Procurement Dynamics: Analyzing Federal Contract Awards to Microsoft*

Microsoft's Dominance in IT Procurement and Relationships with Government

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This paper analyzes federal procurement contracts awarded to Microsoft from 2020 to 2024, focusing on contract values, categories, and relationships with key government buyers. A Bayesian modeling approach was employed to predict contract amounts. The study highlights Microsoft's significant role in securing high-value contracts and maintaining steady partnerships with major departments such as National Defence. These findings provide important trends in federal procurement, drawing attention to the potential risks of dependency on a single supplier and challenges to competition.

Table of contents

*Code and data are available at: https://github.com/eeeee-cmd/Procurement/.

1 Introduction

Government procurement involves the acquisition of goods and services. The construction services by the government span a wide range of purchases, from office supplies to materials and services needed for large-scale infrastructure projects (Global Affairs Canada 2023). This process enables public innovation, economic stimulus, and fulfills strategic objectives. Within this landscape, the relationship between technology providers and government operations has become increasingly prominent. Despite the growing reliance on tech giants, limited research examines the dynamics of such partnerships, particularly in the context of federal procurement contracts.

This paper aims to address this gap by analyzing federal procurement contracts awarded to Microsoft from 2020 up to September 2024. Using publicly available data from the Investigative

Journalism Foundation (Investigative Journalism Foundation 2024a), the study focuses on contract values, categories, and Microsoft's relationships with key government buyers.

The main estimand in this study is the amount of federal procurement contracts awarded to Microsoft. This metric is analyzed across multiple dimensions, including contract categories, duration, and partnerships, to quantify Microsoft's role in federal procurement.

A Bayesian modeling approach is employed to predict future trends in the contract amounts, integrating prior knowledge with observed data to address uncertainty and provide more robust estimates. The findings reveal that Microsoft plays a dominant role in IT infrastructure and modernization, securing most high-value contracts and establishing consistent partnerships with departments such as Employment and Social Development Canada and National Defence. These findings highlight the broader implications of the private tech sector's influence on public sector procurement, raising questions about competitiveness, dependency, and strategic alignment.

This study contributes to understand the procurement landscape, providing valuable information for policymakers, industry stakeholders, and academics. The study underscores the importance of transparency, strategic planning, and balancing innovation with equity in government contracts.

The structure of the paper is as follows: Section 2 outlines the data sources and variables considered, followed by the model setup and justifications in Section 3. The results in Section 4 presents the key findings of the analysis, with a discussion on the implications. Section 5 then discusses potential limitations of data, model and suggestions for future research. The appendix provides additional detailed information about models in Section A and methodology in Section B.

2 Data

2.1 Overview

The data used in this analysis comes from publicly available procurement data (Investigative Journalism Foundation 2024a). The analysis uses the statistical programming language R (R Core Team 2023) and several libraries, including `tidyverse` (Wickham et al. 2019), `janitor` (Firke 2023), `knitr` (Xie 2024), `dplyr` (Wickham et al. 2023), `arrow` (Richardson et al. 2024), `purrr` (Wickham and Henry 2023), and `here` (Müller 2020) for data manipulation. `ggplot2` (Wickham 2016) and `kableExtra` (Zhu 2024) for visualization. The dataset covers the information of chosen Federal Procurement Supplier - Microsoft - capturing the contracts from 2020 to 2024 (up to September).

2.2 Measurement

The dataset used in this analysis originates from Canadian governments of all levels post solicitations for companies to search for business opportunities, as documented in Investigative Journalism Foundation (2024b), then collects data from each of these platforms and unifies into standard format.

The measurement process delegates contracts routed through Public Service and Procurement Canada (PSPC), and blanket disclosures organized by Treasury Board of Canada Secretariat (TBS) to understand the federal procurement. The methodologies of federal solicitations are either competitive or non-competitive. Competitive contracts accept bids from all or some subset of suppliers. Non-competitive contracts do not, citing certain exceptions, including a "pressing emergency in which delay would be injurious to the public interest," or when the estimated cost to the buyer is below certain thresholds defined for some goods and services.

More information about solicitation method can be found in Section B.

2.3 Data Cleaning

After imported the raw dataset using `read_csv` function, I first select specific columns to focus on relevant information towards this study by omitting redundant information, such as the contract link and same value of region. Then I rename key variables from raw data for clarity. The key variables of interest in this analysis include *Contract*, *StartDate*, *AwardDate*, *EndDate*, *Buyer*, and *Amount*.

I standardize the date format of all date related datas for proper parsing by using `mdy()` function and change the dollar format of amount into numeric numbers for future calculation purposes. Due to the error with unknown reason that *EndDate* is before *StartDate* or *AwardDate*, those entries were excluded from this paper.

PreparatoryPhase, *PhaseDays*, and *ContractDays* variables were created for the purpose of analyzing preparatory phase and performance phase corresponding to each contract. *PreparatoryPhase* calculates the days from *AwardDate* to *StartDate*. *ContractDays* calculates the days from *StartDate* to *EndDate*. *PhaseDays* take the absolute value of *PreparatoryPhase* because of the minor effect of either prepare before contract being awarded or prepare after contract being awarded. I also created new variables called *ContractType* and *BuyerCleaned*, which categorizes the most common buyers and contracts based on keywords.

This dataset contains only two entries for 2019 federal procurement contracts awarded to Microsoft. So, I filter out the contracts before 2020 to focus on the records between 2020 and September 2024 as desired. Also, I filtered missing data (NA) of *StartDate*, which only has one entry in this dataset. By summary the data set, I noticed a significant outlier with value of $102,260,150, which largely impact the outcome. So, I decide to drop this entry. Then I check the character type variables, *Supplier* and *Contract*, using `table()` function for the purpose of manipulating input error. I standardize the supplier's name which combine the similar name due to capitalization or some notation differences, and format them with first letter of each word capitalized.

After completing the cleaning, we saved the final dataset in both Parquet and CSV formats for later analysis.

2.4 Outcome Variables

The main outcome variable of interest is the amount of federal procurement contracts awarded to Microsoft. This variable is need to represent the financial magnitude of Microsoft with the federal government and measurement of evaluating procurement dynamics. Figure 1 is a histogram, which illustrates the annual total amounts of federal procurement contracts awarded to Microsoft from 2020 to 2024 (up to September). Figure 1 shows a generally increasing trend of total value of each year's contract. This may reflect the growing of technology in government operations, including software, cloud solutions, and IT infrastructure. The amount in 2023 doubles the amount in 2021, which suggests a heightened investment in federal procurement funding and large-scale projects.

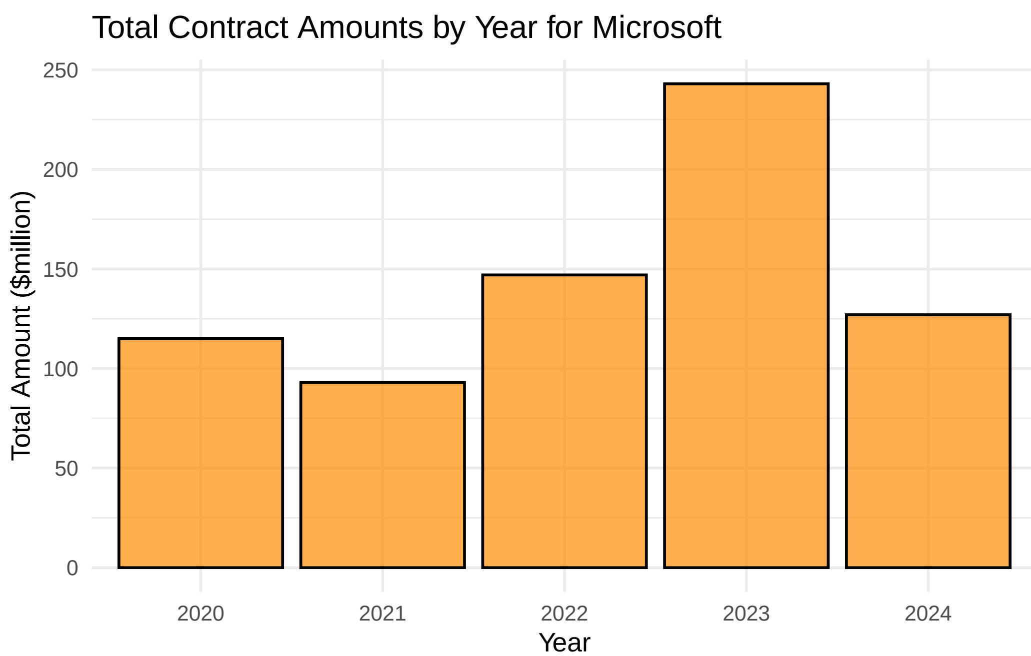


Figure 1: The histogram shows the distribution of the total amount ($million) of each year's federal contract (since 2020).

2.5 Predictor Variables

In this analysis, several key predictors were identified to evaluate procurement data effectively.

ContractType, is a character-type variable that identifies each procurement contract awarded to Microsoft into Categories. License/Maintenance Fees has the highest number of contracts (495) in Table 1, suggesting the recurring need for software and system maintenance. Computer Services has the highest average contract value ($1,763,432) in Table 1, reflecting the complexity and scope of IT services. Database Access Services also shows significant average values ($1,680,453), indicating the importance of large-scale data systems in government operations.

Table 1: The table summarizes the contract type which has over 25 contracts with the total dollar amount, and average dollar amount per contract.

Contract Type	Counts	Total Amount	Average
License/Maintenance Fees Related	495	$250,972,089	$507,014
Computer Services Related	118	$208,084,958	$1,763,432
Distributed Computing Environment Related	99	$25,125,005	$253,788
Consulting Related	83	$72,849,085	$877,700
Database Access Services Related	49	$82,342,191	$1,680,453
Software Related	45	$31,407,778	$697,951

Buyer is a character-type variable representing the federal government department or agency who initiate and award the contract. Table 2 shows the buyer who has over 25 contracts with Microsoft, which identifies key partners and understand the distribution of contracts across sectors. The table highlights that Employment and Social Development Canada (ESDC) and National Defence account over 50% of Microsoft's total awards.

Table 2: The table summarizes top 10 buyers with contract count, total dollar amount, and average dollar amount per contract.

Buyer	Contract	Total Amount	Average
Employment and Social Development Canada	116	$136,615,708	$1,177,722
Global Affairs Canada	71	$30,011,093	$422,691
National Defence	64	$81,913,883	$1,279,904
Natural Resources Canada	35	$12,856,204	$367,320
National Research Council Canada	32	$4,436,990	$138,656
Transport Canada	31	$16,297,432	$525,724
Indigenous Services Canada	28	$5,000,374	$178,585

Natural Sciences and Engineering Research Council of Canada	26	$4,626,898	$177,958
Shared Services Canada	26	$17,588,415	$676,478
Social Sciences and Humanities Research Council of Canada	26	$4,626,898	$177,958

This dataset contains a series of date-type variables capturing key milestones in the procurement process. **Award Date** is the date when the contract was officially granted to Microsoft. **Start Date** is the date when the contracted services or goods provision begins. **End Date** is the date when the contract is completed or terminated. These variables are essential for analyzing procurement timelines and trends over the study period.

PhaseDays is a numeric variable demonstrates the days between AwardDate and StartDate. In Figure 2, there is a high concentration around 0 indicates rapid procurement processes or emergency software services. Figure 2 also shows a few outlying contracts with a mobilization period of over one year. These long mobilization periods reflects issues such as delays in the procurement process, a long negotiation period, or administrative approvals.

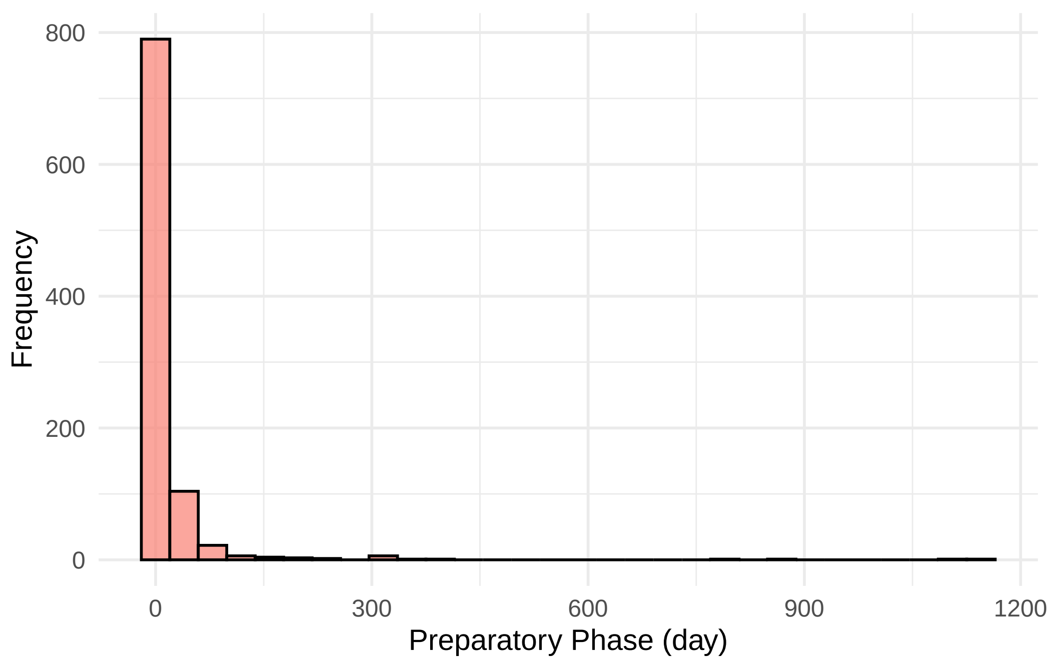


Figure 2: The histogram shows the distribution of preparatory period.

ContractDays is a numeric variable which is the days between $StartDate$ and $EndDate$. Figure 3 shows the distribution of performance period. The right skewed distribution in Figure 3 indicates that the majority of contract duration is within a year. There is an over 5 years performance period in Figure 3 implies a massive project that requires extensive preparation.

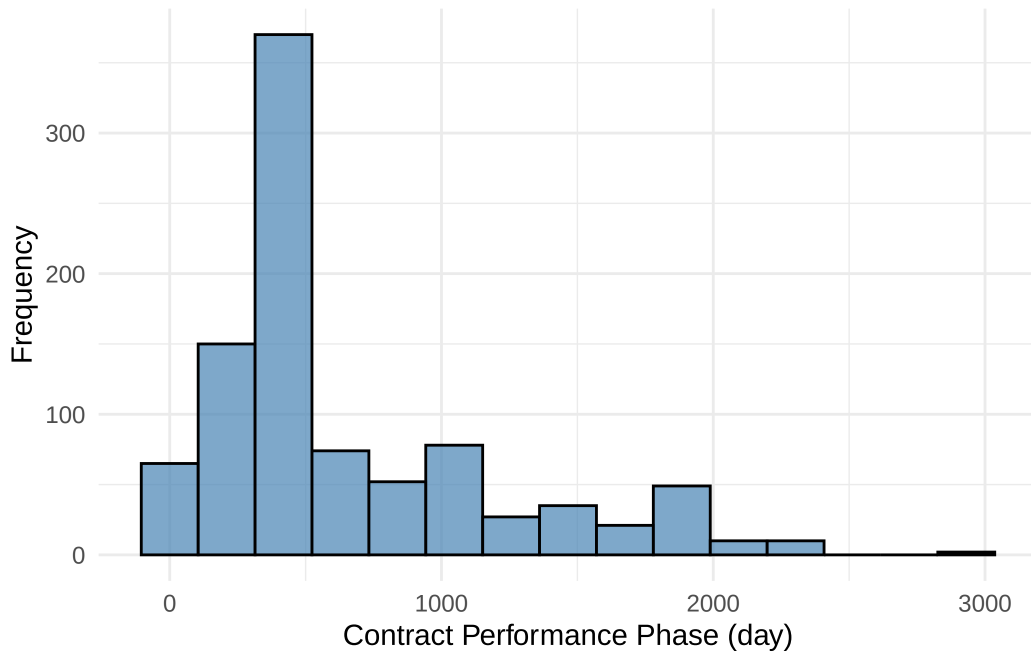


Figure 3: The histogram shows the distribution of performance period, which demonstrates the days between start and end date.

The correlation matrix in Figure 4 visualizes the relationships between key numerical predictor variables and the outcome variable, $Amount$. Figure 4 shows correlations include a weak negative correlations between $PreparatoryPhase$ and $ContractDays$; and weak positive correlations between predictors and $Amount$.

More information about the data analysis can be found in Section 4.

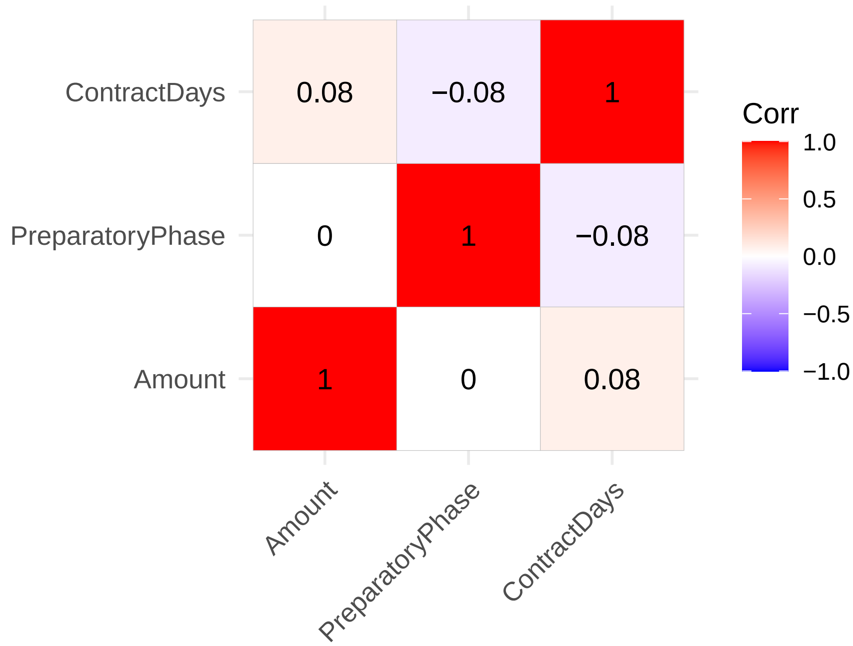


Figure 4: Correlation matrix showing the relationships between numerical predictor variables and the outcome Amount variable

3 Model

3.1 Model Set-Up

This paper utilizes a Bayesian model to examine the factors influencing the dollar amount of federal procurement contracts awarded to Microsoft. Define $Amount_i$ as the dollar amount of the federal procurement contract awarded to Microsoft and μ_i is the expected value of the contract amount modeled as a linear combination of the predictors. The model for predicting $Amount_i$ is specified as follows:

$$
\begin{aligned}
Amount_i \mid \mu_i, \sigma &\sim \text{Normal}(\mu_i, \sigma) \\
\mu_i &= \alpha + \beta_1 \cdot \text{ContractType}_i + \beta_2 \cdot \text{Buyer}_i + \beta_3 \cdot \text{ContractDays}_i + \beta_4 \cdot \text{PhaseDays}_i \\
\alpha &\sim \text{Normal}(0, 2) \\
\beta_1, \beta_2, \beta_3, \beta_4 &\sim \text{Normal}(0, 2) \\
\sigma &\sim \text{Exponential}(1)
\end{aligned}
$$

Where:
- α is the intercept term.
- $\beta_1, \beta_2, \beta_3, \beta_4$ are the coefficients associated with the predictors:

- $ContractType_i$: A categorical variable representing the contract type.
- $Buyer_i$: A categorical variable representing the buyer of the contract.
- $ContractDays_i$: A numeric variable representing the duration of the contract is active.
- $PhaseDays_i$: A numeric variable representing the days between AwardDate and StartDate.

The model is fit using the `rstanarm` package of Goodrich et al. (2022) in R (R Core Team 2023), with the specified priors guiding the model while allowing it to adapt to the data.

3.1.1 Model Justification

This paper expect that the factors - such as $ContractType$, $Buyer$, $ContractDays$ and $PhaseDays$ - will influence the outcome of contract amount. In particular, $ContractType$ captures the service or product, such as software licenses or consulting services, which significantly influences contract value. $Buyer$ reflects the federal department or agency awarding the contract, as some departments have higher budgets and strategic priorities that result in larger contracts. $ContractDays$ and $PhaseDays$ quantify the duration and preparatory timelines of contracts, providing insight into their scope and complexity.

In this paper, I compared linear regression and Bayesian regression to examine the factors influencing the federal procurement contract amount. Each of these models offers different advantages and trade-offs. More detailed justification about model selection will be discussed in Section 5. The Bayesian model is selected due to better performance and flexibility.

Bayesian approach can explicitly model uncertainty by incorporating prior knowledge and provides a full posterior distribution of the model parameters. This is useful when the data is sparse and prior knowledge about the contract types, buyers, or duration is available. The linear regression structure was selected due to its simplicity and interpretability. The numeric dependent variable, $Amount_i$, gives a chance of linear regression for modeling the relationship between the contract amount and its predictors.

By including weakly informative priors for the coefficients and residual standard deviation, the model remains flexible and interpretable, while still preventing extreme parameter estimates. The use of an exponential prior for σ allows the model to adapt a scale of residuals in the data, providing estimates of the variance. The normal prior for the coefficients $\beta_1, \beta_2, \beta_3, \beta_4$ with mean 0 and standard deviation 2 shows the expectation that the coefficients should not be too larg but flexible enough to adapt the data.

This Bayesian regression model balances complexity with interpretability, and its flexibility with quantifying uncertainty around the estimates, especially when the sample size is not large and the predictors have a complex relationship with the outcome.

3.2 Assumptions and Limitations

The model takes several assumptions, including linear relationship between predictors, normality of the residuals, independence of observations, homoscedasticity, and reasonable chosen priors.

While the model presents some valuable observations of Microsoft's federal procurement contracts, there are some model limitations including prior function selection, data quality, potential for endogeneity, generalizability, and unobserved variables. These limitations will be discussed more detailed in Section 5.4.

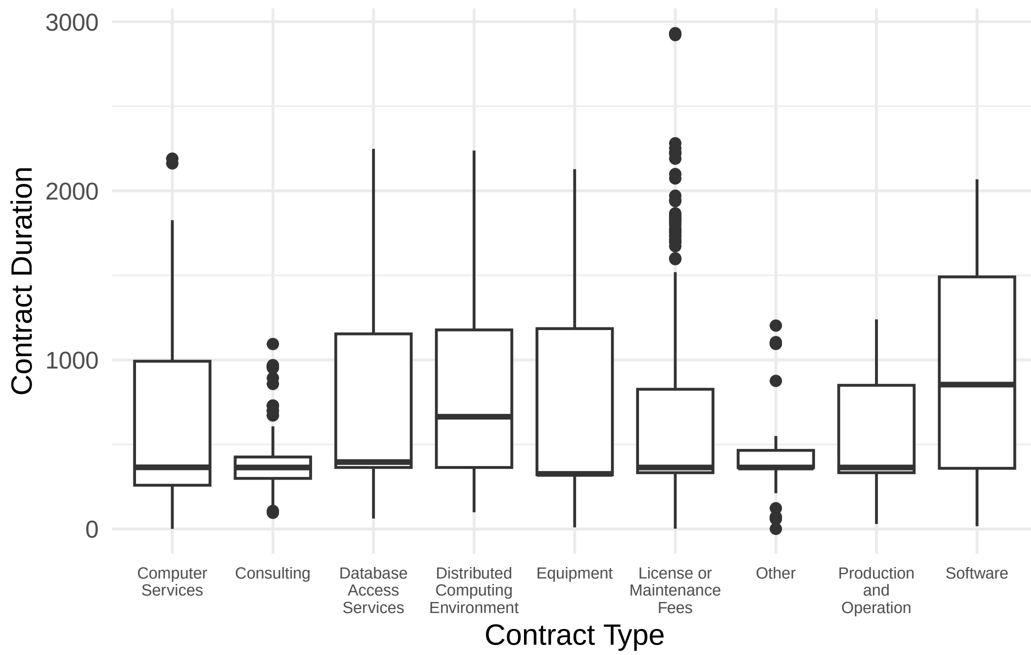
4 Results

4.1 Data

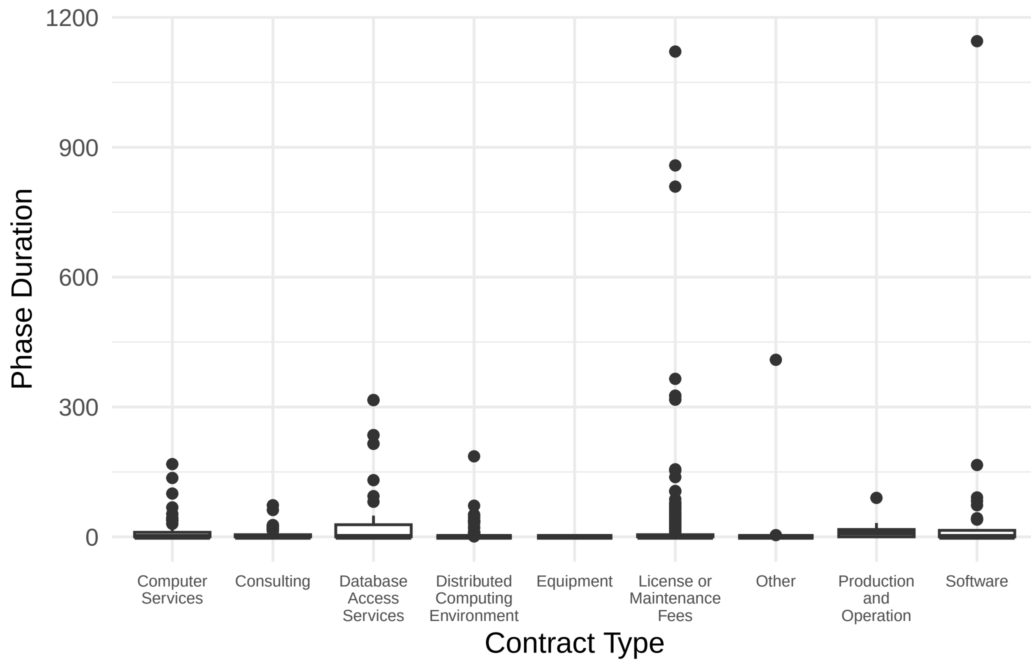
The boxplot Figure 5a shows the Contract Duration across various Contract Types. As we can see in Figure 5a, Computer Services and Consulting contracts tend to have longer durations. This suggests these contracts often involve more complex or ongoing services that require extended timelines. In contrast, License/Maintenance Fees and Software contracts show shorter durations, with tighter interquartile ranges and lower medians, indicating that these contracts are likely less complex and are typically limited to a defined time period.

The boxplot Figure 5b shows the Phase Duration for each Contract Type. Figure 5b highlights Consulting and Distributed Computing Environment have longer preparatory phases, with a higher median and a larger spread. This suggests these contracts require more time for negotiation, planning, or administrative procedures before the actual work begins. On the other hand, Computer Services and License/Maintenance Fees contracts exhibit shorter preparatory phases, as evidenced by the lower medians and narrower interquartile ranges in Figure 5b. This suggests that these contracts are more straightforward and may require less preparation before implementation.

The heatmap Figure 6 shows the distribution of federal procurement contracts awarded to Microsoft over four-month periods from 2020 to 2024. The frequency tends to drop in the September–December period, it suggests the budgetary constraints or the fiscal year-end. A noticeable decline occurs in 2024 because the data only updates until September. The darker shades during early and mid-year in Figure 6 align with expected procurement trends, where departments allocate funds proactively before the fiscal year closes. Understanding this distribution provides critical insights into procurement planning and Microsoft's role during different periods.



(a) Contract Duration in each Contract Type



(b) Phase Duration in each Contract Type

Figure 5: The Boxplots shows the relationship of ContractDays and PhaseDays with ContractType.

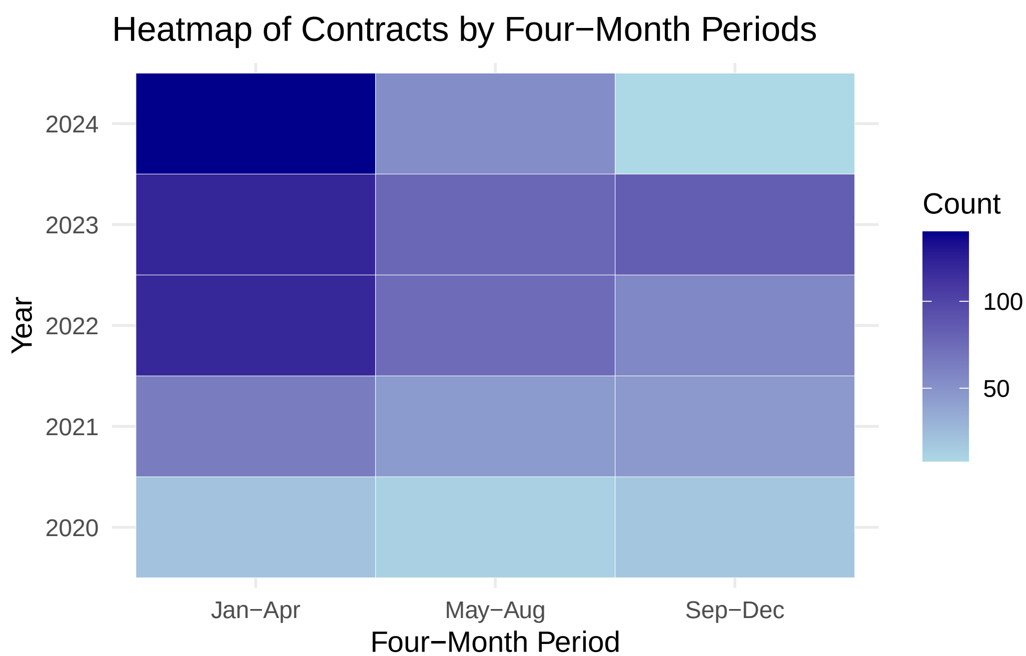


Figure 6: Heatmap of Contracts by Four-Month Periods (2020–2024). The heatmap shows the frequency of federal procurement contracts awarded to Microsoft in each four-month period, with darker colors representing higher contract frequencies.

The scatter plot Figure 7 shows the relationship between the Award Date and the Start Date of federal procurement contracts awarded to Microsoft. Most points lie on the diagonal line indicating the numerous contracts commence immediately after being awarded. This is particularly common for time-sensitive contract types, such as License/Maintenance Fees Related. Contracts in 2020–2021 tend to exhibit a wider spread in start dates, possibly reflecting a slower procurement process during those years. More recent contracts in Figure 7 cluster closer to the diagonal, suggesting streamlined processes or more immediate implementation needs.

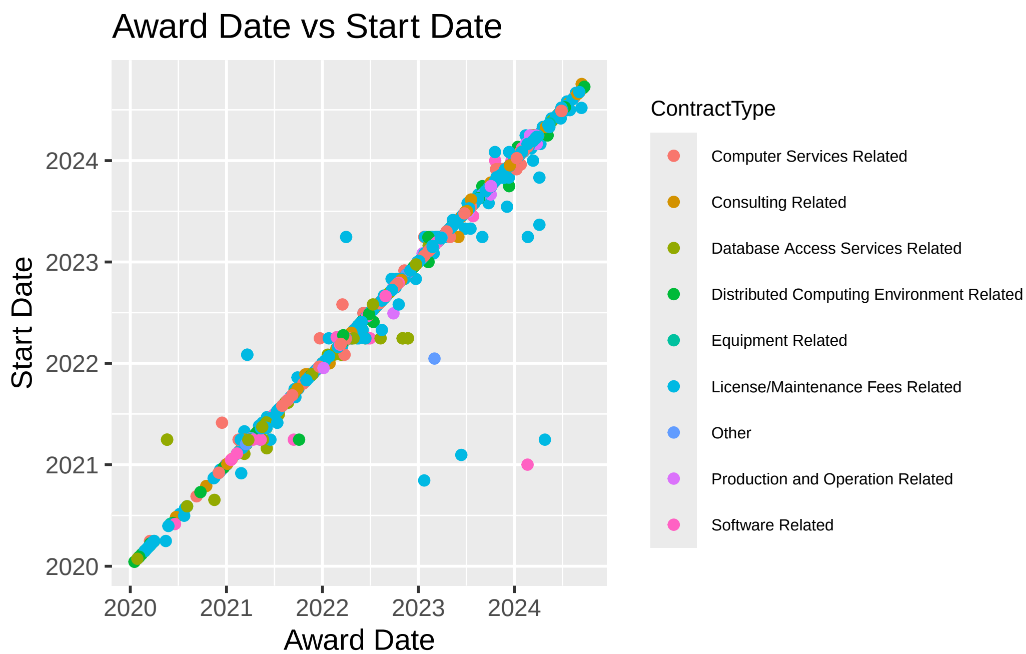


Figure 7: The scatter plot shows the relationship between Award Date and Start Date for the top 10 federal procurement contracts types. Each point represents a contract, with colors indicating different contract types. The plot helps to identify trends in the timing between contract award and commencement.

The scatter plot Figure 8 shows the diversity in contract durations across procurement categories. Most contracts ends within one year of their start dates, suggesting that most federal contracts are short-term. A smaller subset of contracts extends beyond three years, typically associated with large-scale projects or ongoing support agreements. Figure 8 also highlights that the most contract ends in the year of 2026. A few contracts with over 5 years stand out in 2021, suggesting that longer durations are prevalent in service-oriented categories.

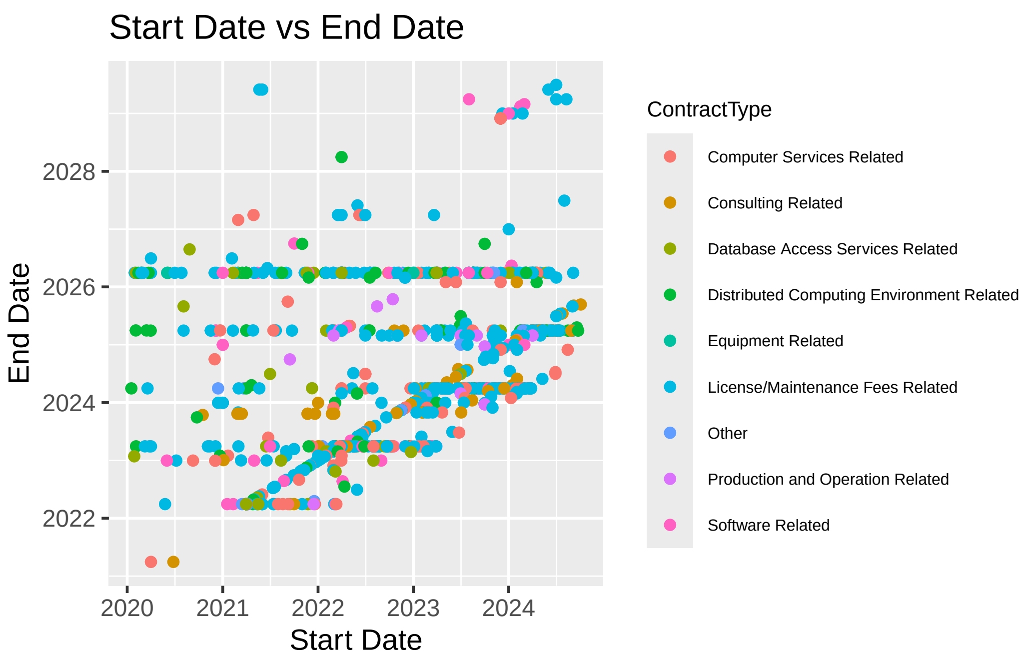


Figure 8: The scatter plot shows the relationship between Start Date and End Date for the top 10 Microsoft's federal procurement contracts types. Each point represents a contract, and the color reflects the contract type. This visualization provides insights into the duration of the contracts and any deviations from expected timelines.

Table 3: Explanatory models of contract amount based on ContractType, Buyer, ContractDays and PhaseDays

	Bayesian Model_Full	Bayesian Model
ContractDays	849.377	593.873
PhaseDays	−606.621	−751.995
Num.Obs.	943	943
R2	0.289	0.080
R2 Adj.	0.034	0.024
Log.Lik.	−15 352.590	−15 398.434
ELPD	−15 513.5	−15 444.8
ELPD s.e.	145.6	180.3
LOOIC	31 027.0	30 889.6
LOOIC s.e.	291.1	360.5
WAIC	30 993.1	30 887.0
RMSE	2 715 600.33	2 972 718.22

4.2 Model Summary

The results are summarized in Table 3, including R^2, Log-Likelihood (Log.Lik.), Expected Log Pointwise Predictive Density (ELPD), Leave-One-Out Information Criterion (LOOIC), Watanabe-Akaike Information Criterion (WAIC), and Root Mean Square Error (RMSE).

The Full Bayesian Model has an R^2 of 0.289, indicating that approximately 28.9% of the variance in the contract amount is explained by the model. In comparison, the Reduced Bayesian Model explains only 8.2% of the variance in the contract amount, suggesting that the inclusion of additional predictors (specific buyers and contract names) improves the model's explanatory power. However, both models have very low adjusted R^2, which suggests that the model is not capturing much of the unexplained variance in the data.

The Full Bayesian Model has a Log-Likelihood of $-15,351.795$ and an ELPD of $-15,519.3$, while the Reduced Model has a Log-Likelihood of $-15,398.022$ and an ELPD of $-15,444.8$. These values suggest that the Full Bayesian Model fits the data slightly better than the Reduced Model, as it produces higher Log-Likelihood and ELPD values.

The Full Bayesian Model has a lower LOOIC $(31,038.7)$ and WAIC $(30,992.3)$ compared to the Reduced Model, indicating that the Full Bayesian Model is better at out-of-sample predictive performance. Lower values of LOOIC and WAIC are indicative of better model fit and predictive accuracy.

The Full Bayesian Model has a lower RMSE $(2,714,467.04)$ compared to the Reduced Model $(2,971,135.35)$, indicating better predictive performance. The lower RMSE value suggests that the Full Bayesian Model is more accurate in predicting the total contract amount.

5 Discussion

5.1 Contract Complexity and Cost

The positive association between $ContractDays$ and contract amount suggests that longer contracts are typically more expensive, reflecting the increased scope, complexity, and resource requirements of these agreements. This is particularly relevant for IT-related contracts, which often involve extensive development, maintenance, and support services.

5.2 Negotiation and Efficiency

The negative association between $PhaseDays$ and contract amount indicates that longer preparatory phases may lead to reduced costs, potentially due to more thorough planning, negotiation, or budgetary constraints. This insight can inform government strategies for managing procurement timelines to achieve cost efficiency.

5.3 Sector-Specific Effects

The significant variation in contract amounts across different contract types (e.g., Consulting, Software) and $buyers$ (e.g., National Defence, Employment and Social Development Canada) underscores the importance of sector-specific factors in procurement dynamics. Departments with higher budgets or critical mandates, such as National Defence, tend to award larger contracts, highlighting their influence in shaping overall procurement trends.

5.4 Model Performance and Limitations

The Bayesian model has low adjusted R^2 values. This means the model explains only a small portion (28.9%) of the variance in contract amounts. This suggests that important predictors may be missing. Also, missing or erroneous values in variables like $ContractDays$ or $PhaseDays$ could introduce bias and reduce the reliability of the results.

One limitation of the model is that it may fail to account for certain external factors or unobserved variables such as political factors, budgetary constraints, and departmental priorities. These external factors could lead to omitted variable bias, which also influence procurement decision.

The model assumes a linear relationship between the independent variables and the dependent variable, which oversimplify the dynamics of federal procurement. The model categorizes contract types and buyers into broad groups, which also oversimplify the true diversity of contracts awarded. Future studies could explore non-linear models, such as splines or machine learning approaches, to capture more complex patterns.

There may be issues of endogeneity, where causality runs in both directions between some predictors and the outcome variable. The amount of procurement from a buyer may influence the allocation of future budgets to that department, which in turn affects future contract amounts awarded to Microsoft. This reciprocal relationship could introduce bias in the coefficient estimates if not properly addressed.

5.5 Alternative Models Considered

Linear regression model was evaluated in the paper. While the linear regression model was straightforward and interpretable, it lacked the flexibility to incorporate uncertainty in parameter estimates. The Bayesian regression model was chosen as a middle ground, balancing flexibility, interpretability, and the ability to quantify uncertainty. However, the limitations observed in model performance suggest that future work could benefit from integrating features of these alternative approaches.

More results about these two models can be found in Section A.

5.6 Weaknesses and Next Steps

This paper provides a foundation for a deeper understanding of federal contract awards to Microsoft, but it also suggests several directions for future exploration. First, the study can expand to include comparisons with other major suppliers. By examining whether Microsoft's procurement trends are unique or reflective of broader patterns across industries. This gives a better understanding on assess whether certain dynamics are systemic within federal contracting practices.

Data quality and consistency issues are also of concern. The anomalies identified in this study, such as incomplete or inconsistent contract dates, highlight the need for improved data reporting standards. These discrepancies can be addressed in collaboration with government agencies to improve the reliability of procurement datasets and ensure that future analyses are more reliable and actionable.

Appendix

A Additional Model details

A.1 Bayesian Model

A.1.1 Posterior Predictive Check

In Figure 9a we implement a posterior predictive check, comparing the observed data, y and the posterior predictive replicated data y_{rep}. This shows how well the Bayesian model replicates the observed data. Figure 9a displays a pronounced spike at 0, where y has a significantly higher frequency of values at $0e + 00$ compared to the predictions from the model. This discrepancy indicates that the model fails to accurately capture the concentration of contracts with a value of exactly zero or near-zero, potentially due to missing covariates or unmodeled structural factors influencing the occurrence of zero-value contracts.

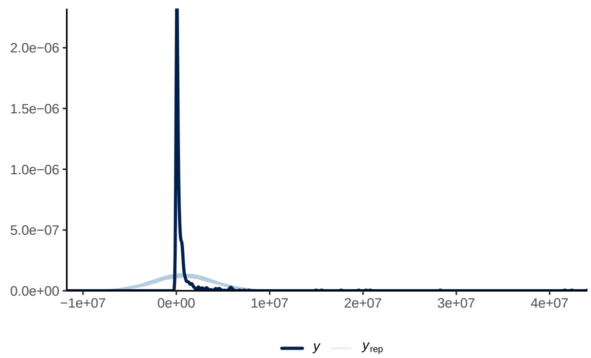
The predicted distribution y_{rep} in Figure 9a aligns more closely with the observed data at larger values, suggesting that the model performs well in capturing the behavior of non-zero contract amounts. However, the inability to replicate the sharp peak at 0 highlights a significant limitation in the model's ability to account for zero-value contracts or extreme sparsity in the data. This suggests a potential need for refinements, such as incorporating a zero-inflated component or additional predictors to explain this phenomenon.

In Figure 9b we compare the posterior with the prior. This shows the influence of the observed data on parameter estimates. For most parameters, the posterior distributions are narrower and shifted away from the priors, indicating that the data provides substantial information to update the prior beliefs. Some parameters, however, show minimal deviation from their priors, which may suggest either weak data informativeness or a lack of association with the response variable.

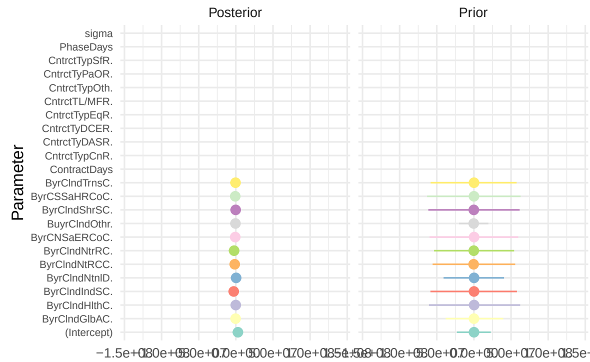
A.1.2 Diagnostics

Figure 10a is a trace plot related to $ContractType$. Each chain shows the sampled values of the parameters over the iterations of the Markov Chain Monte Carlo (MCMC) process. The chains for all contract type parameters appear to mix well and fluctuate around a consistent range, indicating convergence. There is no evidence of trends or drifts in the chains, which suggests that the MCMC process effectively explores the posterior distribution.

Figure 10b is a trace plot associated with $Buyers$. Similar to Figure 10a, the plot shows the sampled parameter values for multiple MCMC chains over iterations. The chains in Figure 10b for most buyer parameters exhibit good mixing and stability, with fluctuations around



(a) Posterior Prediction Check



(b) Comparing the Posterior with the Prior

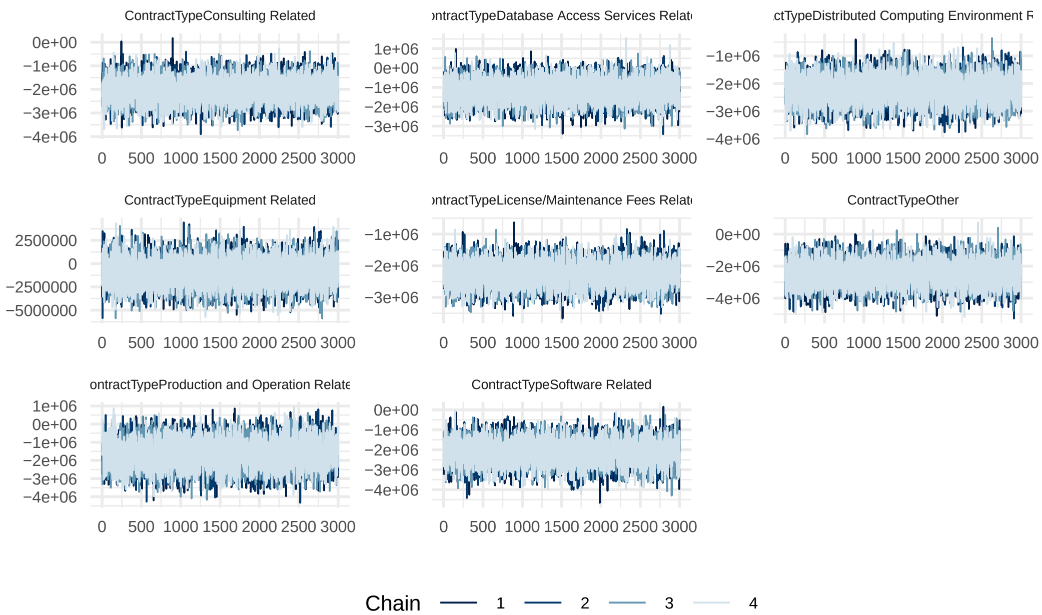
Figure 9: Examining how the model fits and affected by the data

a consistent range. This indicates effective convergence for the majority of buyer-related parameters. A few parameters in Figure 10b exhibit slightly slower mixing, but they still stabilize, suggesting no major convergence issues.

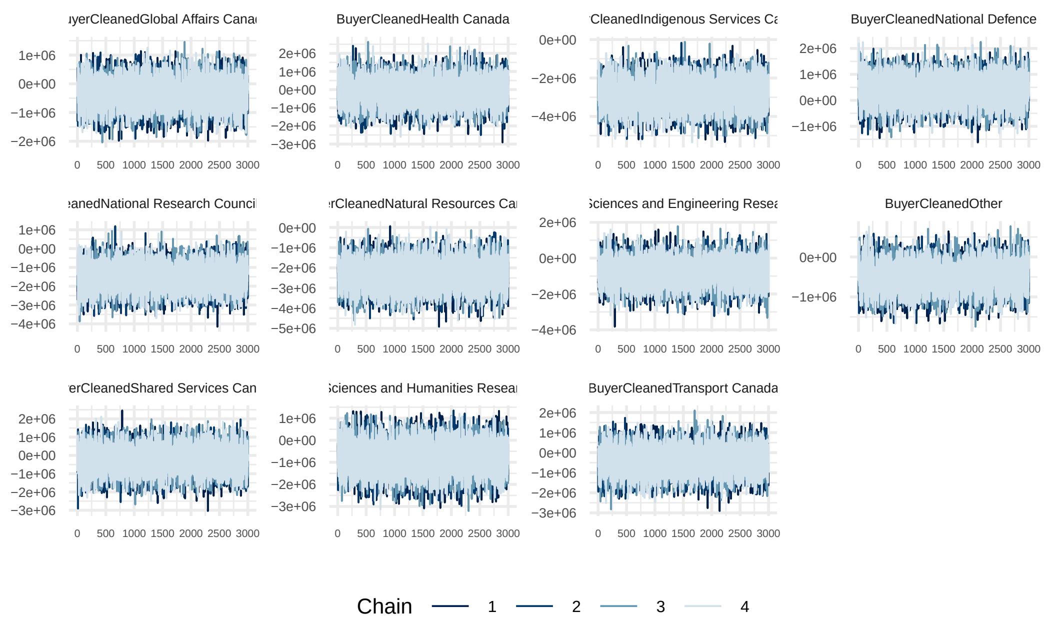
Figure 11 is Rhat plot. An Rhat value of 1.0 indicates that the MCMC chains have converged, meaning they are sampling from the same posterior distribution. If the Rhat value exceeds 1.05, it signals potential issues with convergence, indicating that the chains might not have mixed properly or that there is insufficient sampling to reach stable parameter estimates.

Figure 11a is a Rhat plot for the Full Bayesian model. The Rhat values for most parameters are around 1.0, which suggests that convergence has been achieved for the majority of parameters. There are no parameters with Rhat values exceeding 1.05, indicating that the model's convergence is sound.

Figure 11b is a Rhat plot for the reduced Bayesian model, which shows similar results. All parameters having Rhat values close to 1.0, further confirming that convergence is achieved across both models. There are no parameters with Rhat values exceeding 1.05, which supports the reliability of sampling process.

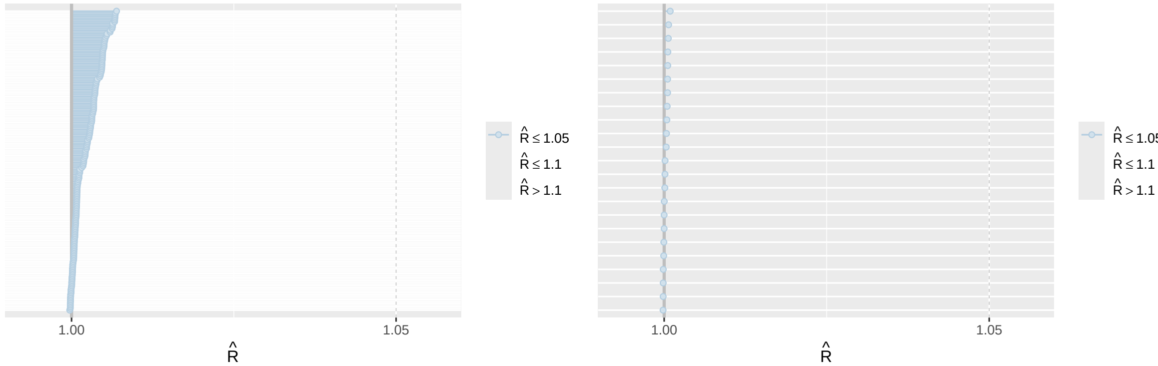


(a) Trace plot - Contract Type



(b) Trace plot - Buyers

Figure 10: Checking the convergence of the MCMC algorithm



(a) Rhat plot - Full model

(b) Rhat plot - Reduced model

Figure 11: Rhat plot for bayesian model

A.2 Linear Regression Model

The linear regression model is the most straightforward and interpretable among the models considered. It assumes a linear relationship between the outcome variable, *Amount*, and predictor variables - *Contract*, *Buyer*, *ContractDays*, *PhaseDays*. This makes it easy to understand how each predictor influences the contract amount. In Table 4, linear regression model achieved an R^2 value of 0.220, shows that only 22% of the variance in contract amounts is explained by the predictors. The Root Mean Square Error (RMSE) was approximately $2.71 million for the full model, indicating substantial prediction errors.

Linear regression models are computationally inexpensive and require fewer resources compared to more complex models like random forests or Bayesian regression.

Table 4: Summary of key model estimates for Microsoft, including coefficients for numeric predictors like Contract Days and Phase Days, with standard errors for each estimate. Model performance statistics, such as sample size, R^2, and adjusted R^2, are also displayed.

	Linear Model
ContractDays	849.091
	(232.512)
PhaseDays	−627.972
	(1707.431)
Num.Obs.	943
R2	0.218
R2 Adj.	0.051
AIC	30 952.0
BIC	31 766.7
Log.Lik.	−15 308.018
RMSE	2 715 207.36

B Methodology

The methodology employed in this study involves analyzing federal procurement contracts awarded to Microsoft, leveraging data from two primary sources: Public Services and Procurement Canada (PSPC) and the Treasury Board of Canada Secretariat (TBS). These two datasets provide information on government procurement, but they come with distinct limitations and reporting structures (Investigative Journalism Foundation 2024c).

B.1 Data Sources and Structure

Federal procurement data is categorized into two main streams:

- PSPC serves as the central procurement body for most federal government departments and is responsible for managing a significant portion of federal contracts. It maintains a public platform called CanadaBuys, where procurement information is published. However, due to migration from the older BuyAndSell platform and the incomplete nature of pre-2022 data, some variables, such as contract types and trade agreement information, are missing or inconsistently reported. The PSPC data is particularly useful for understanding contracts where the PSPC is the managing body, but only contracts above a certain dollar threshold are publicly available.

- TBS consolidates procurement data from all government departments and requires proactive publication under the Access to Information Act. The TBS dataset is more comprehensive in terms of the number of contracts, but it suffers from inconsistencies and gaps in the reported fields. TBS publishes data quarterly, and records before 2017 should not be considered complete. Unlike PSPC, TBS data includes the full details of contract awards but does not incorporate tender or solicitation data.

B.2 Data Integration and Challenges:

There is an overlap between TBS and PSPC data, such that many contracts reported by PSPC are also included in the TBS dataset. However, the two datasets do not always align perfectly. Contracts reported by TBS may contain different details from the PSPC records.

This mismatch is exacerbated by the lack of a consistent unique identifier that would allow for easy linking between the two datasets. While about 20% of PSPC awards have matching TBS records, many contracts do not, making it impossible to perfectly merge the two datasets.

To address this, both datasets were kept separate in (Investigative Journalism Foundation 2024c). PSPC data was used primarily for its comprehensive tender information, while TBS data was relied upon for its broader coverage of contract awards, spanning more years and a greater volume of contracts.

B.3 Solicitation Methods and Contract Types:

Federal procurement processes are governed by various solicitation methods, which determine how contracts are awarded. These methods are categorized into competitive and non-competitive processes.

Four competitive options:

- Open bidding: Any supplier can bid in response to an online solicitation.
- Selective tendering: Only some prequalified suppliers can bid.
- Limited tendering: Deviation from requirements of the relevant trade agreements (see Trade Agreements), still allowing bids.
- Traditional: Many suppliers can bid but not in response to a public, online solicitation; for example, responding to an email sent to suppliers by the government.

Two non-competitive options:

- Advanced Contract Award Notice: Notice to suppliers that the buyer intends to award a contract to a pre-identified supplier, while accepting a Statement of Capabilities, not a bid, from challenging suppliers.
- Non-competitive: Blanket category for all other non-competitive processes.

C Survey

Vendor Relationship Dynamics in Federal Procurement

Introduction

We are conducting a survey to better understand the dynamics of vendor relationships in federal procurement processes, particularly with major technology providers like Microsoft. Your responses will be kept confidential and used only for research purposes.

If you have any questions about this survey, please contact us: deyi.kong@mail.utoronto.ca

Section 1: General Information

1. **What is your role in the procurement process?**
   - Procurement Officer
   - Project Manager
   - Technical Specialist
   - Other (please specify): ______________
2. **How many years of experience do you have in procurement?**
   - Less than 1 year
   - 1–5 years
   - 6–10 years
   - Over 10 years
3. **Which sector or department do you primarily represent?**
   - National Defence
   - Employment and Social Development Canada
   - Natural Resources Canada
   - Other (please specify): ______________

Section 2: Vendor Interaction and Communication

4. **How would you describe your department's relationship with Microsoft?**

- Excellent
- Good
- Neutral
- Poor
- Very Poor

5. **How frequently does your department interact with Microsoft representatives?**
   - Weekly
   - Monthly
   - Quarterly
   - Annually
   - As needed

6. **What is the primary mode of communication with Microsoft?**
   - Email
   - Phone calls
   - In-person meetings
   - Online meetings (e.g., Zoom, Teams)
   - Other (please specify): ______________

Section 3: Relationship Dynamics

7. **To what extent does Microsoft involve your department in the decision-making process for solutions or services?**
   - Always
   - Often
   - Sometimes

- Rarely
- Never

8. **How would you rate Microsoft's responsiveness to your department's needs or concerns?**
   - Very Responsive
   - Responsive
   - Neutral
   - Unresponsive
   - Very Unresponsive
9. **Does your department feel valued as a client by Microsoft?**
   - Strongly Agree
   - Agree
   - Neutral
   - Disagree
   - Strongly Disagree

Section 4: Impact of the Vendor Relationship

10. **What is the biggest benefit of your department's relationship with Microsoft?**
    - Access to cutting-edge technology
    - Reliability of services
    - Cost efficiency
    - Strategic partnership opportunities
    - Other (please specify): ______________
11. **What challenges have you experienced in working with Microsoft? (Select all that apply)**

- High costs
- Limited customization options
- Slow response times
- Difficulty with contract negotiations
- Other (please specify): ______________

12. **How likely are you to recommend Microsoft as a vendor to other departments?**
    - Very Likely
    - Likely
    - Neutral
    - Unlikely
    - Very Unlikely

Section 5: Suggestions for Improvement

13. **What changes would you recommend for improving the relationship with Microsoft?**
    (Open text field)
14. **Are there alternative vendors you believe could meet your department's needs better than Microsoft? If so, please specify.**
    (Open text field)

Thank you for your participation in this survey. Your feedback is invaluable in understanding and improving vendor relationships in federal procurement. If you have additional comments or would like to receive updates on the research findings, please indicate below.
- [ ] Yes, I'd like to receive updates.
- [ ] No, I do not wish to receive updates.

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