	(0.010)	(0.011)	(0.027)	(0.031)
length	-0.001	-0.001	-0.001	-0.001	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
iteration	-0.032	-0.022	-0.023	-0.016	-0.021	-0.009
	(0.026)	(0.028)	(0.024)	(0.025)	(0.021)	(0.021)
proc	-0.496*	-0.561*	-0.476	-0.525*	-0.648**	-0.795**
	(0.287)	(0.324)	(0.319)	(0.289)	(0.299)	(0.384)
sumpossv	-0.127**		-0.078		-0.140**	
	(0.061)		(0.061)		(0.057)	
sumnegsv	0.018		0.000		0.024	
	(0.023)		(0.028)		(0.020)	
sumposcv		-0.027		-0.002		-0.082
		(0.069)		(0.054)		(0.080)
sumnegcv		-0.017		-0.020		-0.001
		(0.035)		(0.027)		(0.039)
army			0.582*	0.612**		
			(0.307)	(0.292)		
navy			0.061	0.010		
			(0.246)	(0.244)		
af			0.218	0.178		
			(0.257)	(0.270)		
lavgemp					0.139	0.249
					(0.261)	(0.273)
lavgdrev					-0.084	-0.168
					(0.153)	(0.179)
avgcrat					0.946	1.104
					(0.607)	(0.771)
avglev					3.977**	4.444**
					(1.781)	(2.064)
Constant	0.754	0.739	0.666	0.665	-1.849	-2.656
	(0.485)	(0.517)	(0.513)	(0.520)	(3.469)	(3.670)
N	56	56	56	56	56	56
R-Squared	0.022	.	0.212	0.187	0.148	0.042
Wald	15.54	12.07	29.01***	32.12***	41.90***	34.98***
DWH P-Value	0.173	0.209	0.295	0.290	0.130	0.154

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 35: IV Estimation: Contractor's Mean Squared Forecasting Error

	(1)	(2)	(3)	(4)	(5)	(6)
	lcmsfe	lcmsfe	lcmsfe	lcmsfe	lcmsfe	lcmsfe
drnk	0.824	0.593	1.746	1.454	0.258	-0.229
	(1.394)	(1.638)	(1.654)	(1.812)	(1.667)	(1.984)
cumdq	-0.051	-0.051	-0.060*	-0.058	-0.007	-0.003
	(0.041)	(0.042)	(0.036)	(0.038)	(0.045)	(0.046)
prevcont	0.038	0.050	0.034	0.045	0.121	0.154*
	(0.061)	(0.059)	(0.066)	(0.065)	(0.089)	(0.091)
duals	-1.178	-0.655	-1.810	-1.342	-0.663	-0.080
	(1.414)	(1.560)	(1.526)	(1.557)	(1.558)	(1.763)
winage	0.095	0.111	0.043	0.064	-0.252	-0.302
	(0.075)	(0.078)	(0.082)	(0.088)	(0.192)	(0.203)
length	0.049***	0.052***	0.046***	0.049***	0.046***	0.045***
	(0.013)	(0.013)	(0.015)	(0.014)	(0.013)	(0.013)
iteration	-0.126	-0.171	-0.103	-0.154	-0.084	-0.113
	(0.193)	(0.187)	(0.187)	(0.186)	(0.199)	(0.198)
proc	0.535	0.995	-0.582	-0.073	1.364	2.172
	(1.847)	(2.117)	(2.180)	(2.333)	(2.000)	(2.307)
sumpossv	1.146**		1.101**		0.953**	
	(0.502)		(0.530)		(0.458)	
sumnegsv	0.382*		0.423*		0.445**	
	(0.230)		(0.248)		(0.193)	
sumposcv		0.779*		0.707		0.902**
		(0.436)		(0.432)		(0.420)
sumnegcv		0.416*		0.427**		0.377
		(0.219)		(0.214)		(0.244)
army			-1.664	-1.741		
			(1.919)	(1.903)		
navy			-0.634	-0.594		
			(1.771)	(1.844)		
af			-2.474	-2.115		
			(1.813)	(1.801)		
lavgemp					-4.324**	-4.887***
					(1.703)	(1.627)
lavgdrev					1.572	1.796*
					(1.018)	(0.965)
avgcrat					-4.202	-5.579
					(4.335)	(4.570)
avglev					-6.351	-11.522
					(10.098)	(9.825)
Constant	-0.447	-0.471	-1.068	-0.959	42.824*	50.077**
	(3.235)	(3.686)	(3.628)	(4.068)	(22.997)	(23.650)
N	66	66	66	66	66	66
R-Squared	0.326	0.343	0.319	0.345	0.393	0.422
Wald	55.61***	82.03***	75.34***	93.91***	75.61***	101.61***
DWH P-Value	0.904	0.980	0.387	0.561	0.949	0.805

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 36: IV Estimation: PM's Mean Squared Forecasting Error

	(1)	(2)	(3)	(4)	(5)	(6)
	lpmsfe	lpmsfe	lpmsfe	lpmsfe	lpmsfe	lpmsfe
drnk	1.231	1.042	1.919	1.602	0.848	0.519
	(1.263)	(1.465)	(1.610)	(1.781)	(1.513)	(1.731)
cumdq	-0.043	-0.040	-0.045	-0.038	0.012	0.017
	(0.058)	(0.056)	(0.048)	(0.047)	(0.053)	(0.052)
prevcont	0.027	0.035	0.031	0.038	0.108	0.134
	(0.064)	(0.062)	(0.068)	(0.066)	(0.097)	(0.096)
duals	-0.468	0.067	-1.378	-0.983	0.267	0.881
	(1.981)	(2.126)	(2.036)	(2.084)	(1.636)	(1.814)
winage	0.057	0.076	-0.005	0.016	-0.340*	-0.381*
	(0.078)	(0.084)	(0.085)	(0.090)	(0.206)	(0.214)
length	0.034**	0.036**	0.032*	0.036**	0.034**	0.033**
	(0.017)	(0.017)	(0.017)	(0.016)	(0.015)	(0.015)
iteration	-0.074	-0.128	-0.068	-0.120	-0.061	-0.096
	(0.188)	(0.187)	(0.192)	(0.191)	(0.193)	(0.189)
proc	-0.231	0.242	-0.997	-0.402	0.204	0.839
	(1.809)	(2.053)	(2.202)	(2.409)	(2.067)	(2.193)
sumpossv	1.463**		1.235**		1.123**	
	(0.572)		(0.529)		(0.462)	
sumnegsv	0.236		0.329		0.407*	
	(0.270)		(0.258)		(0.209)	
sumposcv		0.651		0.489		0.823*
		(0.461)		(0.433)		(0.441)
sumnegcv		0.485**		0.504**		0.477**
		(0.226)		(0.211)		(0.243)
army			-3.408*	-3.689*		
			(2.017)	(2.060)		
navy			-0.803	-0.521		
			(1.819)	(1.846)		
af			-2.422	-1.909		
			(1.794)	(1.728)		
lavgemp					-5.744***	-6.388***
					(1.974)	(1.929)
lavgdrev					2.943***	3.289***
					(1.090)	(1.049)
avgcrat					-5.676	-6.858
					(4.136)	(4.228)
avglev					-11.167	-16.332
					(11.070)	(11.307)
Constant	-0.340	-0.411	-0.127	-0.047	48.937*	55.507**
	(2.885)	(3.188)	(3.276)	(3.571)	(26.299)	(26.398)
N	69	69	69	69	69	69
R-Squared	0.238	0.239	0.262	0.285	0.374	0.412
Wald	30.30***	48.24***	43.77***	55.62***	59.39***	78.47***
DWH P-Value	0.873	0.987	0.396	0.563	0.872	0.999

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

9 Conclusion

The primary purpose of this paper was to provide empirical evidence in support of the debate surrounding the relevance of physical describability in contracting outcomes. Given the presence of the "menu" of contracts made available to US government acquisition officials by the Federal Acquisition Regulation, it seems unnecessary to justify whether or not the describability or complexity of an underlying project is a relevant consideration in the defense contracting environment. However, the internal theoretical debate in economics pertains to whether or not this describability warrants its own contracting approach. The empirical results of this paper seem to suggest that the physical describability of the underlying project can have a tangible effect on the performance outcome for the associated contract in the defense contracting environment. While far from definitive, it seems that military aircraft projects that are capable of being assigned a more "complete" style of contract may perform better, on average, particularly in terms of adherence to contractual timelines. The effect on cost performance is much less clear. Therefore, it seems that the relevance of physical describability is two-fold in the case of DoD contracting. First, it is a major criterion in determining the risk-sharing structure and administrative environment under which a project will operate. Second, even given attempts to accommodate technological complexity with an appropriate contract type, the underlying indescribable nature of the project may produce unforeseeable production difficulties and delays.

Possible extensions of this paper would likely focus on quasi-experimental conditions in which projects of similar complexity were administered under contract types with differing incentive structures. The set of projects under consideration in this paper does not lend itself to this type of scenario as the projects are separated by great degrees of technological heterogeneity. In this sense, I cannot currently comment on the "optimality" of the incomplete contracting approach, only on its relevance in certain environments. Additionally, it would be interesting to further research the underlying costs of EVM application as a matter of policy analysis. Although the FAR clearly views the application of EVM as a costly endeavor, I am not able to directly observe these costs in my data set. It would be interesting to conduct an *ex post* cost-benefit analysis in terms of EVM costs versus contract performance. A study of this type would certainly be useful for policymakers looking to apply EVM in a non-DoD environment.

Appendices

A Categorical Examples of Cost and Schedule Variance Explanations

Change in Manufacutring Inputs

1. Change in material costs. (CV/SV)
2. Change in required amount of materials. (CV/SV)
3. Decision to hire locally led to lower wage costs. (CV)
4. Decreased travel requirements led to lower labor costs. (CV)
5. Contractor forced to fabricate parts it originally intended to purchase. (CV)
6. Increased labor wage rates. (CV)

Supply Chain Management

1. Early delivery of components or receipt of materials from subcontractor. (CV/SV)
2. Sale of over-requisitioned materials. (CV)
3. Delay in delivery of parts or components to the production line. (CV/SV)
4. Parts shortage. (CV/SV)
5. Receipt of parts in excess of baseline requirements. (CV)
6. Over requisition of material. (CV)
7. Cost growth in subcontracted parts or components. (CV)
8. Early completion of all outside vendor tasks. (SV)
9. Delayed off-loading of work packages to subcontractors. (SV)
10. Delayed pull of materials from inventory. (SV)
11. Chain reaction/ domino effect production delay. (SV)
12. Shortage of general procurement items. (SV)

Corrective Actions in Production

1. Correction of deficiencies identified by product testing. (CV/SV)
2. Alteration of fabrication methods to improve performance. (CV/SV)

3. Implementation of "recovery" or "challenge" schedule to improve delivery performance. (CV/SV)
4. Additional testing required due to initially poor performance. (CV/SV)
5. Contractor risk mitigation efforts. (SV)
6. Realignment of prime and sub- contractor work schedules to improve delivery performance. (SV)

Fundamental Change to Contract Details

1. Change in funding scope due to incorporation of additional capabilities. (CV/SV)
2. Re-design of aircraft or major component. (CV/SV)
3. Incorporation of funds spent prior to contract definitization. (CV)
4. Cessation of cost reporting on an under-performing portion of the contract. (CV)
5. Re-baselining of contract or major subcontract established new contract price and schedule milestones. (CV/SV)
6. Re-prioritization of contract due to other operational commitments (Iraq/Afghanistan) of prime contractor. (CV/SV)
7. Extension of contractor's oversight period for program. (CV)

Administrative Factors

1. Change in overhead, general and administrative (G&A), or burden rates by prime contractor. (CV)
2. Change in foreign exchange rates. (CV)
3. Transfer of inventory or materials to other contracts. (CV)
4. Perceived savings or additional costs due to pre-existing delays from previous iterations of the contract. (CV/SV)
5. Errors in the Earned Value Management (EVM) reporting process. (CV/SV)
6. Correction of accounting or invoicing mistakes. (CV/SV)
7. Cost reporting prior to contract definitization is recorded as negative cost growth due to lack of budget. (CV/SV)
8. Implementation of new FAA regulations changes testing requirements. (CV)
9. Staffing vacancies in vital areas of production. (CV/SV)

10. Production delays due to labor negotiations/ strikes. (SV)
11. Change in EVM reporting procedures. (SV)
12. Administrative hold on procurement funds. (SV)

Changes to Required Effort

1. Change in level of effort or work required for design and/or production of contracted item(s). (CV/SV)
2. Change in expertise or worker aptitude level required to complete a specific work package. (CV/SV)
3. Change in staffing levels to address problem areas. (CV)
4. Change in required administrative support for subcontracted efforts. (CV)
5. Change in overtime hour requirements. (CV)

B Regression Results: Instrumental Variable

Table 30 lists the regression results for the OLS estimation of the contract choice model. Using the resulting coefficient estimates, I then construct the expected contract type for each contract in the estimation sample as a function of its associated project and firm characteristics.

Table 37: Regression Results for IV Estimation (Expected Contract Type)

	(1) drnk
ladjip	0.022
	(0.078)
army	1.422**
	(0.706)
navy	1.315***
	(0.447)
af	1.563***
	(0.469)
rd	-2.286**
	(1.001)
proc	0.289
	(0.994)
length	-0.001
	(0.004)
lvar	0.017
	(0.027)
duals	0.791**
	(0.375)
winage	-0.019
	(0.027)
lemp	-0.096
	(0.326)
ldrev	0.079
	(0.225)
prevcont	0.043***
	(0.012)
nsd	8.659
	(6.547)
cratio	-1.923**
	(0.783)
rdper	-0.006
	(0.513)
Constant	4.438
	(3.712)
Interaction Terms with NSD	Yes
N	149
R-Squared	0.614
F-Statistic	26.268

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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