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Predicting Federal Contractor Performance Issues Using Data Analytics

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Abstract

The purpose of this research is to evaluate the degree to which predictive modeling techniques can enhance the quality of contractor source selection decisions. Use risk indicators created from existing publicly available contracting datasets to predict which contractors are most likely to perform successfully. Examples of risk indicators are quantitative measurements of contractor dollar velocity, instability in federal contract business, and level of experience in performing similarly sized contracts. Examine how big data analytics can be used to augment traditional source selection techniques such as proposal evaluation and past performance/responsibility checks.

Introduction

A primary goal of public-sector contracting, and more broadly, public procurement policy, is to ensure value in the use of public funds (Dimitri, 2013; Hawkins et al., 2016; Rendon & Rendon, 2016). The concept of value creation in business-to-government exchange, while latent and challenging to assess, has taken on an increased importance in the policies surrounding public procurement (e.g., Kendall, 2015; Weichert, 2019), just as it has in the management of industrial supply chains (Hendricks & Singhal, 2003; Ketchen & Hult, 2007). However, despite the ubiquity of contracting in the public and private sectors, organizations both public and private struggle to effectively and efficiently contract out for goods and services, often failing to achieve full value for their contract dollars (Rich, 2018). In extreme cases, contractual risks and hazards may lead to severe post-award issues, such as contract failure (Rendon et al., 2014) and contract termination (Davison & Sebastian, 2006, 2009). Understanding these cases is important not only because severe contractual issues (e.g., contract failure) jeopardize value and performance of taxpayer funds but because they may diminish an agency's ability to execute critical programs and deliver governmental services core to agencies' missions.

The purpose of this research is to uncover antecedents and to develop a *predictive* model of severe contractual performance issues, such as those leading to contract failure, in transactions between federal agencies and their suppliers. Existing empirical research into this topic has been limited and has largely focused on transaction-level factors leading to contract performance problems and/or contract termination. In contrast, this research examines factors at the firm-level, and utilizing data now publically available on contractor performance and integrity issues, proposes a predictive model through the application of random decision forests, a machine learning technique. To do this, firm-level antecedents are collected from multiple, publicly available data sources, including the Federal Procurement Data System (FPDS) and the System for Award Management (SAM). Incidents of contract failure are identified within the Federal Awardee Performance and Integrity Information System (FAPIIS). The resulting random forest model exhibits excellent classification performance, as measured by out-of-bag error rate and provides information on the relative importance of firm-level factors.

The remainder of the paper is structured as follows. Within the following section, we provide a brief review of the literature on contract failure in public-sector procurement. Next, we describe the data and our modeling approach, followed by the results of our analysis. The final section provides a discussion of the findings and provides several recommendations.

Prior Research

There has been only limited research into the factors leading to severe performance issues in public-sector procurement, and more specifically, contract failure and the dissolution of government-supplier relationships. Of the prior work in this area, most research has tended to focus on the analysis of transaction-level factors and how these factors correlate to post-award contractual issues. Davison and Sebastian (2009) explored associations between product/service type and the occurrences of severe problems in contract administration, finding that performance delays were the most prevalent problem encountered by contract administrators, with problems arising from other forms of risk—proposal risk, surety and liability risk, contractual risk, and price risk—varying based on the class of goods or services under contract. Rendon et al. (2014) similarly performed an examination at the transaction level, investigating contract failure rates under defense services contracts. The authors found significant differences in failure rates based on contract type and value, but—in contrast to the findings of Davison and Sebastian (2009)—did not find the rates to differ by service type, nor did they find rates to differ by level of competition (Rendon et al., 2014). In a later analysis, Dixon et al. (2015) extended the work of Rendon et al. (2014), in part, by applying techniques common to predictive analytics (logistic regression, decision-tree analysis, neural networks) to uncover the determinants of contractor performance ratings on defense services contracts. Among their findings, Dixon et al. (2015) identified a positive relationship between the workload of contract administration personnel and the likelihood of contract failure, such that failures appear to become more likely to occur as workload increases. Along those lines, prior research (e.g., Brown & Potoski, 2003) has also emphasized the importance of post-award management activities, such as monitoring, arguing that risks of contract failure will increase if these activities are under-resourced. Most recently, Liebman and Mahoney (2017) examined contractor performance on major, public-sector information technology contracts and found performance to be lower on end-of-year (i.e., last week) purchases. Interestingly, the authors found that, upon deeper analysis, these overall performance differences appear to be most strongly driven by an individual component: perceptive evaluations made by agency chief information officers (CIOs). However, these evaluations are not linked directly to incidents of contract failure.

Our examination focuses heavily on one of the most severe cases of failure—also representing the most frequent entry in FAPIIS—the government's termination of a contractor for default of the contractor (or for cause). A termination for default is defined here as the government's exercise of a contractual right to terminate a contract, or some portion thereof, due to the failure of a contractor to perform its contractual obligations (James, 1963).[1] In general, the termination of federal contractors for default involves such "serious consequences for a contractor, they are considered drastic sanctions that should be imposed or sustained only for good grounds and on solid evidence" (GAO, 2008). Yet, terminations for default (and cause) are not uncommon in public procurement. For instance, in 1994, the Government Accountability Office noted that the General Services Administration (GSA) terminated "hundreds" of contracts annually as a result of contractor default (GAO, 1994). As of 2015, terminations for default and for cause, and other severe issues (e.g., instances of defective pricing, subcontractor non-payment) are reported to the FAPIIS (2 CFR § 200.340), with records currently numbering in the thousands. FAPIIS records remain active for five years, during which time agencies are required to review and consider information contained in the system prior to making a contract award over the simplified acquisition threshold (41 U.S.C. 2313(d)(3)). The government's acquisition policy states that contracting officers will consider information in FAPIIS when determining responsibility of a prospective contractor, and separately, when evaluating the past performance of offerors during source selections (48 CFR § 9.104-6). Accordingly, a primary intent of the government's policy (and the resulting FAPIIS system) is to provide acquisition officials across the government insight into the performance and integrity of suppliers; the effect is to broaden knowledge and, potentially, the impact of severe contractor performance and integrity issues beyond that of the individual transaction. In many cases, inclusion of a severe issue in FAAPIS may lead toward ultimate dissolution of the government's relationship with a supplier (e.g., as it applies to new contract awards). The purpose of this study is to add to the existing literature regarding contract failure in public sector procurement through the development of a predictive model for severe performance issues.

Methodology

Introduction

As the intent of this research is to generate a predictive model of performance issues, we rely on techniques from the machine learning statistical tradition, namely the random forest modeling technique (Breiman, 2001). The random forest is a supervised, tree-based prediction strategy that seeks to reduce overfitting and improve generalizability through aggregated estimates from an ensemble of trees. Model performance (e.g., predictive accuracy) is measured utilizing out-of-bag (OOB) estimates which, according to Breiman (2001), eliminates the need for reserving some portion of the data for cross-

[1] Similarly, FAPIIS defines a *termination for cause* as the "exercise of the Government's right by a contracting officer to completely or partially terminate a contract if the Contractor fails to comply with any contract terms and conditions, or fails to provide the Government, upon request, with adequate assurances of future performance. Terminations for Cause are similar to Terminations for Default, but are applicable to contracts awarded using commercial procedures."

validation, while reducing bias. Applications of random forests can be readily found within the scientific literature and across numerous fields. Their popularity is owed, in part, to the ability of the random forest to handle high-dimensional data with relatively few observations, while providing measures for the relative importance of variables (Grömping, 2009).

Sample

Observations of contract terminations and other severe issues were obtained from FAPIIS, which contains reports on terminations and other severe contract issues that have occurred over a five-year period (early 2014 to early 2019). As the unit of analysis for this research is the firm, and since multiple records can exist in FAPIIS for a single firm, we identify for each firm the first date that the firm was entered into FAPIIS. We uniquely identify firms by their DUNS number, resulting in 1,602 distinct entities. After joining FAPIIS records with data from SAM and data from the FPDS, and then removing entities with missing or incomplete data, we are left with a sample of 780 firms. We then pair this sample with a random sample of 780 firms who did not have severe issues reported in FAPIIS during this period, thus creating a balanced dataset. Accordingly, our final sample size is 1,560 firms—a size which is comparable to sample sizes used in prior research within this area (e.g., Dixon et al., 2015).

Response Variable

The response variable in our analysis is a binary indicator of a severe contractual performance or integrity issue, as reported/indicated in FAPIIS. Of the 780 firms in our dataset with this indicator, the first entry in FAPIIS for the majority (734 firms, or 94%) was a termination for default or cause. As previously mentioned, FAPIIS defines termination for default as exercising the government's right to completely or partially terminate a contract because of the contractor's actual or anticipated failure to perform its contractual obligations. Termination for cause is the commercial item contract version of a default termination. For the remaining 46 firms, reasons for inclusion in FAPIIS included Department of Defense Determination of Contractor Fault, Non-Responsibility Determination, and Subcontractor Payment Issues.

Explanatory Variables

We identify and utilize several firm-level features (i.e., variables) to predict occurrences of severe performance issues. Longitudinal data on a firm's contractual relationship with the federal government is obtained from the FPDS, using federal-wide data starting with Fiscal Year 2009. Summary information on total contract obligations for five recent years is shown in Figure 1. We begin our analysis with data at Fiscal Year 2009 as implementation of the Federal Funding Accountability and Transparency Act of 2006 resulted in significant improvements to the quality of contract metadata contained in FPDS (Lewis, 2017). For firms experiencing a severe performance issue, FPDS data used to calculate measures extends through the period prior to a severe issue.[2] We account for time-series components of a firm's contractual exchanges with the federal government in three ways. First, we include a variable *obligations_mean* to account for the average level

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[2] Here, "period prior" means the starting period of the analysis (Fiscal Year 2009) through the fiscal year preceding a firm's first record in FAPIIS. Our measures do not include the fiscal year of the severe issue and associated report in FAPIIS, as contractual deobligations are likely to accompany terminations and thus may confound relationships under study.

(amount in dollars) of annualized business the entity engaged in with federal agencies. Second, we include a variable *obligations_growth* to account for the change in annual obligations over the period of analysis, operationalized as the sum of first differences of the time series data. Third, to account for stability (or variability/volatility) in exchanges with federal agencies, we take the standard deviation of first differences of annual obligations, following Doboeck et al. (2009). We label this variable *obligations_variability*, given that higher values on the measure reflect a greater degree of variability. Next, we account the level of diversification in a firm's federal clientele and in the industries that it operates in within its capacity as a federal contractor. We operationalize diversification in clientele as the pooled mean of the annualized count of distinct federal agencies that the firm conducted business with over the period of analysis. Agencies are identified using the Contracting Agency Code in FPDS; we refer to the resulting variable as *diversification_agencies*. Similarly, we operationalize diversification in industries that a firm operates in (within its capacity as a federal contractor) as the pooled mean of the annualized count of distinct North American Industry Classification System (NAICS) codes as reported in FPDS; we refer to the resulting variable as *diversification_industries*. Following the finding of Rendon et al. (2014) that contract failure rates were highest among competitively awarded contracts, we include a measure, *competition*, reflecting the average number of offers agencies received in response to solicitations for contracts awarded to the firm during the period of analysis.

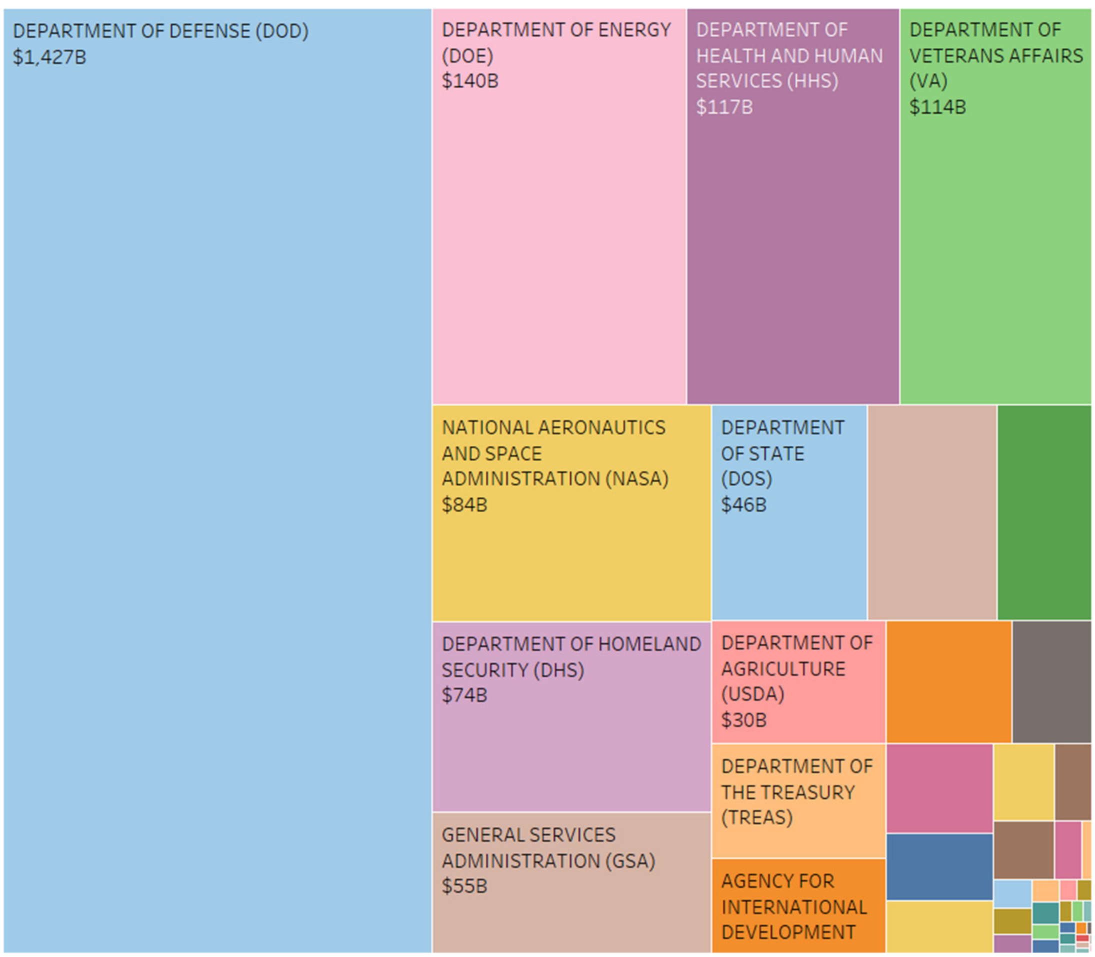

Figure 1. Five Years of Contract Obligations (Fiscal Years 2014–2018)

Next, we obtained entity information on the firms from SAM. We account for a firm's age in two ways, first, as the amount of time elapsed, in days, between the firm's business start date and the period prior to a severe issue (if any). SAM describes their data on Business State Date as follows: "The date the entity was started or acquired." We refer to this measure as *days_since_bus_start*. Second, we account for a firm's tenure in the federal market, *days_since_registration*, measured as the number of days between a firm's registration as a federal contractor and the period prior to a severe issue (if any). SAM describes their data on Registration Date as follows: "The date the initial entity registration was submitted, this date will not change." Lastly, we account for firm's corporate structure, using the Corporate Structure Code field in SAM; SAM defines this field as follows: "The structure of the entity as defined by the IRS, as a code." Of the total 1,560 firms, 70.32% (1097) were corporations, 8.65% (135) were partnerships, 6.03% (94) were sole proprietorships, 3.46% (54) were tax-exempt corporations, 2.44% (38) were international organizations, and 9.10% (142) fell into other categories of corporate structure.

Results

A random forest model was estimated in *R* using the *randomForest* package (Liaw & Weiner, 2002). Two parameters are primarily of interest. First, we set the model parameter corresponding to the number of predictor variables (*p*) sampled at each split to a value of three, which is equivalent to the square root of *p*; this heuristic has been found to be optimal in several empirical studies and, accordingly, is seen as a reasonable default (Strobl et al., 2008). We also observed poorer predictive performance at higher and lower values. Second, we set the number of trees at 4,096. There is no scientific standard for the number of trees to grow in a random forest; however, up to a point, the addition of trees will improve predictive performance and the interpretation of variable importance measures (Strobl et al., 2009). We observed that meaningful improvements to model performance were not realized beyond this point (Figure 2).

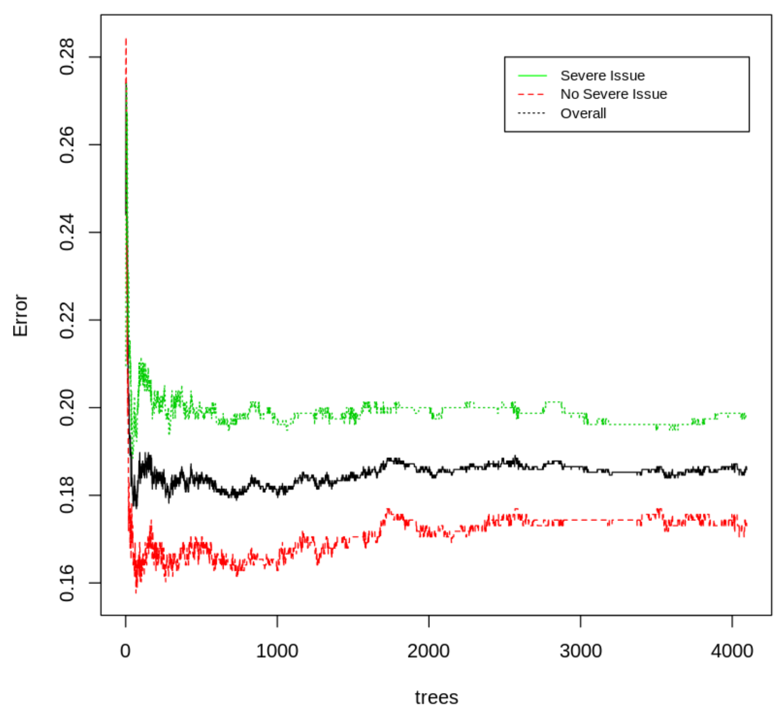

Figure 2. Effect of Number of Trees on Model Error Rate

Estimation of the random forest model resulted in an overall classification performance of 81.41% (i.e., 18.59% misclassification), based on the out-of-bag error rate. The model performed marginally better at classifying firms who did not experience severe issues during the period of analysis (false positive rate of 17.31%) than it did at classifying firms who did (false negative rate of 19.87%). Variable importance measures are provided within Table 1, and importance for each variable is assessed by the associated decrease in node impurities, as measured by the Gini index. Higher values of Gini importance reflect greater importance. As seen in Figure 3, the tenure of firms (days since business start and days since registration as a contractor) was the most important variable in the model, followed by industrial diversification, the average level of competition firms faced on government contracts that they won, the diversification of firms' federal clientele (agencies), the level, growth and variability of firms' business with the federal government, and, lastly, the corporate structure of firms in the sample.

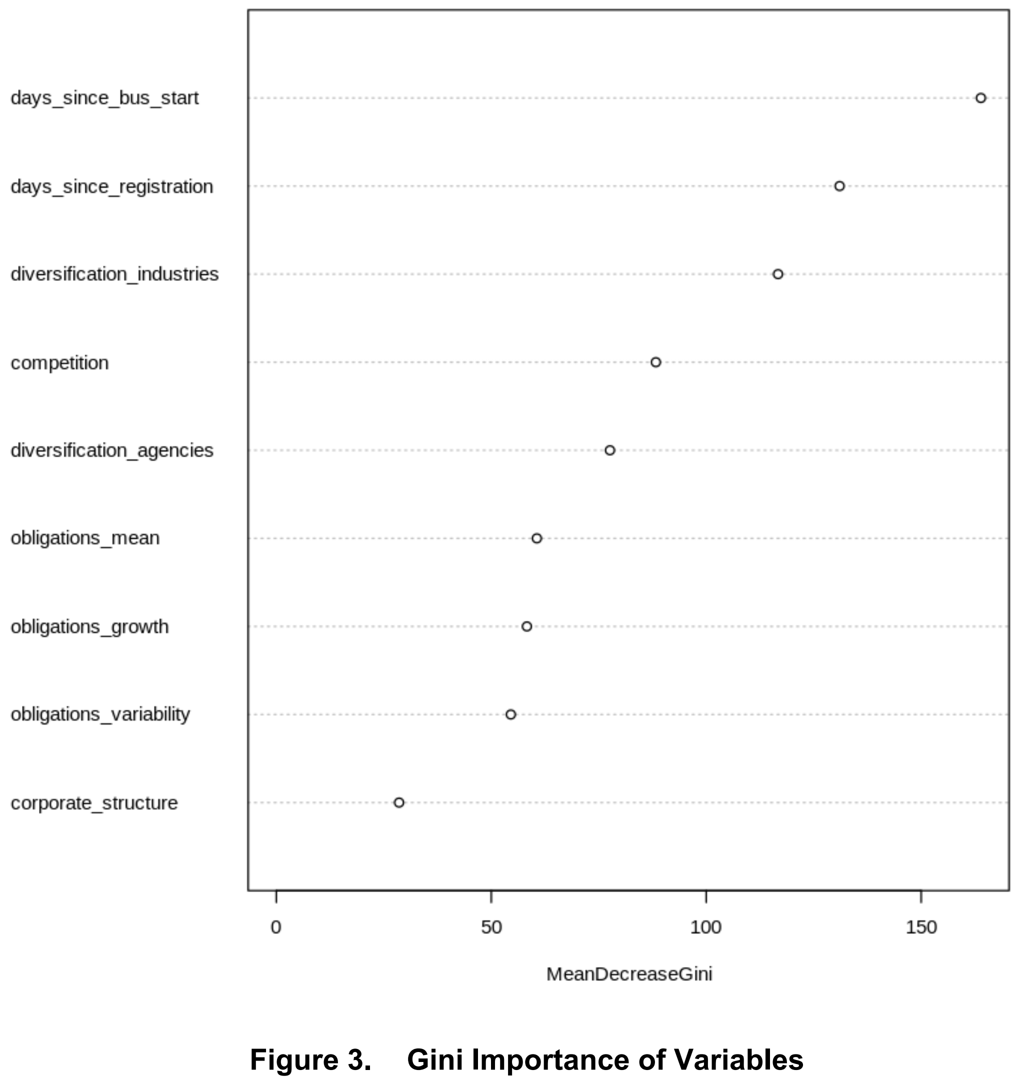

Figure 3. Gini Importance of Variables

Discussion

Each year the federal government receives a large quantity of contractor offers—proposals or other vendor-supplied information (e.g., oral presentations or product demonstrations). These proposals receive carefully written evaluations by government technical experts and contracting officials. Proposals and other vendor-supplied information contain a wealth of information on technical approaches to meeting specific agency mission needs. Further, proposals often contain corporate experience and past performance information. Contracting officers use platforms such as the Contractor Performance Assessment Rating System (CPARS) and FAPIIS to assess the responsibility of prospective contractors and to evaluate past performance. While both platforms are valuable, each has significant gaps. For instance, CPARS past performance narratives are sometimes not completed, have inconsistent information quality, and have a significant time lag (due to the annual evaluation cycle). FAPIIS lists contractors that experienced an adverse termination but does not track all types of contractor performance issues—only those that tend to be severe in nature. Further, both CPARS and FAPIIS are lagging indicators of performance issues. However, our results show some of the most severe contract performance issues might be predicted using publicly available data alone, as classification performance for the random forest model exceeded 80% using only nine variables. While we are careful not to suggest that a statistical model should be used in isolation in source selections, model estimates may very well serve as additional information that prompt deeper research and analysis, or when considered in concert with all other information, help to form an assessment of a prospective contractor's likely future performance.

In general, the results of this analysis suggest that a data-driven predictive modeling approach can be used to correctly identify (classify) a sizeable percentage of contractors who will later go on to experience a severe performance or integrity issue. Given that agency resources are finite, and given that a primary purpose of the public procurement is to ensure value for taxpayer dollars, predicting performance issues early—especially prior to the award of a contract—is important. Again, our analysis highlights the potential role that data analytics may serve to inform and even augment efforts by contracting officials. For one, data analytics can inform contracting officers with a picture of a vendor's overall federal business. The presence of similar, successful past contracts may evidence capability to perform on future requirements of the same type and scale. The absence of similar, federal prime contracts would likewise indicate that more information may be needed to make a determination of contractor responsibility. Further, analytics can help answer often-opaque questions regarding a contractor's ability to comply with the required delivery schedules, taking into consideration existing commercial and governmental business commitments. For example, a recent and sizable (even anomalous) increase in contract awards might prompt scrutiny regarding a contractor's capacity to handle additional volume.

Table 1. Notional Application of Data Analytics for Evaluation of Corporate Experience

Example Evaluation Factor for Corporate Experience	Analytics-Enhanced Evaluation Factor of Corporate Experience
The Offeror shall provide at least two, but no more than three examples of relevant and recent contracts performed. “Recent” is defined as a contract performed within the last three (3) years from the submission deadline. If a contract is ongoing, it must be at least one year into performance by the submission deadline. “Relevant” is defined as a contract that is of similar size, scope, and complexity to the requirements as set forth in this solicitation. A minimum of one (1) contract shall be the experience of the Offeror performing as a prime. The other contract(s) may be experience of the Offeror performing as a subcontractor, or the experience of a proposed subcontractor. Experience where the Offeror performed as a prime will be considered most favorably.	The Government will evaluate offerors experience on federal prime contracts of a similar size, scope, and complexity. Dollar amounts, the type of work, data derived risk metrics, and any other contract data available may be considered in the evaluation of experience. Offerors may submit a supplemental corporate experience narrative describing experience on subcontracts, non-federal contracts, and/or providing additional information regarding prime contract experience.

A primary recommendation is for the development of an open platform for *analytics* to support procurement decisions by federal agencies and their acquisition workforce. Along these lines, Executive Order 13859 (Trump, 2019) states that the government should prioritize the development of open data models and reduce barriers to their deployment. Contracting officers would benefit from having a website that summarizes data and risk characteristics of a vendor. Currently, USASpending.gov does allow viewing dollars by year and the top five transactions for specific contractors (recipients). That said, the below prototype shows the potential for more robust information that could be evaluated during a source selection. Notably, the vendor shown below experienced a rapid, five-fold increase in dollars during Fiscal Year 2018. Further, notice the two dollars (each representing a different agency that obligated over $10 million). The dots for the large dollar obligations are separated from small actions by quite a lot of whitespace (this is a relatively small vendor that suddenly received much larger than typical contracts).

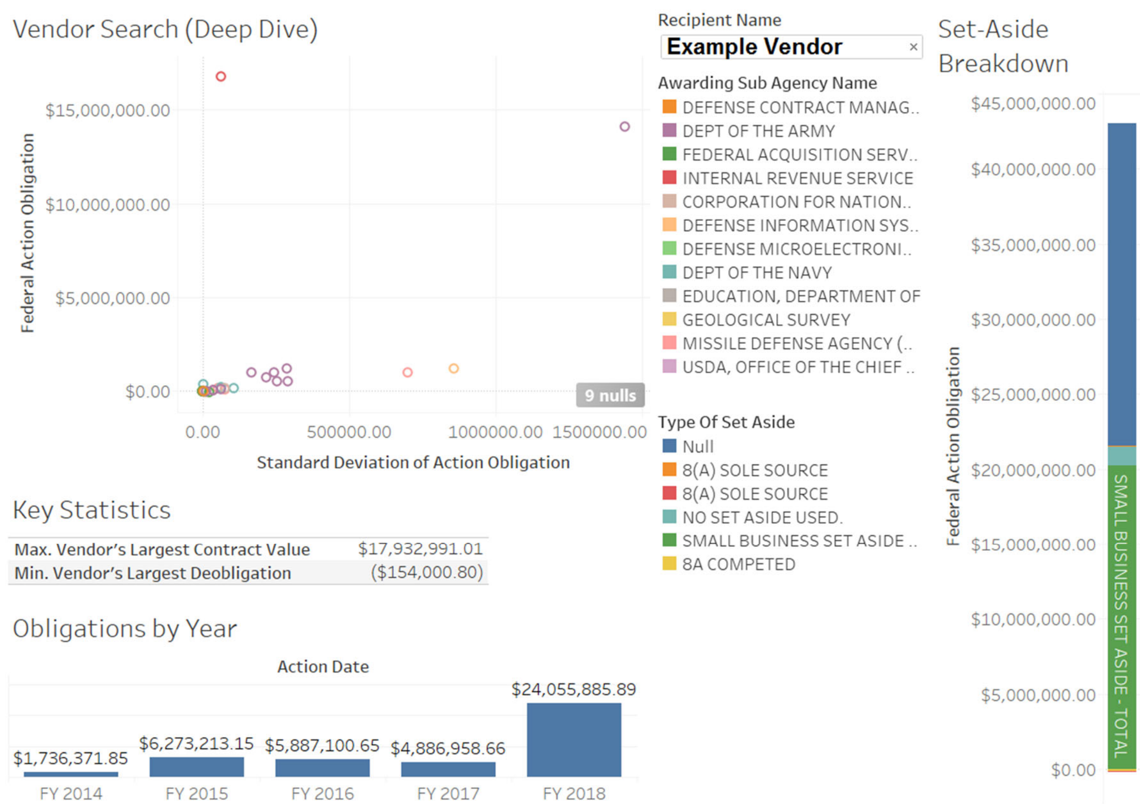

Figure 4. Prototype of a Procurement Analytics Platform

Limitations

We would be remiss not to acknowledge that limitations exist in our study and analysis. First, as the focus of our research is on firm-level characteristics, factors at other levels may influence the likelihood of contract failures. For instance, at the agency level, increases in an agency's capability and capacity to manage (i.e., administer) contracts and monitor contractor performance should decrease the likelihood of contract failures (Brown & Potoski, 2003). Further, evidence suggests that macroeconomic factors can exert a strong influence on the behavior of parties in buyer–supplier relationships (Krause & Ellram, 2014). We are unaware, to date, of research that has investigated how contract outcomes in the public sector might be influenced by between or within-industry variation (e.g., those relating to cyclical nature of the economy). More broadly, the literature recognizes that numerous forces come to bear on the effectiveness of public procurement, including market forces, internal forces, legal forces, social and economic forces, and forces internal to governments (Thai, 2001).

An additional limitation of our research involves the generalizability of findings. Given that our objective was to develop a *predictive* model, we sought to generalize to future times. We selected a model technique—random decision forests—as to minimize overfitting to the data (e.g., fitting to sample-specific idiosyncrasies in the data set). However, we are unable to state with certainty that the relationships uncovered in the data analysis are truly time-invariant.

Lastly, our choice of statistical technique comes with several trade-offs. One primary benefit of the approach is that it is able to account for non-linearities in the relationships between our explanatory variables and the response. However, this also comes at a cost of interpretability, as an easily interpretable coefficient reflecting the direction and magnitude of a relationship, such as what one might obtain in log-odds form from a logistic regression, is not directly estimated. As such, while we are able to assess the overall performance of the model and even assess the relative importance of variables in the model, we are not able to readily express and interpret relationships as might be accomplished after estimation of a parametric regression model.

Future Research

This research effort represents an initial, and very limited, investigation into the feasibility of predicting severe, future contractual issues through the analysis of open data. As such, it represents a first iteration, albeit one that suggests a high degree of promise. Future work should expand the variables and features under analysis (e.g., to include transaction-level variables, to include data on the economy) and explore alternative parametric and non-parametric modeling techniques.

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